# Modelling and Simulation of Urban Road Network Evolution Using Generative Network Models

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**Submitted in accordance with the requirements for the degree of**

**Doctor of Philosophy**

**University of Leeds**

**Institute for Transport Studies**

**May, 2019**

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## Acknowledgments

I would like to thank my supervisors Professor David Watling and Dr Richard Connors, my undergraduate supervisor Professor Jin Qin, my parents and friends, and the Chinese Scholarship Council.

## Abstract

Empirical and modelling Road Network Evolution (RNE) research from a network science perspective has increased in recent years. Empirical RNE research has quantified real-world urban road network characteristics and dynamics. Modelling RNE research has proposed Generative Network Models (GNMs) to reproduce statistically empirical urban road network characteristics.

This thesis proposes a novel framework to address the evolution of urban road networks through modelling and simulation of Node Addition and Link Connection, respectively.

First, this thesis generalises the Link Connection generative mechanism of urban road networks, as a process of examining the proximity relationship between a new spatial location and the urban road network, using β-skeletons proximity relationships with $\beta \in [1.0, 2.0]$. Proximity relationships come from a family of proximity graphs, which determine node connections by various geometric closeness definitions.

Second, the proposed GNM of urban road network evolution and the generalised Link Connection are shown to be capable of giving rise to both static and dynamic network structures, raising in correspondence to empirical RNE findings. The simulation identifies originally parallels between the simulated network dynamics and empirical RNE characteristics, demonstrating the proposed model's capacity in modelling the dynamic RNE in addition to network generation. By controlling the $\beta$ parameter, the proposed GNM is shown to be capable of modelling a broader range of plausible urban road network structures than previous studies in this field.

Third, this thesis proposes an original hybrid model of population and urban road network coevolution, which models population and road network dynamics on two inter-dependent layers and integrates GNM and RNE into the urban system through Node Addition. Various spatial decision combinations are explored, instead of assuming fixed population and road network spatial preferences.

Fourth, the proposed coevolution model is shown to be capable of giving rise to diverse road network and population spatial structures, from centralised to decentralised on the global scale, clustered to dispersed on the local scale. The simulation suggests that related push and pull forces across urban system layers drive the coevolution, leading to a spatial structure spectrum, rather than fixed clear-cut types (Marshall, 2004; Huynh et al., 2017; Moosavi, 2017). The proposed model also simulates the emergence of population-driven dispersed spatial structure and road network-driven linear spatial structure. The simulation finds the variation of network spatial structure is one potential cause of differences in network characteristics, demonstrating a necessity to consider the spatial structure in urban road network structure analysis.

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## List of Abbreviations

| | |
|---|---|
| **BC** | Betweenness Centrality |
| **DE** | Densification and Exploration |
| **DT** | Delaunay Triangulation |
| **GNM** | Generative Network Model |
| **MST** | Minimal Spanning Tree |
| **RNE** | Road Network Evolution |
| **RNG** | Relative Neighbourhood Graph |
| **USS** | Urban Spatial Structure |

# Chapter 1 Introduction

## 1.1 Background

### 1.1.1 Transport and Urban Questions

Cities are there at the dawn of human civilisation, and so are the questions about cities - their origins, transformation, and prospect (Mumford and Copeland, 1961). After more than a hundred years of industrialisation and urbanisation, cities become central to the majority of the global population. Urban problems arise, some of which are density, poverty, congestion, social injustice, connectivity. The city turns into a study object of its own right (Burgess et al., 1925), and urban studies proliferate. Faced with current urban problems, the understanding of cities and how they develop is expected to lay the foundation of an alternative urban future (Mumford and Copeland, 1961).

Transport and transport studies accompany the development of cities and urban studies. Before modern urban studies, the understanding of cities is mostly geographical, of their locations along critical water, land, and railway transport routes (Knox and McCarthy, 2012). Urban economics establishes theories of the relationship between urban land price, transport cost and land-use utility (Alonso, 1960; Isard, 1956; Fujita et al., 2001), refines with individual decision-making behaviours (O'sullivan, 2007), and provides a leading strand of urban theory (Wilson, 2014). After the Second World War, private car ownership increases, followed by road construction and congestion (Knox and McCarthy, 2012). Transport studies divert the research focus from rural and interurban to urban transport with pioneering studies of Detroit and Chicago, develop the Origin and Destination survey, and predict travels between transport analysis zones (Black, 1990). Applying the gravity models from social physics which use physics analogy to construct mathematically human interactions and urban scaling relations (Carrothers, 1956; Stewart, 1941; Zipf, 1942), pioneering urban models evaluate and predict locations of work, residence, and transport efficiency, and set up a framework to model urban development according to the land-use and transport interaction (Lowry, 1964). Car dominance and suburbanisation (Knox and McCarthy, 2012) attract attention of urban design and planning to problems such as the urban sprawl, through the perspective of urban form and function: whether the transport system should be designed to fit a city or the city should grow oriented by transport development (Kelly, 1994).

In short, the transport system performs critical urban functions and poses critical urban challenges, constituting both essential urban problems and answers. The development of urban and transport systems, of urban and transport studies intertwines; understanding one system requires understanding the other. Various research fields bring their theories and methods into solving the urban and transport problems, leaving diverse research perspectives and approaches.

### 1.1.2 The Quantitative Revolution and Networks

The research history that this study is further linked, begins in the mid-20th century with the social science revolution which aims at studying the society scientifically, and the rise of system theory, which enables different disciplines to approach their research subjects using a transferable system approach (Batty, 1976).

The quantitative geography revolution applies graph theory to analyse the flow-accommodating network structure in geographical systems, including transport networks (Garrison and Marble, 1962; Kansky, 1963). From a topological and geometrical perspective, quantitative geographical network analysis further explains how geographical networks form and change. For example, three network spatial growth sequences are identified: node-connecting, space-filling, and space-partition; also, simulation models are proposed to explain or reproduce geographical networks by generating targeted network characteristics, rather than picture a step-by-step growth process (Haggett and Chorley, 1969). Compared to deterministic models, e.g. with a predefined goal to optimise, these early probabilistic models and computer simulations are regarded as feasible and appropriate to explore systems resulting from numerous individual decisions over time and space (Gould, 1970).

With the prevalence of transport demand and land-use modelling in the following years, the research interest in transport networks shift from network structural to functional.

Transport networks channel spatial interaction flows in transport demand and land-use-transport modelling (Haggett et al., 1977; Sheffi, 1985). Transport geography studies the spatial organisation of mobility; from this perspective, changes of a transport system are influenced by the interactions between the transport system and the urban spatial structure but are fundamentally driven by transport technology development (Rodrigue et al., 2016). The transport system, urban form and urban spatial structure are considered as intrinsically related (Rodrigue et al., 2016). The transport system consists of nodes (e.g. transport terminals), network (spatial organisation of transport infrastructure), and transport demand. Urban form refers to the spatial imprints of transport infrastructure as well as adjacent physical built environment. Urban spatial structure refers to the spatial interactions of people, goods, and information underlying the urban form, which consists of nodes (clusters of socio-economic activities) and links (connections between socio-economic activity locations).

Transport demand modelling uses a framework of transport supply, demand, time and space to approach transport system development and network growth. Transport supply refers to transport infrastructure and is represented by a geographical network; supply decisions are realised through changes in the network by expanding or adding links. Transport demand is derived from land-uses. Changes of the transport system are explained as driven by the interaction of demand and supply while constrained by time and space (Xie and Levinson, 2011). Transport network design optimises transport performance and minimises travel cost with link improvement or addition (Yang and H. Bell, 1998).

The network structure research interests of transport networks revive with the development of network science (Xie and Levinson, 2011). Network science provides for transport studies the network representation, interdisciplinary knowledge and measures, while transport studies provide problems for network science to study and domain knowledge (contributors, 2011). Reviving quantitative geography's initiatives from decades ago in network analysis and modelling, network science differs from the former by utilising substantial amount of data and exploring how statistical physics can contribute to the subject. Statistical physics studies the statistical regularities in large systems by a few system characteristics: empirical statistical regularities indicate mechanisms behind their emergence, which further lead to the construction of simple models that agree with empirical findings (Barthelemy, 2017). Therefore, this perspective explores transferable mechanisms and processes across urban systems that direct the evolution of transport network as well as of urban system, putting aside different local influences (Barthelemy, 2016).

### 1.1.3 Complexity

Besides the quantitative revolution, system theory's applications across disciplines around the same period increase the recognition of complexity in natural and artificial systems, which further develops into complexity theory. A complex system consists of simple components, which follow local rules rather than central control; hard-to-predict system behaviours emerge, hence “the whole is more than the sum of its parts” (Mitchell, 2009). Complexity theory enables different disciplines to view their research subjects using a transferable complex perspective.

Complex networks represent complex systems; some systems are networked; some have structures better revealed with the network representation (Barabasi, 2016). The small-world (Watts and Strogatz, 1998) and scale-free (Barabási and Albert,

1999) properties in real-world complex networks reveal that complex networks are not random and do not come into being by chance. Explanations of these properties by network formation and dynamics mechanisms manifest that complex networks are intrinsically dynamic, and the mechanisms behind network formation and dynamics are essential to understand their structures (Boccaletti et al., 2006).

The evolution of complex networks shows in the emergence and changes of their characteristics (Dorogovtsev and Mendes, 2013). Static network structure refers to network characteristics at a fixed time, and dynamic structure refers to the changing network characteristics with time (Barabási et al., 2002). Complex networks' evolution can be studied through a sequence of static network snapshots, by analysing network characteristics of each snapshot and the changes of network characteristics across snapshots (Rocha, 2017).

Further, complex systems co-evolve within a broader “ecosystem”. The co-evolution here means that a system’s evolution depends partially or totally on related systems; adaptation of the system during its evolution influences both related systems and the environment (Mitleton-Kelly, 2003). Accordingly, it is recognised that the evolution of transport and the urban system cannot be viewed separately. For instance, the transport network accesses spatial locations while buildings occupy spatial locations; their dynamics and development feedback on each other; the transport system and the urban system co-evolve(Schweitzer and Nanumyan, 2016).

Viewed as complex systems, complexity theory and methods are applied to transport and urban systems. Transport networks have been perceived as changing by top-down transport supply policies from a central authority to maximise efficiency; acknowledging their complexity, transport systems' changes are viewed increasingly as resulting from public and private suppliers’ interactions, pursuing different interests (Xie and Levinson, 2011). At the same time, the new science of cities thinks of the urban system as emergent macroscopic phenomenon based on microscopic urban components’ self-organisation; the urban system is considered as a networked structure built from bottom-up; external forces do not determine system behaviours but trigger the internal self-organisation instead; complex urban phenomena emerge (Barthelemy, 2016; Batty, 2013; Portugali, 2012b). Moreover, a bottom-up complex urban theory bringing together essential urban components - population, transport infrastructure, and socio-economic welfare, is proposed: urban system exists and operates because of individuals’ social interactions, which are realised through the transport network, when socio-economic welfare created by social interactions exceeds the infrastructure cost (Bettencourt, 2013).

System theory also stimulates bottom-up simulations and computational experiments in urban modelling. The all-encompassing land-use-transport models are criticised as overly comprehensive, having a gap between many objectives and variables and the limited control over modelled content (Lee Jr, 1973). Simple bottom-up models are developed instead (Batty, 2009), such as Tobler (1970)'s urban growth model of Detroit, which demonstrates a simple modelling framework and mechanism can as well simulate complex urban phenomena. This bottom-up modelling and simulation approach aims at understanding rather than predicting, does not impose optimisation as a goal of the urban system, and considers the urban system as intrinsically dynamical, which distinguish it from other operational urban and transport models (Batty, 1976).

Recognition of the urban complexity manifests in the qualitative urban studies as well.

Urban morphology reads cities through their physical form. Streets, together with buildings and blocks, are basic elements used to read cities (Moudon, 1997; Oliveira, 2016). The structure and transformation of human settlements, such as towns and villages, are attributed to historical and socio-economic factors (Kropf, 2017), such as developing period and cycle (Conzen, 2018). Streets are thought as a framework of socio-economic changes (Whitehand, 2001), whose current form can be explained in terms of historical development and will persist in influencing future socio-economic changes (Kropf, 1996). Complexity and evolutionary thinking are recognised with the unresolved paradox regarding the urban form being both planned and emergent (Kropf, 2009).

Historical geography traces details of urban development since early human settlement (Mumford and Copeland, 1961); in particular, history of urban form studies patterns and elements of urban form, as well as changing processes and influencing factors (Morris, 2013). Cities are classified by historic origins of their urban form - streets, plots, and buildings, into historic periods, such as early settlements, Greek, Roman, Islamic, Medieval, Renaissance, 19$^{th}$ century and modern (Oliveira, 2016). From a historical perspective and analysing socio-economic changes, urban form is thought as a result of human purposes, and no urban form can be viewed as totally unplanned; however, urban planning is not single-minded but negotiated and broadly shared, and urban form is ever-changing and never at rest (Kostof, 1991). The evolution of urban form is thought as incremental and continuous in the traditional cities but are massively interrupted by major human initiatives like the WWII and Modernity, causing typological differences of urban form between the tradition and modern (Marzot, 2018), before and after the WWII (Dibble et al., 2019). Streets are an essential element of urban form: once invented, streets rise as public space with political powers and experience regulation to improve safety, public health and traffic situation; returning from the modernist treatment as traffic corridors, streets resume the recognition as public space for individual human beings (Kostof, 1992).

Urban design regards cities as individual historical phenomena (Lynch, 1984), which are never final results but phases of constant changes (Lynch, 1960). Cities and their changes are not and cannot be controlled by a central authority or masterplan (Alexander, 1977) but are due to constant building processes (Lynch, 1960) and cumulative decisions (Lynch, 1984), which are reflected in the history of shifting planning paradigms (Hall, 1988). Still, the urban form has been considered as an issue of design (Lynch, 1960), mirroring good or bad values (Lynch, 1984). Repeated problems or patterns occur in urban form, each of which can be solved by design (Alexander, 1977). For example, streets, together with other elements of urban form, should be legible to citizens, thus enabling them to grasp a coherent image of the city easily; consequently, the design goes into streets' continuity and direction to ease orientation (Lynch, 1960). Streets are also designed to follow the intrinsic spatial hierarchy on different urban scales (Alexander, 1977). However, it is increasingly recognised that most spatial developments emerge largely autonomously resulting from a mix of factors and would have occurred even without planners (de Roo and Rauws, 2012). New approaches to urban design and planning orient around the urban complexity, with strategies of the collective planning (Batty and Marshall, 2012), self-planned cities (Portugali, 2012a), and the adaptive design (Salingaros, 2012).

The complexity perspective to think about urban and transport systems is becoming a new paradigm, which unites ideas and development in urban and transport studies in the last century (Batty, 2013). Quantitatively, the geographical network analysis since the 1960s and the urban modelling since the 1970s are a pioneering effort which contributed to the emergence of the complexity perspective. Qualitatively, research fields, such as historical urban morphology, urban planning and design, all describe the urban form as not static but constantly changing, in which urban streets and their changes play an essential role. Though changes of urban streets have been attributed to socioeconomic, historical, design and planning respectively, these qualitative fields perceive such changes as resulting from many interacting forces rather than from central control, demonstrating the complexity thinking of urban systems.

### 1.1.4 Generative Modelling and Simulation

Merging the urban complexity and the bottom-up urban modelling, some urban models look specifically into generating urban form. Batty and Longley (1994) apply fractal geometry to generate physical urban form and urban properties, such as boundaries, networks and population spatial distribution. The urban form, geometry, layout and configuration are seen as manifestations of socio-economic processes, urban problems and intrinsic order in cities, and fractal geometry is used as an urban theory to explain self-similar patterns in urban form across scales. Urban growth is modelled through generating urban form by cumulative addition and deletion of basic urban units and is seen as a space-filling process with physics analogy; simulations are used to explore possible ways, densities, and patterns to fill the urban space (Batty, 2013). Hillier and Hanson (1984) propose space syntax to analyse urban form, in particular streets and buildings; further, a generative syntax model is proposed to generate physical urban form by applying local rules to add and attach basic urban form elements “cell”, with certain randomness. Urban form is regarded as individual interactions’ embedment in space, in which streets generate transport flows and influence urban form and land-use (Hillier, 2007). Bejan (2000) proposes a constructal law which sees geometrical forms as a result of optimisation, and transport systems are explained by a mechanism to minimise travel time from one point to a finite area, leading to a dendritic structure.

In these generative urban form models, the concept “generative” stands out as a bottom-up approach to model urban growth. This approach relates emerging geometrical and topological structures to their formation mechanisms. The proposed mechanisms do not picture step-by-step urban growth but advance understanding of the urban system through the urban form generation. This generative modelling and simulation approach is rooted in complexity theory and explores generatively how local rules of microscopic urban components’ behaviours and interactions give rise to macroscopic urban form, in order to model the urban system and its dynamics (Epstein, 1999).

A Model represents a simplified real-world system, built to understand the original system better; a simulation implements and explores the model when the real system is mathematically and analytically difficult to track, especially with open systems in which not all the factors of interest can be controlled (Kelton and Law, 2000). Varying with data availability and current understanding of system structure and operation mechanism, modelling and simulation realise different research purposes (O'Sullivan and Perry, 2013). With reliable and detailed data as well as a thorough theoretical understanding of system structure and operation mechanism, simulation can make predictions and help decision-making. With well-understood mechanism and insufficient empirical support, simulation can guide data collection, by identifying critical factors to collect data on. With available data and limited theoretical understanding, simulation can be “tools to think with”. Simulation with working hypotheses of the system and comparison made between simulation results and empirical evidence can advance understanding of the system.

Complexity theory aligns with the bottom-up generative modelling and simulation approach. Deconstructing and reconstructing complex systems using their most simple components enable modelling mechanisms of component behaviours and interactions. Because complex systems are hard to tract analytically with emergent and hard-to-predict characteristics, simulation is a suitable tool to explore complex systems (O'Sullivan and Perry, 2013). Simulation can carry out computational experiments to test hypothetical mechanisms about the formation and dynamics of the complex system, study long term system dynamics, and explore potential future scenarios.

Understanding of cities enters the complexity era, and cities are increasingly perceived as networked complex urban systems. The urban questions may be updated to understand the origin, transformation and prospect of complex urban systems. As it has been in the urban and urban studies development, transport persists in the complex urban system to constitute an essential part of both urban problems and answers. With the network, complexity, generative bottom-up modelling and simulation lenses, how to understand urban road network structure and dynamics, and how may this contribute to understanding the complex urban system and urban future?

## 1.2 How Urban Road Networks Evolve: Research Dimensions

Xie and Levinson (2011) identify various dimensions to study the evolution of transport networks: topological, hierarchical, morphological, temporal, technological, economic, managerial, political. As discussed in section 1.1, research effort draws from different disciplinary perspectives to understand the urban system and diversifies into even more perspectives and research fields. In this broad background, the urban road network has been studied as a crucial component of both the transport and urban system. Multiple research dimensions can be identified regarding the research question – How urban road networks evolve? Table 1-1 summarises the economic, historical, design and planning, topological, geometrical, and modelling and simulation dimensions. These research dimensions all have their urban theories and methods, demonstrated in their varied perspectives on the evolution of urban road networks.

Dated back to quantitative geographical network analysis and revived with complexity theory and network science, an approach combining quantitative network analysis, complex systems, bottom-up generative modelling and simulation, to understand the evolution of urban road networks takes shape. This approach focuses on the network structure, perceives the transport system as complex and arising from simple components and local rules, and explores the system structure and dynamics through modelling and simulation. New insights into the urban questions may occur through bottom-up explorations of urban road network formation and dynamics, improving understanding of the spatial and temporal urban road network structure as well as urban road network's interactions with other urban components to realise population's social interactions and urban system's functions. Acknowledging these opportunities, an increasing number of studies look specifically into urban road networks' structure and dynamics from a network science perspective. Next section 1.3 introduces briefly this group of studies, which extends Table 1-1 with the network science perspective.

**Table 1-1 Research Dimensions of Urban Road Network Evolution**

| Research Perspectives | Objectives | Subjects | Road Network Evolution Theories | Dimensions |
|---|---|---|---|---|
| **Transport Geography**<br>(Rodrigue et al., 2016) | Understand the spatial organisation of mobility. | Transport system;<br>Land-use system. | Changes in the transport system are influenced by the complex relationship between the transport system and urban spatial structure but are fundamentally driven by transport technology development. | Economic |
| **Transport Demand Forecasting**<br>(Xie and Levinson, 2011) | Solve the transport problems. | Transport system;<br>Land-use system. | Transport network growth is driven by the interaction of transport demand and supply while constrained by time and space. | Economic;<br>Modelling |
| **Urban Morphology**<br>(Kropf, 2017) | Read cities from their physical form. | Urban form | Physical urban form, e.g. urban streets, are the framework of socio-economic changes and persist in influencing future socio-economic changes. | Design and planning |
| **History of Urban Form**<br>(Kostof, 1991) | Trace details of the development of cities and urban form. | Urban form | Urban form results from human purposes; no urban form can be viewed as totally unplanned. However, the planning is not single-minded but is negotiated and broadly shared. | Historical |
| **Urban Design**<br>(Lynch, 1984) | Propose normative theory of cities and urban form. | Urban form | Urban form is an issue of design, has good or bad values, and has repeated problems and solutions. | Design and planning |
| **Quantitative Geographical Network Analysis**<br>(Haggett and Chorley, 1969) | Quantitatively analyse the shared network structure of geographical systems. | Geographical networks | Geographical networks change by sequential patterns: node-connecting, space-filling, and space-partition. | Topological and Geometrical; |
| **Generative Urban Form Models**<br>(Batty and Longley, 1994; Hillier and Hanson, 1989; Bejan, 2000) | Generate the geometrical urban form. | Urban system | Urban system components' microscopic behaviours and interactions give rise to spatial and temporal patterns and orders in urban systems. | Topological and Geometrical;<br>Modelling and simulation;<br>Complexity theory |
| **Generative Road Network Models**<br>(Section 1.3) | Model the evolution of urban road networks. | Urban road network | Road network components' microscopic behaviours and interactions give rise to macroscopic network characteristics. | Topological and Geometrical;<br>Modelling and simulation;<br>Complexity theory |

## 1.3 Road Network Evolution (RNE)

In recent years, an increasing number of studies on Road Network Evolution (RNE), both empirical and modelling, approach the structure and dynamics of urban road networks from a network science perspective. This perspective studies topological and geometrical network structures, explicitly represent and analyse urban road networks. With the inherent complexity theory perspective, urban road networks are perceived bottom-up from elementary components. This perspective further enables the modelling and simulation of urban road networks in a generative manner, experimenting with hypothetical mechanisms behind the formation and dynamics of macroscopic network characteristics. In particular, this perspective considers network evolution as changes of the network structure through a sequence of static network snapshots and with trajectories of network characteristic dynamics, thus quantifying RNE.

Empirical RNE research studies a sequence of urban road networks' historical snapshots, as the examples in Figure 1.1. Using such historical road network data, these studies visualise urban road network evolution with time, analyse the static network structure in each snapshot, and quantify the changes of network characteristics with snapshots. Urban road networks studied include the Groane region in Italy, London, Paris, Sheffield, Khorramabad, Kerman, and Dundee (Strano et al., 2012; Barthelemy et al., 2013; Masucci et al., 2013; Mohajeri and Gudmundsson, 2014; Gudmundsson and Mohajeri, 2013). Based on observation and quantification, these studies propose RNE theories. For instance, the study of Groane road network proposes that road network grows by two elementary processes – the increase of road density around the urban centres and the addition of new roads at the urbanisation front (Strano et al., 2012). The study of London road network proposes the evolution of urban road network exhibits two properties: major roads exist before the beginning of urbanisation and persist, while minor roads are added in urbanisation through fractal space filling (Masucci et al., 2013).

Empirical RNE research, compared to other research dimensions discussed in 1.1, studies specifically the urban road network structure and quantifies explicitly changes of the network structure with network characteristics. Focusing on the urban road network structure, instead of the whole transport system or urban form, distinguishes this perspective from other research dimensions and may improve the understanding of mechanisms behind road network formation and dynamics, as well as of various influences on RNE. The empirical RNE research is reviewed in Chapter 2.

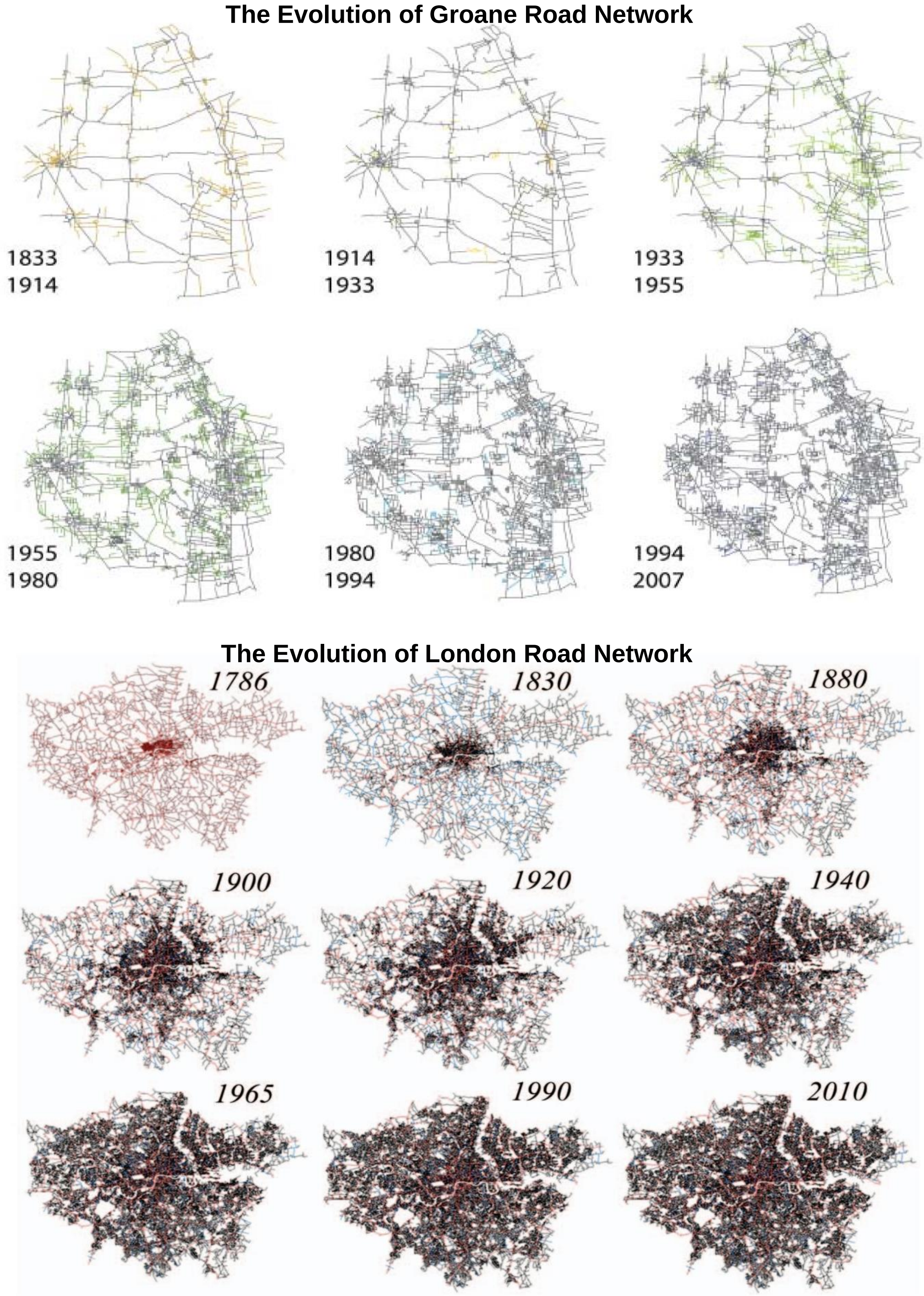



**Figure 1.1 Empirical Evolution of Urban Road Networks**: The upper six snapshots visualise the evolution of the Groane road network from 1833-2007 (Strano et al., 2012); the lower nine snapshots visualise the evolution of the London road network from 1786-2010 (Masucci et al., 2013).

At the same time, increasing modelling RNE research sets out to generate the urban road network structure and reproduces empirical network characteristics(Barthélemy and Flammini, 2008; Courtat et al., 2011; Rui et al., 2013; Barthélemy and Flammini, 2009; Yang et al., 2011), as shown by the example in Figure 1.2. Modelling RNE research has generated network structures with visual and statistical similarities to real-world urban road networks, which distinguishes them from other transport and urban models mentioned in 1.1 that model the transport system or urban form, on other scales or as static.

The Generative Network Model (GNM) is used, which proposes generative mechanisms behind network formation and dynamics (Newman, 2010). Simulation experiments are performed using the GNM, and simulation results are examined to evaluate the proposed generative mechanism. If the generated network resembles real-world urban road networks, its generative mechanism may have explanatory power of real network structures. This model follows the bottom-up generative modelling and simulation approach. By putting aside various other potential influences on RNE and only modelling local rules of simple network components' behaviours and interactions, it is easier to understand the relationships between the generative mechanism and the emerging road network structure.

In short, modelling RNE research uses GNM to simulate the urban road network structure from bottom-up and is capable of generating network structures that agree with empirical urban road networks' characteristics. The modelling RNE research is reviewed in Chapter 4.

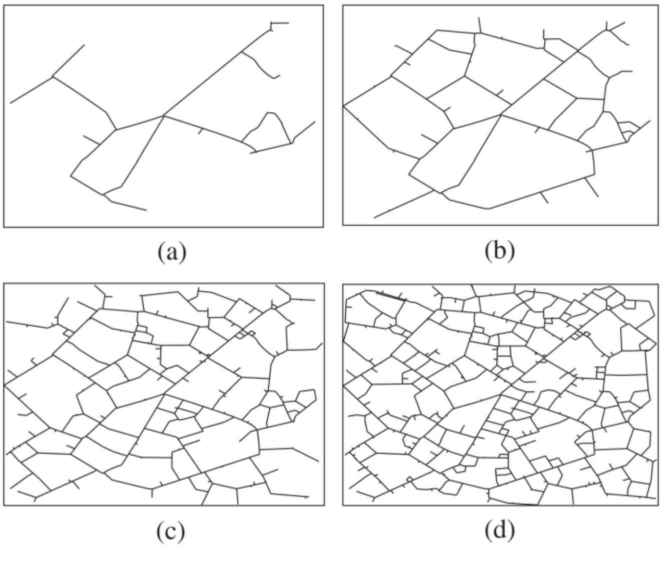



**Figure 1.2 Modelling Evolution of Urban Road Networks**: Four snapshots (a)-(d) visualise the urban road network generation using a Generative Network Model (GNM) (Barthélemy and Flammini, 2008).

## 1.4 Research Questions

Existing empirical and modelling RNE research has accumulated a considerable number of findings. Especially, potential parallels are observable between the empirical RNE process as in Figure 1.1 and the modelled network generation process as in Figure 1.2, indicating the integration of these two groups of research. Meanwhile, existing research has shown the following limitations.

Empirical RNE research studies individual road networks; with different research interests, various aspects of the urban road network structure have been examined without sufficient horizontal comparison regarding findings, measures, and data treatment. The uniqueness of individual urban road networks and different research questions lessen the generality of empirical findings. Different methods to quantify RNE and insufficient consensus on findings leave inconsistency when attempting to put together an empirical RNE understanding. Further, proposed RNE mechanisms are inferred from urban road networks observed at a few discrete historical time points, rather than from a continuous RNE process.

Modelling RNE research has generated plausible topological and geometrical urban road network structures, yet existing models lack horizontal comparison regarding generative mechanisms, model design, and simulation results. First, existing research has not explained the working mechanism of GNM in modelling the urban road network structure. Efforts have been focused on reproducing network characteristics, without establishing the relationship between the network generation mechanism and the generated network structure. Second, existing modelling RNE research aims at generating static urban road network structure, rather than modelling the dynamic RNE process. Generative mechanisms of previous models propose theoretical RNE hypotheses, yet research efforts stop at the reproduction of statistical characteristics of empirical urban road networks. Whether GNM is a plausible tool to model the dynamic RNE process, beyond network generation, has not been explored. Further, existing modelling RNE research has not integrated empirical RNE findings into simulation result examination. Aiming at network generation, these studies have not examined simulated networks' dynamic structure – the changes of network characteristics along the network generation process, which may be compared with observed network changes in empirical RNE research. Existing modelling RNE research may not fully utilise GNM's potential.

Finally, focusing on topological and geometrical road network characteristics, both empirical and modelling RNE research has limited consideration of urban road networks' spatial structure and relationship to the urban system. The spatial structure of road networks relates to the urban system, as shown in transport and urban studies' association of road network to urban form and urban spatial structure. Road network resides and changes in the urban system and has been regarded as influenced by various interrelated urban factors, such as mentioned in Table 1-1 from different RNE research dimensions. Existing empirical and modelling RNE research has not sufficiently distinguished road network structure from or further integrated it into the urban system. For example, previous models have equated road network to the urban system, by using nodes to represent urban centres, and links to represent the road network. This representation may reflect a regional transport network in which nodes represent transport terminals and links represent the transport network (Rodrigue et al., 2016), or an urban network in which nodes represent urban centres and links represent the transport network (Salingaros, 2005). However, this structure is different from and should not be evaluated by the primal urban road network findings - nodes represent urban road network intersections, and links represent road segment. which constitute most empirical RNE studies.

Both empirical and modelling research requires syntheses to piece together a more comprehensive picture of existing RNE knowledge. Also, both empirical and modelling findings require further understanding to establish the relationships between the empirical RNE characteristics at discrete time points, the proposed network generation mechanisms and network generation processes, and the continuous RNE process. Finally, both empirical and modelling research lacks characterisation of the road network spatial structure, as well as the integration of road network with the urban system.

Identifying these limitations, this thesis attempts to answer the following research questions:

1. What are the existing empirical and modelling knowledge on road network evolution (RNE)?
    a. How to quantify RNE?
    b. How do the Generative Network Model (GNM) of urban road networks work?
2. Can GNM model the dynamic RNE process, in addition to generate static urban road network structures?
    a. What is the relationship between the simulated static and dynamic network structure and the generative mechanism?
    b. Can modelling and simulation provide insights into the empirical RNE findings?
3. How to integrate RNE and GNM into the urban system?
    a. What is the relationship between the road network and the urban system?

   b. How to represent both the road network and the urban system?
4. What road network spatial structures may emerge during RNE?
   a. How to characterise the spatial structure of urban road networks?

## 1.5 Research Objectives

This thesis attempts to address the proposed research questions by RNE modelling and simulation. First, this thesis proposes a generative network model (GNM) of urban road network evolution, generalising the generative mechanism of urban road network evolution. Existing empirical RNE findings are integrated to compare the observed empirical RNE characteristics with simulated network structure and dynamics, bringing together empirical and modelling RNE research. Further, the proposed model's capacity to model the continuous RNE process beyond network generation is explored by establishing the relationship between the generative mechanism and the modelled network static and dynamic structures. Second, this thesis attempts to integrate GNM and RNE into the urban system, explores the emergence of road network spatial structure as well as the relationship between the road network and the urban system. Through two modelling and simulation studies, this thesis aims at achieving the following research objectives:

1. Synthesise existing empirical and modelling RNE understanding from previous studies, in terms of
   a. Empirical urban road network structure and dynamics, characterisation;
   b. Generative network models and generative mechanisms of urban road network structure;
   c. Urban road network spatial structure and relationship to the urban system, characterisation.
2. Propose a generative network model of urban road network evolution:
   a. Propose generalised generative mechanism of urban road network evolution;
   b. Use simulation experiments to explore the capacity of GNM to model the dynamic RNE process, in comparison to the empirical RNE characteristics.
3. Propose a hybrid model of road network and urban system co-evolution;
   a. Propose a co-evolution mechanism of the road network and the urban system;
   b. Use simulation experiments to explore the emerging road network spatial structure and its relationship to the urban system.
4. Reach a more comprehensive RNE understanding based on these two modelling and simulation studies.

## 1.6 Research Scope

As discussed in section 1.1, there are many potential research dimensions to understand how urban road networks evolve. This thesis aims at modelling and simulating the evolution of urban road networks from a network science perspective. This approach may differ from alternative research dimensions in terms of the network structure considered, the theoretical foundation on which to interpret road network evolution, the modelling style and objectives. Nevertheless, all the elements of this approach exist in the research history and background, as discussed in 1.1, which lead to this approach and situate it with other research approaches.

### 1.6.1 Modelling

Models have been used for prediction but have also been increasingly recognised as a tool for understanding and exploration. Whether models are used for prediction, directing critical data collection, or exploration and understanding depend on the adequacy of existing data and theories regarding the studied system (O'Sullivan and Perry, 2013). This thesis uses models as a tool for understanding and exploration, as network science perspective RNE studies have accumulated important results had insufficient consensus on findings or RNE mechanisms. Modelling and simulation at this stage of RNE research shall explore the relationships between modelled network structures and dynamics and generative mechanisms to improve the understanding of empirical findings and the theorisation of RNE.

### 1.6.2 Network

Road network structure in this study refers to selected urban network characteristics, including characteristics of elementary road network component nodes, links, blocks, which have both static and dynamic empirical findings. Static and dynamic network structures, based on the selected network characteristics, are to be compared with simulation results, which yields a general understanding of urban road network structure and dynamics. This thesis does not conduct empirical studies of individual urban road networks nor compares simulation results to any road network in particular. Instead, it surveys and synthesises a framework of network characteristics from reported empirical urban road network findings. This effort brings together scattered empirical RNE knowledge in existing research and maximumly utilises existing empirical findings.

Compared to research dimensions such as the transport demand modelling, which emphasises on transport function and performance, this study’s scale and level of details are different regarding the road network structure. There may be a concern of over-simplification, regarding whether the urban road network can be reduced to a topological and geometrical network. There have long been discussions revolving around form and function. On the one hand, form, including the network's topological and geometrical structure, is thought to manifest socio-economic processes, urban problems, and intrinsic urban order, as with the generative urban from models discussed in 1.1.4, which emphasise on the importance to understand the network structure. On the other hand, research perspectives like transport studies emphasise on the functional structure; the relationship between form and function remains theoretical rather than empirical and quantitative (Ewing and Cervero, 2001; Ewing and Cervero, 2010).

Batty (1976) note that urban models may always be insufficient to represent the reality, thus are always questioned of their relevance; but the existence of spatial and temporal patterns and orders in the urban system justifies modelling and simulation of such urban phenomena. Recognising the limitation in considering topological and geometrical network structure from a network science perspective, results and implications of this approach shall be interpreted within the research scope.

### 1.6.3 Evolution

The success of Darwinian evolution in explaining the biological system leads to applications of evolutionary theories in other systems and fields (Fracchia and Lewontin, 1999); all the research dimensions mentioned in Table 1-1 use "evolution" to describe the transport system and urban form. From a complexity theory perspective, evolution may be viewed as an emerging phenomenon in the biological system (Mitchell and Newman, 2002). Meanwhile, the meaning of the evolution of other complex systems, especially social systems, are often not clearly defined. The emergence of hard-to-predict phenomena leaves the intuition that these systems evolve, and evolution seems the most appropriate way to describe hard-to-predict phenomena in these systems but no clear definition or quantitative characteristics are given when describing their evolution. Regarding urban road networks, evolution has been referred to as the interaction of public and private suppliers to pursue different interests (Xie and Levinson, 2011), the application of design rules by many hands in the incremental urban growth (Marshall and Sutton, 2014), and so on.

Evolution in this study refers to the complex network evolution as discussed in 1.1.3, which means the emergence and changes of network characteristics. Such a complex network evolution can be studied through a sequence of static network snapshots, by analysing each static network's characteristics and measuring changes of these network characteristics with time. This study does not intend to define the evolution of complex urban or transport systems, nor finds exact correspondences of the Darwinian evolution in the urban road network but restrains the meaning of evolution to usages of the complex network evolution.

### 1.6.4 Generative Mechanisms

GNMs propose and implement hypothetical generative mechanisms regarding the formation and dynamics of complex networks; the generation of network structures with statistical similarities to real complex networks suggests, though not proves, that the proposed generative mechanism is plausible as an evolutionary mechanism behind complex network formation and dynamics (Newman, 2010). For example, observing that many complex networks' node degree distributions exhibit the power law decay, Barabási and Albert (1999) propose a generative mechanism that complex networks develop with two features: growth and preferential attachment of node degree. The power-law node degree distribution emerges by implementing this mechanism; hence, growth and preferential attachment are plausible as a mechanism to understand the formation of this scale-free property.

The generative modelling and simulation approach is not new or unique to Network science and has been relevant in urban and transport modelling for decades. Haggett and Chorley (1969) review geographical network models which "simulate certain features of complete networks rather than giving a step-by-step picture of their evolution through time"; similarities between the modelled network and the real-world counterpart are thought to bring insights into the real-world network evolution mechanisms and processes. Bejan (2000) point out applying a simple geometrical structure like a leaf or a tree from other systems to model the transport system does not imply the modelled systems are identical but provides a potentially transferable understanding of such structure which exists in all these systems. The dendritic structure widely exists in systems that accommodate flows; at the same time, the dendritic structure is easily identifiable but difficult to describe. A generative mechanism that models the dendritic structure, which can be applied across systems, manifests its potential to improve the understanding of different systems by applying a transferable understanding of this shared structure. Batty and Longley (1994) hypothesise the urban growth process as cumulative addition and deletion of basic fractal geometric units and generate fractal urban form on this basis. GNMs follow this long-existing generative modelling and simulation approach. As a few characteristics characterise complex networks, GNMs reproduce these characteristics using a minimal model with a set of rules designed for the target characteristics, while unique attributes of individual networks are put aside (Barthelemy, 2017). Besides modelling network structures, generative mechanisms may also incorporate street design rules and are used as an alternative approach to design and planning (Marshall and Sutton, 2014).

GNMs emphasise on modelling key characteristics of general complex network structures and dynamic processes behind the formation of these characteristics, acknowledging the fundamentally dynamic nature of complex networks. Generated network structures that share similarities with real complex networks increase the understanding of the targeted structure. On the other hand, the generative mechanism does not equal the modelled system to the simplified model, or reproduces step-by-step any evolution process in particular, but applies a transferable understanding of the modelled structure. Bottom-up generative modelling and simulation have been applied to the urban system, with generative urban form models as outstanding examples. Implications of generative mechanisms are to be interpreted generally within the scope of the modelled structure instead of for any evolution process in particular. Generative mechanisms of urban road networks have been exploratory and contested, utilising theories from land use-transport interaction (Barthélemy and Flammini, 2009), urban land division (Courtat et al., 2011), urban spatial structure (Rui et al., 2013), and urban design (Marshall and Sutton, 2014).

### 1.6.5 Randomness

Randomness is considered on two levels. First, when human decisions are inexhaustive in modelling while knowledge of human decisions are limited, e.g. individual location choices, randomness is as regarded as effective as other arbitrary explicit assumptions of decision making rules; second, randomness imposes an extent of heterogeneity preferences in decision making which will reflect in the variety of simulation outcomes (Batty, 2007). Acknowledging the fundamental role of human decision making in the evolution of urban and transport systems, randomness in modelling and simulation does not imply the evolution of these systems are inherently random but is a modelling decision when not attempting to model human decisions explicitly.

### 1.6.6 Human Agency

Understanding of cities in the 20$^{th}$ century is impossible without the human intervention performed (Batty, 2013). As discussed in 1.1.3, historical and modern urban design and planning are essential research dimensions to understand the evolution of urban form and the urban road network. Though human intentions and actions are present throughout the urban history, there are urban areas without central planning and are subject to local changes, hence the classification of organic or self-organised cities and the planned cities (Portugali, 2012b). Nevertheless, no urban areas can be thought as fully “organic” since all urban areas ultimately result from human purposes, yet design and planning change through time and space with the urban system, rather than being constrained under a single planning regime (Kostof, 1991). Extending this dynamic urban nature, the urban design and planning community recognises the complexity of the urban system through “wicked problems” which demonstrate that some urban issues are too complex to fully track impacts of the proposed design and planning solution, and conditions may become more problematic than if no plans were devised and implemented in the first place (Batty, 2013). With the recognition of urban complexity, design and planning are increasingly considered as agents participating in urban decision-making along with other agents (Batty, 2013).

Urban design and planning are not the research focus of this study, along with other alternative research dimensions identified in 1.2. The network science perspective may be insufficient, if economic, historical, planning and design, and other potential research dimensions were to be considered. Nevertheless, the research interest of this thesis lies in studying a general urban road network structure, rather than a particular urban road network, so that factors such as socio-economic historical development path, natural environment, design and planning are put aside temporarily. Nevertheless, this does not mean this generative modelling and simulation approach is incompatible with alternative research dimensions. Factors of interest in other research perspectives may be designed into generative mechanisms, allowing convenient integration of GNM with established transport and urban theories. For example, urban design and planning have been perceived as a perturbation in the urban road network self-organisation (Benoit and Jabari, 2019), and may serve as an initial simulation condition or as part of a designed generative mechanism to influence system components’ behaviours and interactions.

## 1.7 Chapter Conclusion

This chapter set the research background in 1.1 and identified various research perspectives and dimensions in 1.2 Table 1-1 to understand the evolution of urban road networks. Research interests in the evolution of urban road networks agree with the long-standing urban questions regarding cities’ origin, transformation and prospect, in which the transport system poses both questions and answers. From this broad background, an approach combining the complexity theory, network science, and generative modelling and simulation takes shape, which emphasises on the network structure and perceives the urban road network evolution as emerging from bottom-up. 1.3 briefed existing RNE research, both empirical and modelling, from the network science perspective. Following the limitations of existing empirical and modelling RNE research, 1.4 and 1.5 proposed research questions and objectives of this thesis. The generative network modelling and simulation approach involves research perspectives and methods long existing in urban and transport studies; 1.6 stated the research scope of this thesis, which both differs from and relates to alternative research dimensions.

Figure 1.3 outlines this thesis's structure. This thesis consists of five parts: Introduction, Literature review, Methodology, RNE modelling and simulation studies, and Conclusion. Literature review spans three chapters: Chapter 2 reviews network science perspective empirical RNE research, from which a framework of urban network structure and measures is synthesised for simulation result examination in later chapters; Chapter 3 reviews road network's spatial structure as well as the representation and relationship of road network and the urban system together; Chapter 4 reviews modelling RNE research. After literature review, Chapter 5 proposes the methodology of this thesis, as a framework of RNE modelling and simulation. Two RNE modelling and simulation studies constitute the following four chapters. Chapter 6 and 7 propose a generative network model of the urban road network evolution and perform simulation experiments to explore how GNM's generative mechanism works and the proposed model's capacity in modelling the dynamic RNE process. Chapter 8 and 9 propose a hybrid model of population and urban road network co-evolution and perform simulation experiments to explore urban road network's spatial structure and relationship to the urban system. Chapter 10 concludes this thesis.

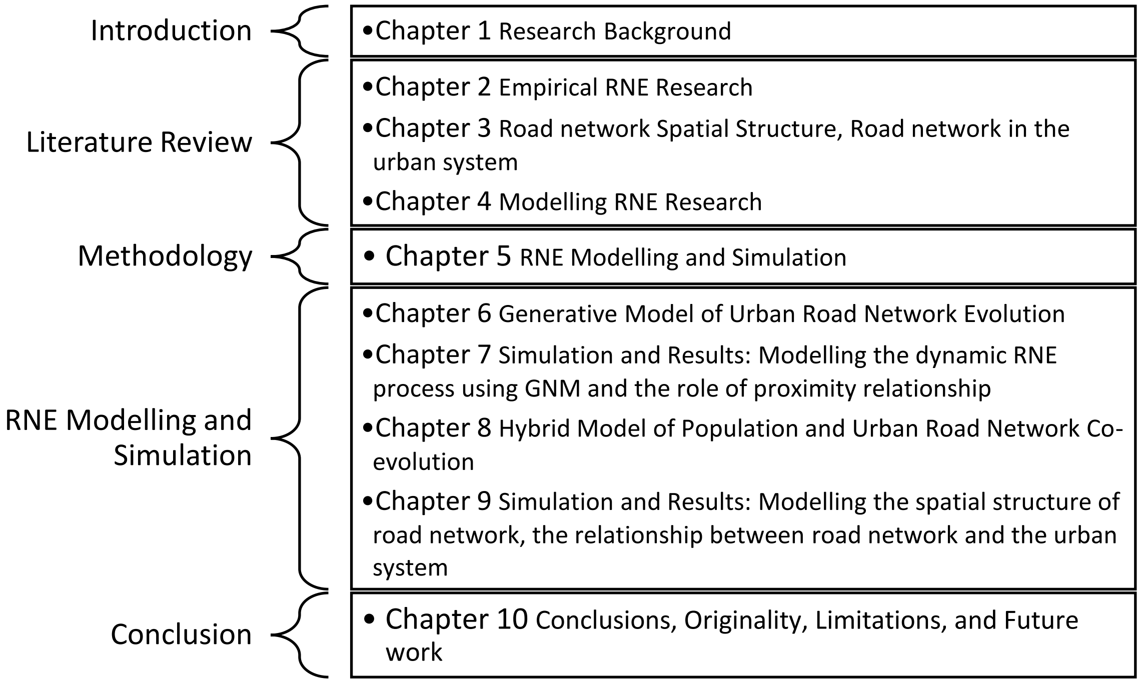



**Figure 1.3 Thesis Structure**

# Chapter 2 Empirical Urban Road Network Evolution

## 2.1 Chapter Introduction

Quantitative transport networks analysis was established in the 1950-60s quantitative geography revolution (Garrison and Marble, 1962; Haggett and Chorley, 1969; Kansky, 1963). Graph theory measures introduced back then have been one essential research approach in this field (Taaffe, 1996; Black, 2003; Ducruet and Rodrigue, 2011). Research interests shifted from network structure to function in the 1970s and 80s (Ducruet and Lugo, 2013), such as to transport demand modelling, urban economics, and statistical studies on the correlations between transport supply and socio-economic factors (Xie and Levinson, 2011), while that of network analysis decreased. Network science since the 1990s has provided new opportunities for transport network analysis (Xie and Levinson, 2011). Network science explores how statistical physics can contribute to the subject, focusing on empirical network structure analysis using a substantial amount of data and generating potential implications from new theoretical models which agree with empirical findings (Barthelemy, 2017).

The understanding of the urban road network structure depends largely on the road network structure measured. Complex networks have small-world and scale-free properties, which can be efficiently captured by the topological characterisation. However, these non-spatial characteristics are not enough for spatially embedded complex networks like urban road networks; spatial network research has been establishing its methodology to characterise complex networks' space dimension. At the same time, complex networks result from dynamic formation and change processes. The study of the dynamic network formation distinguished complex networks from random networks, thus the dynamic structure is indispensable in understanding complex networks.

The spatial network characterisation and the emphasis on the dynamic structure are reflected in the current empirical research on road network evolution (RNE). An increasing number of empirical studies have used historical data, visualised and quantified road networks' changing structure with time - the network evolution, through analysing snapshots of real-world urban road networks. These studies have provided empirical evidence of road networks' dynamic structure; together with research on road networks' static structure, a more comprehensive understanding of road networks' formation and dynamics may be formed.

Following the first research question laid out in Chapter 1 regarding existing knowledge on RNE, this chapter aims at establishing an empirical RNE understanding by piecing together existing studies. This chapter aims to review and synthesise an empirical RNE understanding from a network science perspective, of both static and dynamic urban road network structures.

Figure 2.1 shows the structure of this chapter. Section 2.2 develops from characterising complex networks to spatial networks 2.2.1, then discusses the importance to understand dynamic network structure beyond static structure 2.2.2, leading to the spatial network characterisation of urban road networks. Section 2.3 reviews the static and dynamic structure of urban road networks based on characteristics of elementary road network components nodes 2.3.2, links 2.3.3 and blocks 2.3.4. Section 2.3.4.4 reviews the static and dynamic structure of road network Betweenness centrality, which includes RNE phenomena proposed by empirical RNE research – the Backbone of urban road networks 2.4.3 and Densification and Exploration 2.4.4. Section 2.5.1 synthesises an empirical understanding of RNE 2.5 and discussed the limitations of existing empirical RNE research 2.5.2.

**Theoretical and Methodological Foundation**

- Measure the Urban Road Network Structure from a Network Science Perspective 2.2
  - From Characterisation of Complex networks to Spatial networks 2.2.1
  - From Static to Dynamic Network Structure 2.2.2

**Empirical Urban Road Network Structure**

- Elementary Road Network Components 2.3
- Node 2.3.2
- Link 2.3.3
- Block 2.3.4
- Betweenness Centrality 2.4
  - RNE Phenomenon: The Backbone of Urban Road Networks 2.4.3
  - RNE Phenomenon: Densification and Exploration 2.4.4

**Synthesis**

- Framework to Examine RNE 2.5
  - Synthesise Existing Empirical RNE Knowledge 2.5.1
  - Limitations of Existing Empirical RNE Research 2.5.2

**Figure 2.1 Chapter 2 Structure**

## 2.2 Measure the Urban Road Network Structure from the Network Science Perspective

### 2.2.1 From Complex to Spatial Networks

Two trends can be observed in urban and transport studies and network science, respectively. On the one hand, urban and transport studies recognise the complexity of urban and transport systems and include complex theory and network science into their research methods. On the other hand, network science recognises the space dimension of certain complex networks and has been establishing a methodology to study spatial networks.

Complex systems consist of simple networked components; the systems self-organise – components microscopic behaviours follow local rules instead of central control; hard-to-predict macroscopic system characteristics emerge from collective individual component behaviours - the systems adapt, learn and evolve (Mitchell, 2009). Correspondingly, the new science of cities thinks of urban systems as emergent macroscopic phenomena based on microscopic system components' self-organisation. Urban systems are considered as network structure built from bottom up by simple urban system components; external forces do not determine the system behaviours but trigger internal self-organisation instead; complex urban phenomena emerge (Torrens and Torrens, 2004; Portugali, 2012b; Batty, 2013; Barthelemy, 2016; White et al., 2015). Transport systems are traditionally explained to change through top-down transport supply policy-making processes by a central authority to maximize efficiency; acknowledging complexity in these systems; their changes are viewed instead as a result of interactions between public and private suppliers with different interests (Xie and Levinson, 2011).

Complex networks encode behaviours and interactions of system components and represent complex systems (Barabasi, 2016). Some complex systems are networked; while others, when represents as networks, relationships between system components are better revealed. Graph theory is the formal language to describe networks, and provide basic concepts and tools to analyse networks; Social network analysis further provides measures of networks (Newman, 2010; Barabasi, 2016). The discoveries of small-world (Watts and Strogatz, 1998) and scale-free (Barabási and Albert, 1999) properties shape complex network structure examination as a process of topological characterisation regarding these properties: complex networks differ from random networks by small average path length and power-law node degree distribution, these topological characteristics can capture their structure.

Complex networks are generally considered as lying in abstract space, where positions of nodes and links have no meaning (Costa et al., 2007). However, many real complex networks' nodes locate in space with metric, which is usually two dimension plane with Euclidean distance; the probability to form a link between two nodes is considered as a function of spatial distance (Barthélemy, 2011). According to the difficulty to form long-distance links, spatial networks can be categorised as "strong geographical" and "weak geographical" (Xulvi-Brunet and Sokolov, 2007). Weak geographical spatial networks exhibit small-world and scale-free characteristics like general complex networks. Strong geographical constraint leads to planar networks, in which links do not cross without forming intersections; planarity limits possibilities of small-world and scale-free characteristics. Consequently, topology does not contain all information about spatial networks. In other words, spatial networks cannot be described by topological characterisation using only degree distribution, average path length and other such topological characteristics. Various methods have been proposed to characterise spatial networks informatively (Strano et al., 2012).

Strategies for spatial network characterisation switch from initial attempts of adapting complex network topological characterisation, to gradually establishing its methods. At first, spatial network characterisation characterised planar properties of strong geographical spatial networks and adopted spatial distance for complex network characteristics instead of network distance (Barthélemy, 2011). For example, the planar network’s geometric characteristics have been measured, such as link angles and orientations (Perna et al., 2010; Gudmundsson and Mohajeri, 2013), cell (block) shape and size (Lämmer et al., 2006); complex networks’ measures have been adapted with spatial distance, e.g. measure Euclidean distance instead of number of links along a path as in various centrality measures (Porta et al., 2010). Gradually, spatial network characterisation has been assembling its methods instead of mainly applying complex network topological characterisation, as the most often used complex networks’ characteristics like degree distribution and average path length are not informative under strong spatial constraints (Barthelemy, 2017). Still, spatial network characterisation has not standardized on measures like the complex network topological characterisation; though some informative measures stand out, with betweenness centrality being one successful example (Barthelemy, 2017).

In short, urban and transport systems have been gradually recognised as complex with complexity integrated as part of the theoretical foundation to think about such systems; network science has become an essential approach to study the often networked complex urban and transport systems. However, the fundamental spatiality of urban and transport networks cannot be fully understood by the prevalent complex network topological characterisation. Thus, spatial network characterisation has been establishing its methodology to account for this spatial dimension.

### 2.2.2 From Static to Dynamic Structure

The discoveries of small-world and scale-free properties reveal real complex networks' deviation from random networks and their structure do not come into being by chance. Instead, complex networks are regarded as forming by continuous evolution, which affects complex systems' function and operation (Boccaletti et al., 2006). The evolution of complex networks shows in the emergence and changes of network characteristics (Dorogovtsev and Mendes, 2013). Consequently, knowledge of how complex networks change may reveal mechanisms behind network formation and dynamics, thus are of considerable significance to study.

Static structure refers to network characteristics at a fixed time; dynamic structure refers to changes in network characteristics with time (Barabási et al., 2002). Measuring the dynamic structure attempts to characterise the formation and changes of complex networks. Trajectories record behaviours of network measurements as networks undergo structural changes; similar trajectories suggest networks have a similar dynamic structure which may result from similar evolutionary mechanisms behind their formation and dynamics (Costa et al., 2007). Complex network evolution can be studied through a sequence of static network snapshots: each static networks' characteristics are analysed, and the changes of characteristics with time are analysed (Rocha, 2017).

Complex network structure being fundamentally dynamic leads researchers to think about road networks' dynamic structure. Beyond studying one static road network or comparing several static road networks and inferring the formation and dynamics of road network structure, the network evolution studies have analysed a series of road network snapshots in time, provided direct observations of the formation and dynamics processes, therefore provided more RNE information. These studies (Strano et al., 2012; Barthelemy et al., 2013; Masucci et al., 2013; Mohajeri and Gudmundsson, 2014) have increased in recent years because of the availability of historical road network data and data processing ability. Their results have been the primary source of empirical dynamic road network structure. Together with results from static road network structure studies, a more comprehensive understanding of road network structure may be synthesised.

The next two sections 2.3, 2.3.4.4 review the spatial network characterisation of urban road networks' static and dynamic structure. Together, these two sections synthesise an understanding of RNE characterisation and characteristics from a network science perspective.

## 2.3 Elementary Road Network Components Characteristics

This section introduces first the representation of urban road networks as a spatial network 2.3.1, then reviews characterisation and the static and dynamic characteristics of road networks' elementary components – Node 2.3.2, Link 2.3.3, Block 2.3.4.

### 2.3.1 Represent Road Network

A complex network is defined as $G = (V, E)$, in which $V$ represents a set of nodes and $E$ represents a set of links connecting nodes in $V$ (Newman, 2010; Barabasi, 2016). Based on this definition, a spatial network further requires a list $C$ that contains spatial locations of nodes in $V$ (Barthelemy, 2017). Besides nodes and links, blocks – the nonoverlapping cells of planar networks (Barthelemy, 2017), are considered as elementary road networks components as well (Haggett and Chorley, 1969). There may be many possible ways to characterise the structure and changes of $G$; for instance, measuring $V$, $E$, and $C$, as well as their changes. The following sections review the measures and findings of static and dynamic characteristics of elementary road network components: nodes, links, and blocks.

The representation of an urban road network as a graph, where intersections correspond to nodes and road segments correspond to links, has been widely referred to as the primal representation. Meanwhile, the representation of streets as nodes and intersections as links has been referred to as the dual representation, in which street may contain several road segments. Compared to the usage in mathematics, "primal" and "dual" urban road networks are often not symmetrical, causing information loss. Also, though the primal representation provides a mathematical formalisation that preserves the intuitive geometry of the road network, it removes urban road networks from the physical reality and selectively singles out main elements and relations, therefore limiting analytical possibilities. Alternative approaches which take streets as the primary study unit can preserve the continuity and hierarchy in urban road networks. (Marshall et al., 2018)

### 2.3.2 Node Characteristics

Degree $k_i$ of a node denotes the number of links connecting to it. $\langle k \rangle$ is the average degree of $G$. (Barabasi, 2016) $k$, $\langle k \rangle$ are topological measures and reflect the urban road network's elementary connection patterns. $k$ of planar networks is bounded by 6 (Barthélemy, 2011). The peaked $k$ distribution and small $k$ range differ from scale-free degree distributions of many complex networks, and network science regards road network $k$ as “irrelevant” (Barthelemy, 2017). Therefore, some have instead studied the dual representation, under which road networks display small-world and scale-free characteristics (Jiang and Claramunt, 2004b; Porta et al., 2006a; Jiang, 2007).

Though not significant for small-world and scale-free properties, $k$ is used to distinguish “organic” and “planned” urban road networks (Wang, 2015; Buhl et al., 2006), which makes it relevant to characterise the evolution of urban road networks. Historically, $k_4$ nodes have been associated with centrally planned layouts, while organic or more self-organised layouts typically have a higher proportion of $k_3$ nodes. This aspect is described by the organic ratio $r_N = \frac{k_3+k_1}{\sum_i k_i}$ (Courtat et al., 2011), measuring the proportion of $k_1$ and $k_3$ nodes to indicate the network's organic extent.

Node degree also shows directly the result of urban planning and design. $k_4$ nodes suggest a grid road network layout, which is considered as a signature of urban planning. Prominent grids include the Roman gridiron inner-city land division, the Renaissance's geometry of straight streets, the American grids used for rapid urban expansion with railroads in the 18th century, and the new urbanism's interconnecting street patterns. On the other hand, $k_3$ nodes' popularity can be associated with road engineering standards in the 1950s-1960s, which regarded T-junctions as safer than crossroads. $k_3$ nodes also relate to cul-de-sacs, which are often suburban residential streets to provide private access and discourage through traffic. (Southworth and Ben-Joseph, 2013)

#### 2.3.2.1 Static Node Characteristics

Boeing (2017) investigated with OpenStreetMap (OSM) “driveway” data and reported, by 2016, $\langle k \rangle$ of all US urbanised areas (497 US metropolitan level urbanised areas with a population larger than 50,000) was $2.76$, in a range of $[2.22, 3.22]$. On average there were $18.7\%$ $k_4$ nodes with range $[5.4\%, 42.2\%]$, $59.3\%$ $k_3$ nodes with range $[44.4\%, 77.8\%]$, and $21.3\%$ $k_1$ nodes with range $[7.7\%, 41.6\%]$. This study concluded US urbanised areas were “overwhelmingly similar”, in terms of having dominant proportions of $k_3$ nodes.

Barrington-Leigh and Millard-Ball (2015) investigated with TIGER shapefiles and reported, by 2013 $\langle k \rangle$ of all US urbanised areas was $2.74$, with on average $21.5\%$ $k \geq 4$ nodes, and $23.5\%$ $k_1$ nodes. (Their data treatment to extract road networks from shapefiles tended to decrease $\mathrm{k}_3$ nodes while increasing $\mathrm{k}_4$ nodes.)

Empirical findings of European urban road networks have reported similar $\langle k \rangle$ to the US road networks; centrally planned road networks standed out with $\langle k \rangle$ larger than the US average, such Barcelona with $\langle k \rangle = 3.43$ (Chan et al., 2011; Strano et al., 2013). Overall, empirical research has reported similar proportions of node degrees with a majority portion of $k_3$ nodes and similar average node degree $\langle k \rangle$; planned cities with a dominant grid layout had higher $\langle k \rangle$ with larger proportions of $k_4$ nodes.

#### 2.3.2.2 Dynamic Node Characteristics

As shown in Figure 2.2 (a), Strano et al. (2012) reported, from 1833 to 2007, $\langle k \rangle$ of the Groane road network was almost constant, and the growth of link number had a linear relationship with and the growth of node number. They concluded that Groane's $\langle k \rangle$ dynamics reflected the self-organised growth. As shown in Figure 2.2 (b), Masucci et al. (2013) reported, from 1786 to 2010, $\langle k \rangle$ of the London road network decreased, suggesting London road network changed from more circuitous to more tree-like. They interpreted this finding as London's changing from planned to self-organised. As shown in Figure 2.2 (c), Barrington-Leigh and Millard-Ball (2015) reported, from 1920 to 2013, $\langle k \rangle$ of US urbanised areas started from high value around $3.2$, decreased to the lowest point of $2.6$ in 1994, and had increased since then to $2.8$ in 2012. They explained this $\langle k \rangle$ dynamics with the changing proportions of $k_4$ and $k_1$ nodes and interpreted $\langle k \rangle$ reflected urban sprawl in the US from 1920 to 1994, characterised by a large number of $k_1$ nodes (dead-ends), relatively small number of $k_4$ nodes, and decrease of urban sprawl after 1994.

In empirical evidence, $\langle k \rangle$ has been reported to increase, decrease, or first decrease then increase with the urbanisation; how $\langle k \rangle$ changed in empirical road networks were not consistent; researchers reached different conclusions from interpreting $\langle k \rangle$ dynamics. Nevertheless, $\langle k \rangle$ dynamics reflected proportion changes of different degree nodes; the increase of $k_1$ and $k_3$ nodes which was likely to decrease $\langle k \rangle$ has been associated with road network growth without central planning; the increase of $k_4$ was likely to increase $\langle k \rangle$ and has been associated with central planning.

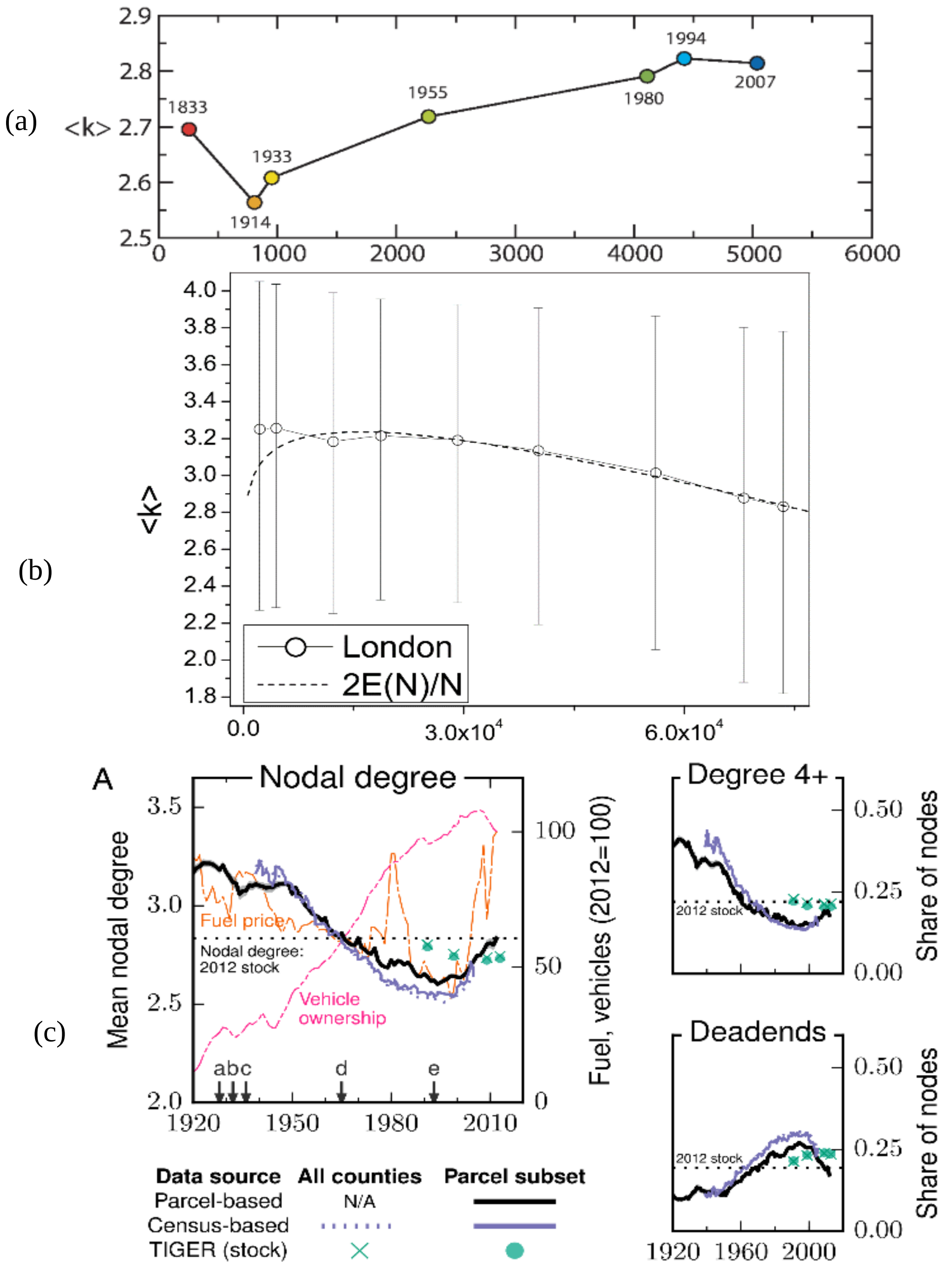



**Figure 2.2 Empirical Average Node Degree $\langle k \rangle$ Dynamics**: (a) $\langle k \rangle$ dynamics of the Groane road network from 1833 to 2007. The x-axis represents the number of nodes; the y-axis represents $\langle k \rangle$ (Strano et al., 2012). (b) $\langle k \rangle$ dynamics of the London road network from 1786 to 2010. The x-axis represents the number of nodes the y-axis represents $\langle k \rangle$; dashed line was $\langle k \rangle$ fitted as a function of node number (Masucci et al., 2013). (c) The left plot shows $\langle k \rangle$ dynamics of all US urbanised areas: the black line represents $\langle k \rangle$ dynamics of all the US counties from 1920 to 2012. The x-axis represents the number of nodes; the y-axis represents $\langle k \rangle$ (Barrington-Leigh and Millard-Ball, 2015). The right column shows two smaller plots with $k \geq 4$ and $k_1$ dynamics accordingly. (a) and (b) show different trends of $\langle k \rangle$ dynamics in individual road networks: Groane's $\langle k \rangle$ increased with time, while London's $\langle k \rangle$ decreased. (c) shows on a nationwide aggregated level, $\langle k \rangle$ correlated with urban sprawl, as it changed with the proportions of $k \geq 4$ and $k_1$ nodes, which were associated with compact and sprawl urban development.

#### 2.3.2.3 Node Characteristics Discussion

Empirical research has found a majority of $k_3$ nodes in urban road networks, reported inconsistent $\langle k \rangle$ dynamics and attributed $\langle k \rangle$ dynamics to road network self-organisation or central planning, which has been shown by the changing proportions of $k_1$ and $k_3$ nodes against $k_4$ nodes. Following the empirical findings, further research questions may be asked:

- How do $k_1$, $k_3$ and $k_4$ nodes emerge respectively, and what RNE mechanisms does the emergence of different degree nodes reflect? Does node degree relate to self-organised and centrally-planned urban road dynamics? How do different $\langle k \rangle$ dynamics emerge, and why does $\langle k \rangle$ increase, decrease, or remain constant with time? What RNE mechanism does this reflect?**Link Characteristics**

Link length $l$ denotes the Euclidean distance between the two nodes connected by this link. Total link length $L_{tot} = \sum l$, summing all the link length in $E$. In contrast to the complex network topological characterisation in which link length is abstract, measuring the Euclidean distance $l$ of links reflects that spatial network characterisation adopts geometric measures to address the space dimension.

#### 2.3.3.1 Static Link Characteristics

Boeing (2017) reported all the US urban road networks followed lognormal $l$ distribution and resulted from having very few very short links (e.g. 10 m), abundant short links (e.g. 80 m), many medium links (e.g. 250 m), and very few very long links (>1 km) in typical road networks. Exceptions were mainly grid layouts, e.g. cities and towns in the Great Plains and Midwest of US with the Homestead act signed in 1862 giving applicants free land and stimulating grid town layout. As in Figure 2.3 (b), Strano et al. (2013) reported most of 10 European cities' road networks followed lognormal $l$ distributions. On a log-log plot, the tail of $l$ distribution, e.g. the long links, fit power-law distribution as in Figure 2.3 (a), while most short links in the head of the distribution did not. They explained previous research which concluded that $l$ followed a power-law distribution overlooked short links. They further added the exceptions that did not follow the lognormal $l$ distribution were mainly influenced by historical central planning which favoured particular link lengths. As in Figure 2.3 (d), Chan et al. (2011) reported that 20 largest German cities' road networks had a bimodal $l$ distribution: the majority of short links formed a 'plateau', and the tail of long links fit power-law distribution. The 'plateau' here might result from their data treatment, which removed all $k_1$ and $k_2$ nodes, resulting in the underestimation of the short link abundance. As in Figure 2.3 (c), Masucci et al. (2013) reported the Great London Area (GLA) in 1786 had an exponential $l$ distribution.

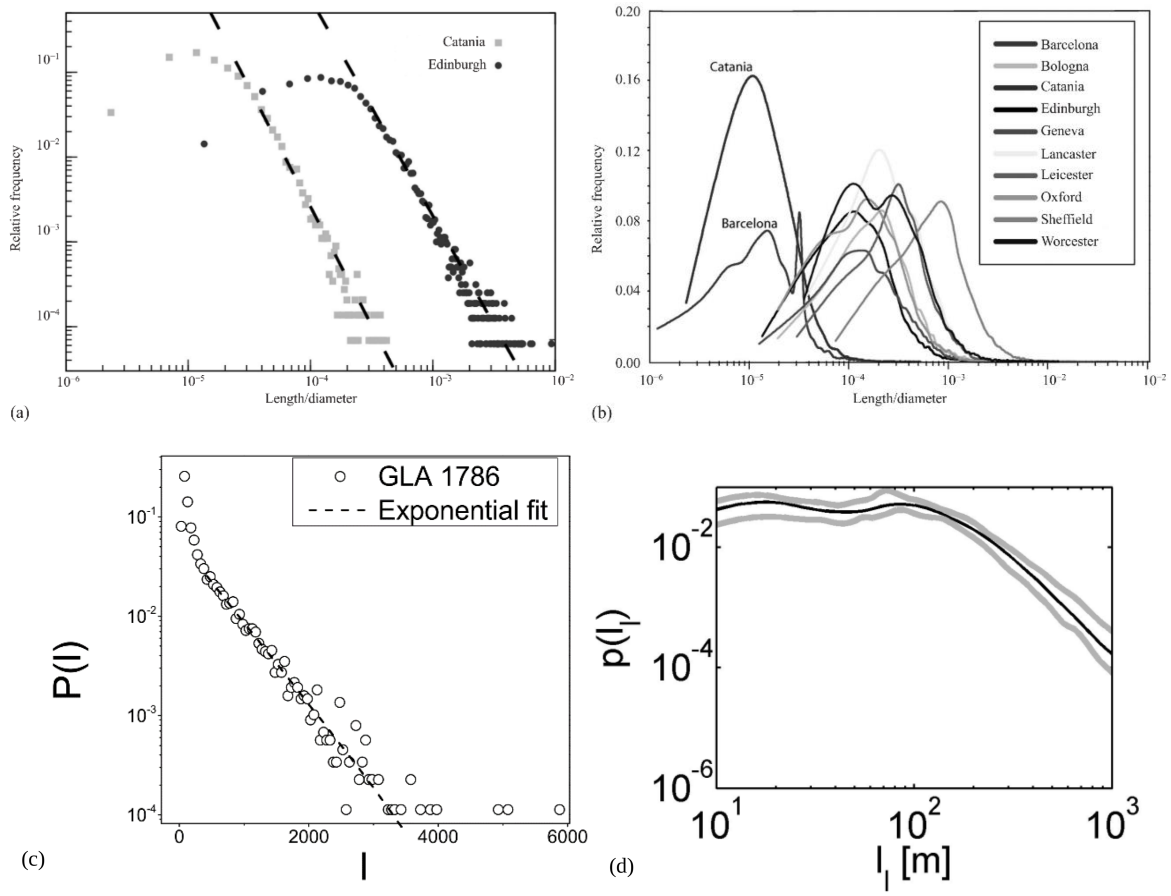



**Figure 2.3 Empirical Link Length $l$ Distributions**: (a) shows $l$ distributions of two cities – Catania and Edinburgh on a log-log scale. The x-axis represents link length; the y-axis represents probability density. (b) shows $l$ distributions of 10 European cities on a semi-log (log x) scale; the x-axis represents link length; the y-axis represents probability density. Most cities' $l$ displayed lognormal distributions in (b), while on the log-log scale in (a), the tails of $l$ distributions fit power-law distributions (Strano et al., 2013). (c) $l$ distribution of Great London Areas (GLA) on semi-log (log y): the x-axis represents link length, the y-axis represents probability density; GLA's $l$ in 1786 followed an exponential distribution (Masucci et al., 2013). (d) $l$ distributions of 20 largest German cities on a log-log scale: the x-axis represents link length, the y-axis represents probability density (Chan et al., 2011).

### 2.3.3.2 Link Characteristics Discussion

#### 2.3.3.2.1 The Lognormal Distribution

Lognormal distribution describes a random variable whose logarithms follows the normal distribution. Two main theories explain the generation of lognormal distributions: the law of proportionate effect proposed by Gibrat in the 1930s to describe the growth of firm size and the breakage model proposed by Kolmogoroff in the 1940s to describe the successive breakage of a particle; the latter is an inverse of the former. For a random variable $X_n$, the law of proportionate effect proposes the change of $X_n$ between any two successive states $X_j - X_{j-1}$ is proportionate to its size $\varepsilon_j X_{j-1}$ by a small rate $\varepsilon_j$; thus $X_j = (1 + \varepsilon_j)X_{j-1}$. Assuming the initial state is $X_0$, $X_n$ and its generation process is described by $X_n = X_0(1 + \varepsilon_1)(1 + \varepsilon_2) \cdots (1 + \varepsilon_n) =$

$X_0 \prod_{j=1}^{n}(1+\varepsilon_n)$. Assuming the rate of change $\varepsilon_j$ is small compared to 1 and approximating using Taylor expansion of $\ln(1+\mathrm{x})$ , $\ln X_n = \ln X_0 + \sum_{j=1}^{n} \varepsilon_j$. Assuming $\ln X_n \gg \ln X_0$ and the rate of change $\varepsilon_j$ follows the normal distribution, the logarithm of this random variable $\ln X_n$ follows the normal distribution since $\sum_{j=1}^{n} \varepsilon_j$ follows the normal distribution because of the central limit theorem. Similar to this proportionate growth process, the breakage model describes a proportionate breakage process which leads to a lognormal distribution as well. (Crow and Shimizu, 1987)

Different probability distributions reflect different generating mechanisms of the random variables. As described above, a random variable $X_n$ following the lognormal distribution changes in proportion to its previous state $X_{n-1}$; therefore, $X_n$ is a product of proportionate changes and is generated by a multiplicative process. The lognormal distribution is first distinguished from the normal distribution. The lognormal distribution differs from the normal distribution by its skewness shown in the heavy tail of the distribution; a random variable following a normal distribution is generated by an additive process, namely the variable is not the product but the sum of changes; because of the ubiquitous normal distribution, the skewed heavy-tail distributions used to be overlooked (Limpert et al., 2001). Among the heavy-tailed distributions, the lognormal distribution can be easily confused with the power-law distribution; generation of the latter differs slightly from the former in the presence of bounded minimum (Mitzenmacher, 2004).

#### 2.3.3.2.2 Link Length Distribution and Dynamics Summary

Empirical findings of the link length $l$ distribution have shown inconsistency among several skewed distributions with a heavy tail, yet the latest findings have reported that $l$ followed a lognormal distribution. With the growth of the road network over time, more short and medium length new links were added, and $l$ persisted in following the lognormal distribution with a concentrating peak. The lognormal $l$ distribution has been explained by a typical urban road network's composition of a few extremely short or long links, many medium links, and a lot of short links. Reporting inconsistent findings, empirical research has not explained $l$ distribution through formation processes and generation mechanisms. Different distributions may result from different generation mechanisms and processes, which may lead to the inconsistency in reported empirical $l$ distribution findings. Further research questions may be asked:

- How does the lognormal $l$ distribution emerge in urban road networks and what RNE mechanism does this reflect?

- Does $l$ persist in following the lognormal distribution? How do new links influence $l$'s distribution? What RNE mechanism does it reflect?

### 2.3.4 Block Characteristics

Blocks have long been studied as one of the fundamental urban morphology elements, together with streets and buildings (Moudon, 1997), in which the block boundaries and dimensions are analysed to infer the history of block development (Whitehand, 2001). Among different potential measurements of the morphology of urban blocks, two suitable spatial network characteristics to describe urban road network blocks are area and shape (Louf and Barthelemy, 2014).

#### 2.3.4.1 Static Block Characteristics

Lämmer et al. (2006) reported $P(A)$ of 20 largest German cities followed a power-law distribution $P(A) \sim A^{-\alpha}$, with Dresden being an example in Figure 2.4 (a) whose $\alpha = 1.892$, (excluding all the blocks with $A \leq 10000$ $m^2$). Louf and Barthelemy (2014) reported that the tails of $P(A)$ of 131 world cities followed a power-law distribution $P(A) \sim A^{-\alpha}$, $\alpha \approx 2$. However, the head of $P(A)$ , e.g. the small block areas, did not follow power-law and had different shapes. Long et al. (2016) reported 70% areas of Chinese cities' $P(A)$ followed a power-law distribution $P(A) \sim A^{-\alpha}$; large and high administrative status cities had a better fit. As in Figure 2.4 (b), Beijing's $\alpha = 1.37$; while $\alpha = 1.78$ if only considered values larger than the mean, namely $A \geq \bar{A}$. As in Figure 2.4 (c), Riascos (2017) separated blocks of built-up areas and natural areas (park, river, etc.), and reported $P(A)$ of building blocks followed a power-law distribution $P(A) \sim A^{-\alpha}$, $\alpha \approx 3$, considering only $A \geq 2000$ m$^2$; $P(A)$ of natural blocks followed power-law distribution $P(A) \sim A^{-\alpha}$, $\alpha \approx 1$. As in Figure 2.4 (d) - (e), Fialkowski and Bitner (2008) divided concentric urban, suburban, rural zones from the urban centre, and reported $P(A)$ of urban blocks followed a power-law distribution $P(A) \sim A^{-\alpha}$, $\alpha \approx 2$; $P(A)$ of suburban blocks followed a lognormal distribution; $P(A)$ of rural blocks followed a power-law distribution $P(A) \sim A^{-\alpha}$, $\alpha \approx 1$. Jiang and Liu (2012) reported $P(A)$ of the UK, France, Germany nationwide road networks all followed lognormal distributions, and the average block area $\bar{A}$ separated 80% of small urban blocks and 20% large blocks. Usui and Asami (2018) reported $P(A)$ of Tokyo followed a lognormal distribution, (excluding blocks with $A \geq 10000$ $m^2$).

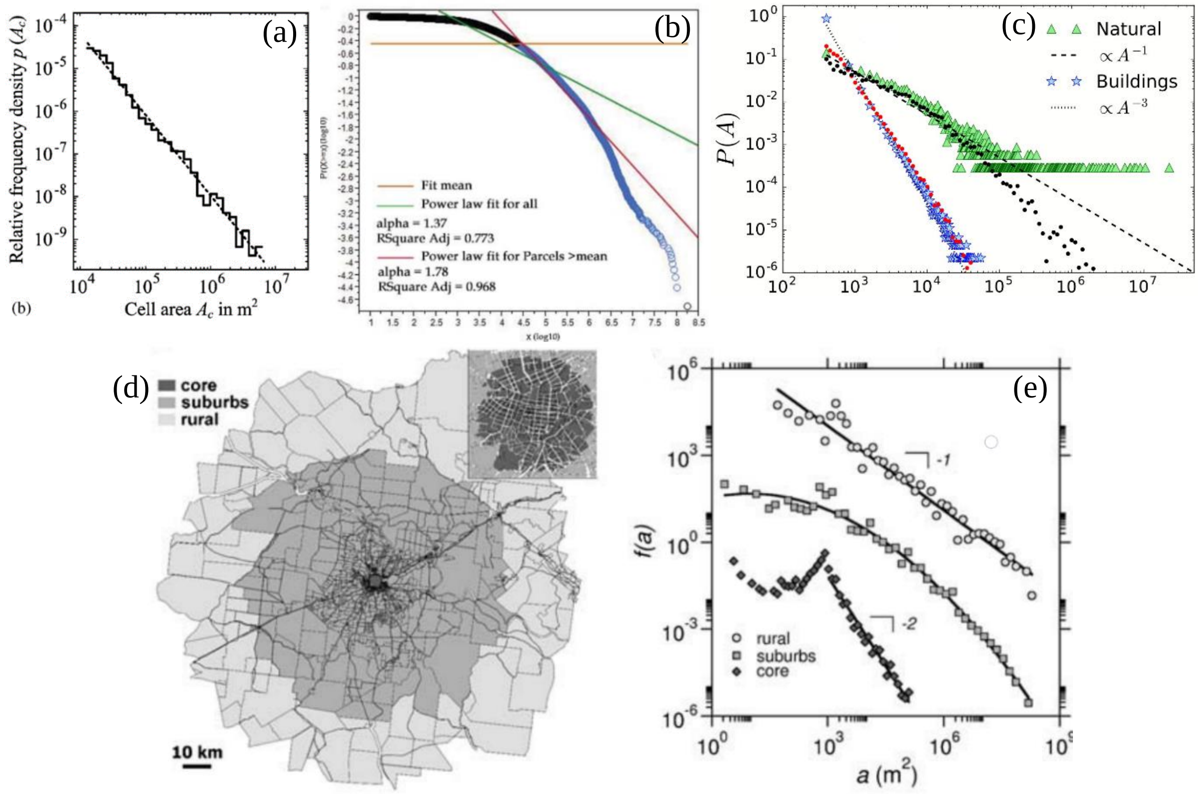



**Figure 2.4 Empirical Block Area Distributions $P(A)$**:(a) - (c), (e) the x-axis represents block area $A$; the y-axis represents probability density; both axes are on the logarithmic scale. (a) $P(A)$ of Dresden, not considering $A \leq 10000$ m². The power-law fit yielded $\alpha = 1.892$ (Lämmer et al., 2006). (b) $P(A)$ of Beijing; the blue circles represent the actual data; the yellow line represents the probability density of the average area $\bar{A}$; green line is a power-law fit for all the data, $\alpha = 1.37$; red line is a power-law fit for values whose $A \geq \bar{A}$, $\alpha = 1.78$ (Long et al., 2016). (c) $P(A)$ of Berlin. Blue stars represent built-up blocks' $P(A)$, the dotted line represents its power-law fit with $\alpha = 3$, red dots are values under logarithmic binning. Green triangles represent natural area blocks' $P(A)$, the dashed line represents its power-law fit with $\alpha = 1$, black dots are values under logarithmic binning. (Riascos, 2017) (e) $P(A)$ of Charters Towers, Australia. Diamonds represent urban core $P(A)$; its tail fits he power-law distribution with $\alpha = 2$. Squares represent suburban blocks $P(A)$, which followed a lognormal distribution. Circles represent rural blocks $P(A)$, which fit the power-law distribution with $\alpha = 1$. (d) displays the urban core, suburban, rural areas of Charters Towers, defined as concentric rings from the urban centre (Fialkowski and Bitner, 2008).

#### 2.3.4.2 Dynamic Block Characteristics

As in Figure 2.5 (a), Strano et al. (2012) reported $P(A)$ of the Groane road network followed a power-law distribution and $\alpha$ increased from $1.2$ in 1833 to $1.9$ in 2007 as in the inset plot. As in Figure 2.5 (b), Masucci et al. (2013) reported $P(A)$ of London persisted in following lognormal distributions, with peak decreasing and moving towards the right.

$P(A)$ dynamics in the Groane road network agreed with the static $P(A)$ findings that the slope $\alpha$ of $P(A)$ on the logarithmic scale increased with urban density along with the urbanisation. At the beginning of the studied period, the Groane road network was in a pre-urbanisation state and had $\alpha = 1.2$, which was close to $\alpha$ found in static rural and suburban road networks. With the urbanisation, Groane's $\alpha$ increased to 1.9, which agreed with $\alpha$ found in static urban road networks.

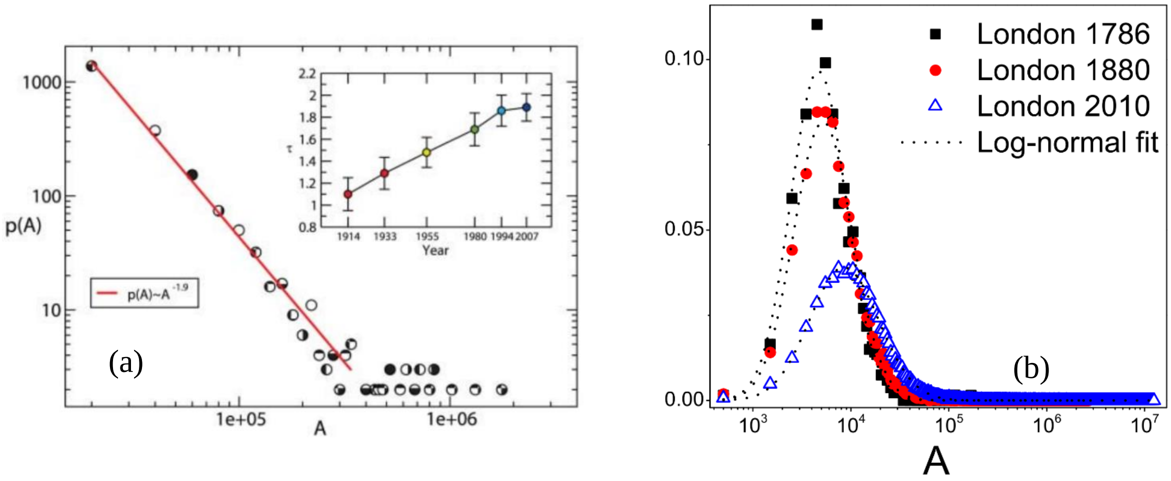



**Figure 2.5 Empirical Block Area Distribution $P(A)$ Dynamics**: (a) $P(A)$ dynamics of the Groane road network followed a power distribution. The x-axis represents block area $A$; the y-axis represents probability density; both axes are on the logarithmic scale. The inset plot shows $P(A)$'s power-law exponent increased from 1.2 in 1833 to 1.9 in 2007. (Strano et al., 2012) (b) $P(A)$ dynamics of the London road network persisted in following a lognormal distribution. The x-axis represents block area $A$ and is on the logarithmic scale, the y-axis represents probability density. (Masucci et al., 2013)London showed contradicting characteristics: in the dynamics of a lognormal distribution, $P(A)$ moved towards the right, suggesting an increase in block areas $A$ instead of subdivision of larger urban blocks into smaller ones. This finding might result from the examined area – the greenbelt was much larger than the studied initial road network. The London road network expanded during the studied historical period and the inclusion of new urban land led to the increase of block areas. On the other hand, the Groane road network did not expand during the studied historical period and reflected mainly a process of increasing density within the initial road network – the subdivision of the larger blocks into smaller ones, which could be described by increasing $\alpha$ of a power-law $P(A)$.

#### 2.3.4.3 Block Characteristics Discussion

Empirical findings of urban blocks area probability distributions $P(A)$ have been inconsistent. However, the reported $P(A)$ shared the same characteristics for large $A$, which could be fitted on a log-log plot by a straight line. Mainly two $P(A)$ distributions have been reported: power-law and lognormal. Previous studies have acknowledged the head of $P(A)$ may not fit power-law: Lämmer et al. (2006) - Figure 2.4 (a) excluded small values; Louf and Barthelemy (2014) pointed out this issue. These studies decided not to consider the head of $P(A)$ and concluded $P(A)$ followed a power-law distribution with exponent $\alpha \approx 2$. Studies that concluded $P(A)$

followed the lognormal distribution chose instead to consider the head of $P(A)$ as in Usui and Asami (2018). Consequently, they have faced the problem that very large $A$ may not fit lognormal distribution and limited considerations of these very large $A$.

As mentioned in 2.3.3.2.1, power-law and lognormal distributions are very similar on a log-log plot; the lognormal distribution may appear to be a straight line similar to the power-law distribution (Mitzenmacher, 2004). The power-law distribution Long et al. (2016) presented in Figure 2.4 (b) appears to be lognormal since it displayed a similar shape as the lognormal curve in Figure 2.4 (e). The slope of $P(A)$'s tail of the log-log plot seems to increase with urban density and the level of urbanisation, which divides large urban blocks into many smaller ones. For dense urban areas, the slope $\alpha$ is likely to have value $\alpha \approx 2$. If the density increases - for example, only consider the building blocks as Riascos (2017) did in Figure 2.4 (c), the slope $\alpha$ is likely to have value $\alpha \geq 2$. Expanding the examined area to include suburban and rural areas is likely to decrease $\alpha$ and leads $P(A)$ to fit better the lognormal distribution. Long et al. (2016) found Beijing's $\alpha = 1.37$. Jiang and Liu (2012) found lognormal in national road networks. Fialkowski and Bitner (2008) found lognormal for suburban and $\alpha = 1$ for rural road networks. Riascos (2017) found $\alpha = 1$ for natural urban blocks such as a river, a park. Usui and Asami (2018) reported lognormal for Tokyo, excluding very large blocks.

Empirical findings of the $P(A)$ dynamics have not been consistent either. The type of distribution appears to persist as the urban road network develops. The average and overall block areas have been reported to increase and decrease; this contradiction may result from the studied urban road network's expansion.

Existing findings suggest that $P(A)$ is highly sensitive to the chosen study area or density of the chosen area. $P(A)$ may exhibit power-law or lognormal distributions accordingly. Block area dynamics may be a process of the land subdivision because new roads divide larger urban blocks into smaller ones. Assuming $P(A)$ follows power-law distribution, this process has been reflected in the increasing slope $\alpha$ of $P(A)$ on the logarithmic scale. Meanwhile, in case of an expanding road network, urban density may not increase monolithically as the road network expands; average and overall block areas may instead increase with the inclusion of new land.

Similar to the link length distribution, existing empirical studies have focused on reporting the different probability distributions but have not investigated the generation mechanisms of these distributions and the corresponding changing processes of urban road networks that led to these distributions. Further research questions may be asked:

- How do the lognormal or power-law $P(A)$ distributions emerge in urban road networks and what RNE mechanism does this reflect?
- How does $P(A)$ change - does it persist in following a lognormal or power-law distribution, and how do the characteristics of the distribution change? What RNE mechanism does this reflect?

#### 2.3.4.4 Dynamic Link Characteristics

As in Figure 2.6, Masucci et al. (2013) reported London road network $l$ distribution persisted in being lognormal from 1786 to 2010. Strano et al. (2012) reported the quantity $l_{\geq 90\%}$ in the Groane road network, which was the 90th percentile of all new link length during a historical period, decreased from 625m to 325m from 1833 to 1925, and further from 325m to 225m from 1994 to 2007. This finding meant most new links persisted in decreasing in length.

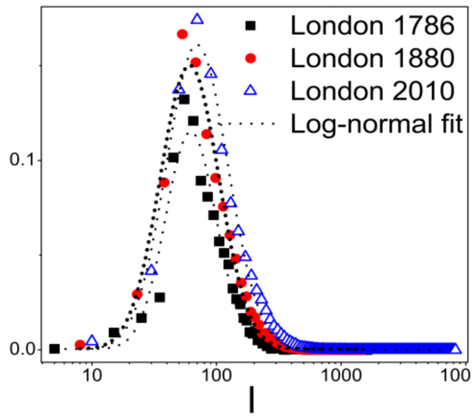



**Figure 2.6 Empirical Link Length $l$ Distribution Dynamics**: $l$ distribution dynamics of London from 1786 to 2010 on a semi-log scale (log x); the x-axis represents link length, the y-axis represents probability. (Masucci et al., 2013)

## 2.4 Betweenness Centrality Characteristics

Betweenness Centrality (BC) is a type of centrality first proposed in social network analysis (Freeman, 1978; Borgatti, 2005; Borgatti and Everett, 2006), and later becomes an essential concept and measure in network science. Among all the centrality measures, BC has been the most informative in revealing the road network structure (Barthelemy, 2017). This section reviews BC's application in characterising the urban road network structure.

BC measures how frequent a node or link lies on the shortest paths in the network. A path is a sequence of nodes, along which each pair of adjacent nodes is connected by a link (Barabasi, 2016). Instead of referring to the number of links along a path as in complex network topological characterisation, spatial network characterisation can adopt the total Euclidean link length of a path as the path length. Then, BC of a node or link $i$ is defined as

$$BC(i) = \frac{1}{(N-1)(N-2)} \sum_{s \neq t} \frac{\sigma_{st}(i)}{\sigma_{st}},$$

in which $\sigma_{st}$ is the number of the shortest path between node pair $s$, $t$, and $\sigma_{st}(i)$ is the number of shortest path between node pair $s$, $t$ on which $i$ lies (Barthelemy, 2017).

Centrality has been applied in urban studies for decades and associated with the central places. Centrality is a fundamental concept to understand cities. It refers to "prominent locations", and tries to understand "the generation and changes of centres" (Hillier, 1999). It suggests how cities work – around central places,  and the urban evolution mechanisms – the emergence of central places (Porta et al., 2010). Centrality contains functional and spatial information (Hillier, 1999). Functionally, it may represent accessibility, high density, intense land use, and principal urban functions; spatially, it may reveal the urban spatial structure, such as the concentration and distribution of economic activities (Porta et al., 2010).

Centrality measures, including BC, have been used to study road networks for more than one decade (Crucitti et al., 2006a; Crucitti et al., 2006b). Debates of BC's usage have revolved around two main issues: whether BC relates to traffic flows and how informative BC is in revealing road network structure. BC uses the frequency of shortest path traverse between node pairs to measure the importance of network components; it assumes equal transport demand between each node pair and indicates high BC components are important because more flows brought by shortest paths pass these components. In other words, regarding high BC components as important implicitly admits they accommodate more flows.

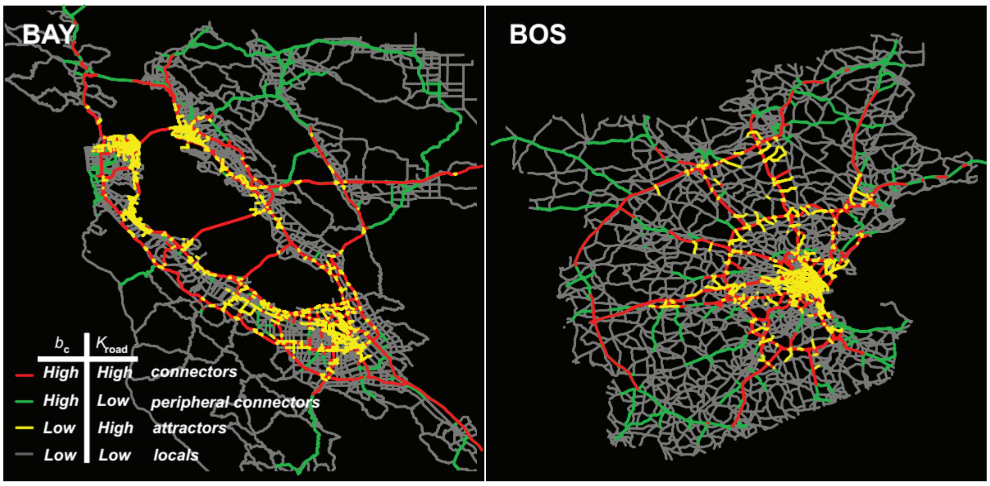



**Figure 2.7 Betweenness Centrality and Road Network Usage Patterns**: These two plots compare road segments' BC and road network usage which was defined as origins of trips at road segment and calculated by mobile phone data in San Francisco Bay Area and Boston Area. Roads are coloured according to the correlations between link BC and usage: red roads have both high BC and usage; grey roads have both low BC and usage; green roads have high BC but low usage; yellow roads have low BC but high usage. (Wang et al., 2012)

Deficiencies of these assumptions, when applied to road networks and traffic flows, have shown in the treatment of both transport demand and supply (Zadeh and Rajabi, 2013). First, transport demand origins and destinations are likely to distribute alongside road segments instead of being at each node pairs and are likely to be inhomogeneous as assumed in calculating BC. Second, as transport supply is limited, accessibility to shortest paths is likely to be inhomogeneous either, which means traffic flows are unlikely to all travel on the shortest paths as assumed in calculating BC (Gao et al., 2013). Third, transport demand and traffic are dynamic, e.g. vary during the day, whereas BC is a static measurement of a road network (Kazerani and Winter, 2009). Following these arguments, some empirical studies reported low correlations between BC and traffic flows (Gao et al., 2013; Wang et al., 2012). However, BC has been shown as capable of capturing important routes with high traffic flows as in Figure 2.7 - the red major routes captured by high BC as critical agreed with the empirical data of road usage. Besides, the grey components also show the correspondence of low BC and road usage.

In terms of revealing informatively the road network structure, BC's limitation lies in the broader debate regarding the relationship of network configuration and function, and between urban form and function at large. Regarding BC, correlations have been found between high BC network components and major travel routes (Crucitti et al., 2006a), essential land uses (Rui and Ban, 2014), other transport networks (Strano et al., 2015), crucial economic activity locations (Porta et al., 2009; Porta et al., 2010; Wang et al., 2011), and transport accidents locations (Sarkar et al., 2017), suggesting positive correlations between high BC and important locations.

Despite potential limitations in predicting traffic flows and urban functions, BC has been shown as competitive to measure the road network structure.

### 2.4.1 Static BC Characteristics

As the example of Dresden shown in Figure 2.8 (a), Lämmer et al. (2006) found BC distributions of 20 largest German cities' road networks followed the power-law distribution. They concluded that this finding reflected the hierarchy of road networks, with the following calculation. For example, in Dresden, 50% road length had only 0.2% high BC concentration, while 80% of high BC concentrated on 10% of road length and 50% on 3.2%. Crucitti et al. (2006a) found BC distributions of planned road network followed a Gaussian distribution, while that of self-organised ones followed an exponential distribution (Crucitti et al., 2006b; Crucitti et al., 2006a; Porta et al., 2006a).

Kirkley et al. (2017) found 97 world largest cities' road network BC distributions followed the same bimodal distribution, as shown in Figure 2.8 (b). They pointed out previous studies suffered from small sample size (e.g. 1 mile$^2$ road network sampling) and noise created from binning data thus used 3000 km$^2$ of the road network instead for each city. They explained the found bimodal BC distribution by an underlying spanning tree high BC backbone and minor low BC roads from alternative loop paths. The bimodal BC distribution had a tail of high BC values peaking at $BC = |V|$(the bump in Figure 2.8 (b)); this value corresponded to the BC of components next to the leaves of an underlying spanning tree in the network; the high BC values were bounded by $|V|^2$. The head of the bimodal BC distribution corresponded to low BC components; these components formed alternative loop paths which diverted part of the BC flows away from the high BC components on the spanning tree. This bimodal BC distribution was not affected by changing local topology and rewiring, i.e. change node degree locally, or changing local geometry, i.e. uniformly distribute nodes or change edge weights. It was determined by planarity and a network density quantity $\rho_e = \frac{|E|}{E_{DT}}$, which was the ratio of link number and maximum link number. (Given a set of points on a plane, MST is the planar network with the smallest number to connect all the points, while DT is the planar network with the maximum number of links (Kirkley et al., 2017). MST and DT are benchmark networks for overall connectivity and normalise road networks for comparison (Crucitti et al., 2006a). )

In short, empirical findings have reported urban road networks' BC distribution to be bimodal, which was regarded as a topological characteristic shared by planar networks. High BC components are likely to come from an underlying spanning tree of the network while low BC components form alternative loop paths.

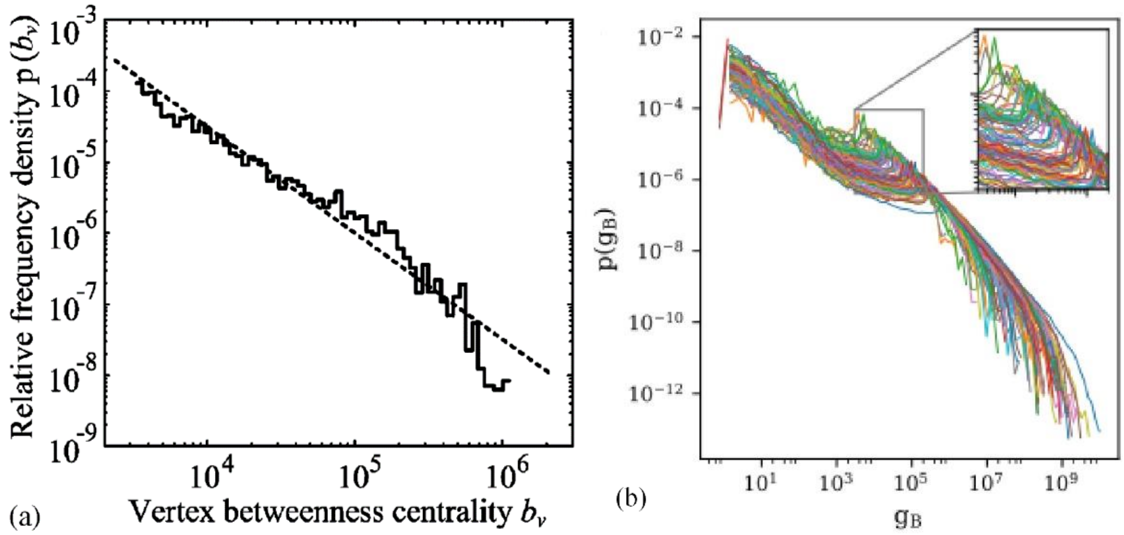



**Figure 2.8 Empirical Betweenness Centrality Distributions**: (a), (b) The x-axis represents betweenness centrality (BC); the y-axis represents probability density; both axes are on the logarithmic scale. (a) shows BC probability distribution of Dresden road network, which followed power-law distribution $P(BC){\sim}BC^{-\beta}$, $\beta = 1.355$ (Lämmer et al., 2006); (b) shows BC distributions of 97 most populous cities' road networks, all following a bimodal distribution with the tails of larger values peaking around $\mathrm{BC} = |V|$ – the number of nodes (Kirkley et al., 2017).

### 2.4.2 Dynamic BC Characteristics

Kirkley et al. (2017) found the hierarchy or rank of BC was stable with time because network density $\rho_e = \frac{|E|}{E_{DT}}$ which determined the bimodal BC distribution had a small value range and was stable in real urban road networks. If network density was low – a spanning tree being the lowest as in the upper panel of Figure 2.9, BC distribution peaked at $|V|$ and high BC nodes did not show spatial correlation. When network density increased and alternative loop paths were created, BC distribution started to show the bimodal characteristics, and high BC nodes concentrated towards the barycentre of the network, as in the lower panel of Figure 2.9. Real-world road networks have a small $\rho_e$ range around $[0.4, 0.6]$, thus have stable BC distributions. Paris road network has $\rho_e = 0.5$; its BC distribution remained stable with time, as shown in Figure 2.10 (b), though the spatial distribution of BC changed drastically because of the Haussmann planning, as shown in Figure 2.10 (a).

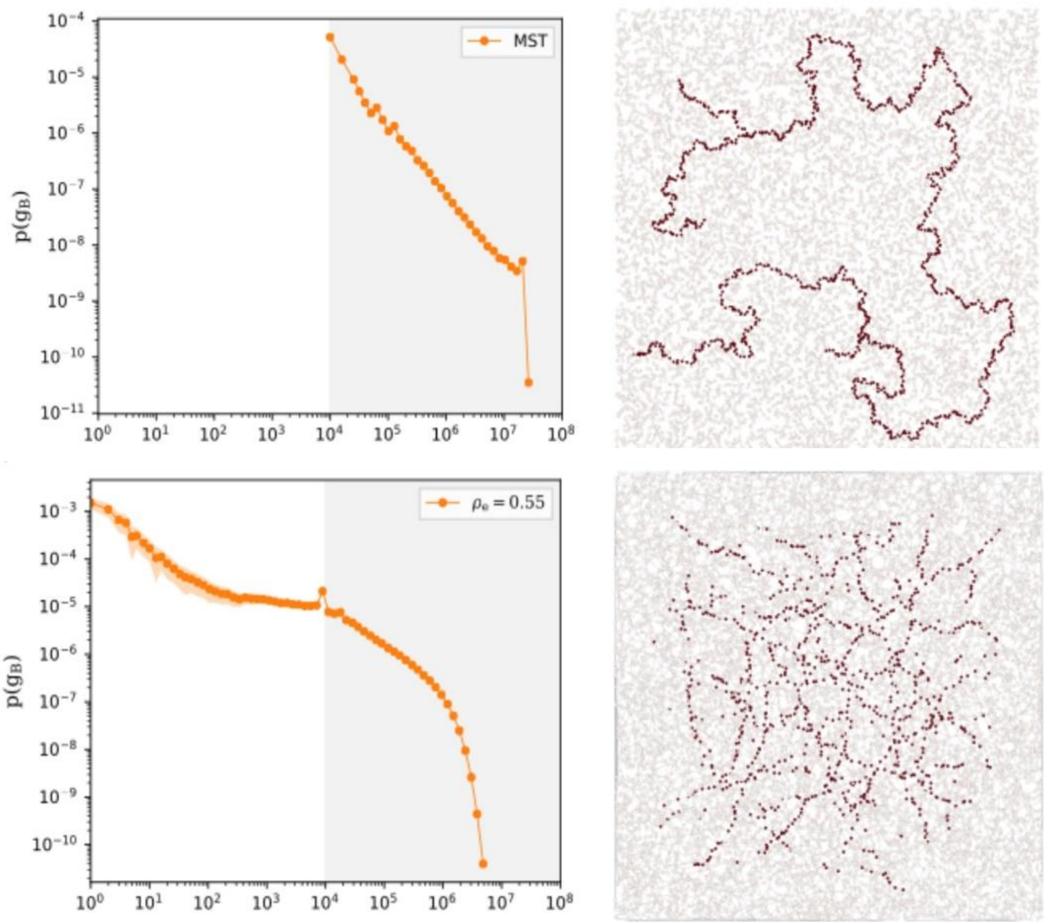



**Figure 2.9 The Emergence of Bimodal Betweenness Centrality Distribution**:
Upper and lower panel demonstrate how network density $\rho_e = \frac{|E|}{E_{DT}}$ - the ratio of link number $|E|$ and maximum link number $E_{DT}$ (of DT realised on the same nodes), determined BC distribution. The upper panel sets $\rho_e = \rho_{MST}$ (of MST realised on the same nodes) and was the lowest possible $\rho_e$; the lower panel set $\rho_e = 0.55$. The left column plots BC distributions; the x-axis represents BC; the y-axis represents probability density. The right column shows in grey one sample network at the set $\rho_e$, and in purple the highest BC nodes (larger than the 90th percentile). The upper panel shows at $\rho_e = \rho_{MST}$, BC resembled the tails of road network BC distributions, indicating road network's largest BC components belong to an underlying spanning tree within urban road networks; high BC nodes did not show spatial correlation. The lower panel shows at $\rho_e = 0.55$, close to real-world road networks; BC resembled the empirical bimodal BC distribution. At this $\rho_e$, high BC nodes showed spatial correlation and concentrated towards the barycentre of the network. (Kirkley et al., 2017)

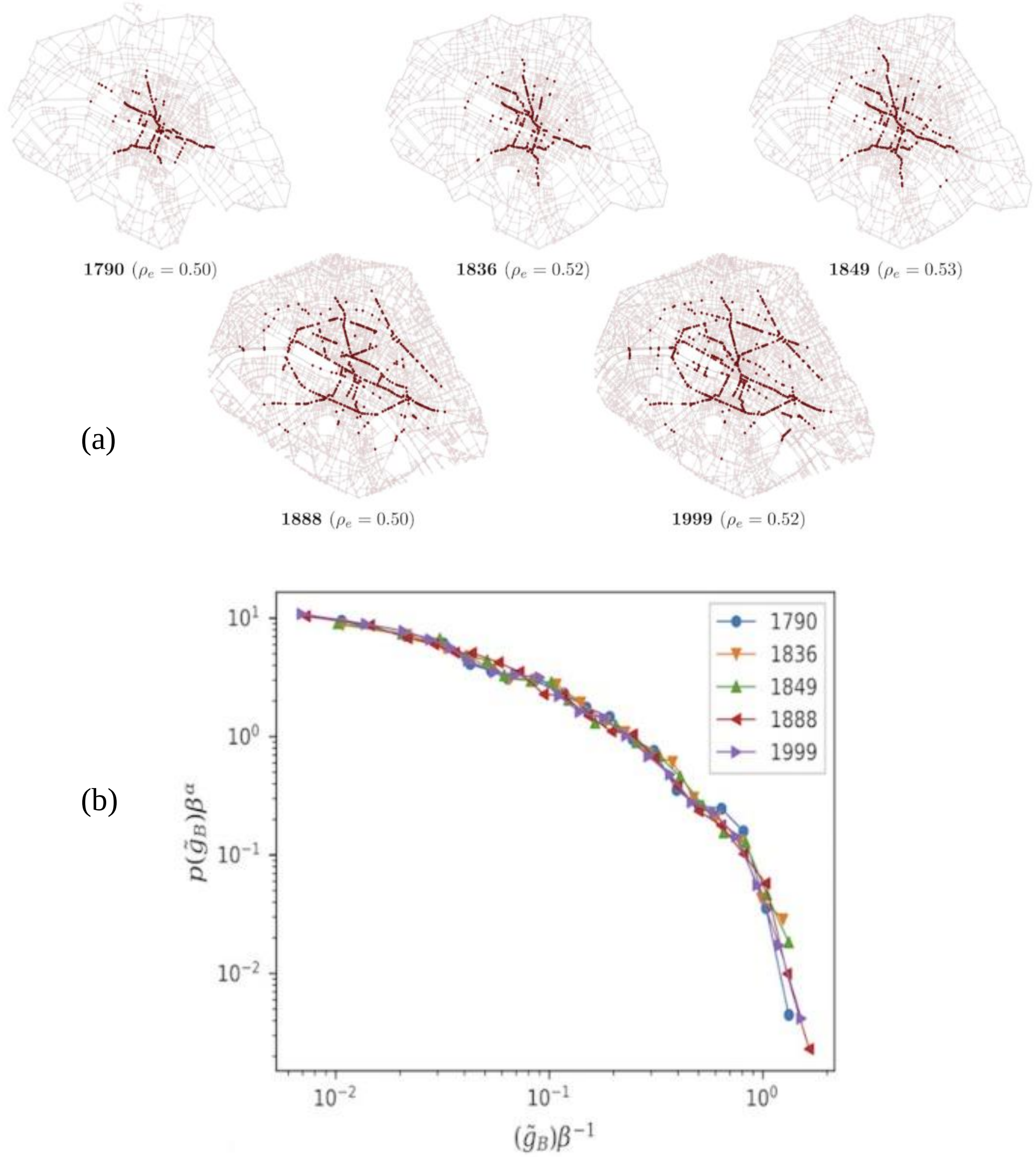



**Figure 2.10 Empirical Betweenness Centrality Dynamics**: BC dynamics of Paris road network from 1790 to 1999. (a) shows the spatial distribution of high BC nodes, which was a persistent tree structure, except for an added ring of high BC nodes because of the Haussmann planning. (b) shows the correspondent BC distributions of different periods remained stable as network density $\rho_e$ was stable. (Kirkley et al., 2017)

In summary, empirical research has proposed that BC dynamics depend on network density $\rho_e = \frac{|E|}{E_{DT}}$ and stay stable if $\rho_e$ does not change. Real-world road networks' $\rho_e$ lies within a small range, leading to observed similar bimodal BC distributions. Also, high BC components are likely to concentrate towards the barycentre with increasing $\rho_e$, explaining the high BC around urban centres.

### 2.4.3 RNE Phenomenon – The Backbone of Urban Road Networks

Empirical RNE research has proposed a few RNE phenomena, which were more sophisticated network characteristics besides elementary network components' characteristics, attempting to capture overall changes of urban road networks. Two

RNE phenomena are characterised based on BC. This section introduces the RNE phenomena – the backbone of urban road networks.

As shown in Figure 2.11, Strano et al. (2012) found a correlation between road segments' existence time and BC. 60% of 1000 highest BC links in the 2007 road network existed before 1833. They interpreted these high BC and long-existing road segments as the 'backbone' of the urban road network, which persisted in history without many modifications and drove local development through industrialisation, urbanisation, de-industrialisation. This finding might be associated with urban morphology's view that backbone roads are the framework of urban development, which influence on different scales the urban forms by influencing accessibility and land-use (Whitehand, 2001).

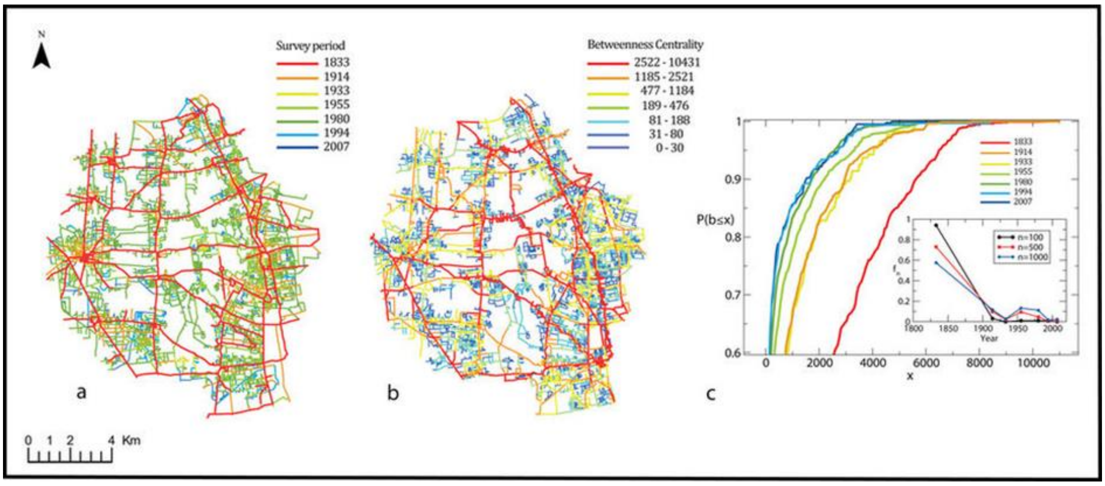



**Figure 2.11 The Backbone of Urban Road Networks – Relationship Between Roads' Existence Time and Betweenness Centrality**: Plot *a* colours the network links according to their existent time, red links exist before 1833, and so forth; Plot *b* colours links according to BC, red links have highest BC, and so forth. Plot *c* shows the BC cumulative distributions of 7 groups of links in plot *a*, red links, which existed before 1833, had higher BC than other groups, and in general links' BC correlated positively with their existent time. Plot *c*'s inset plot shows how the proportion of links (y-axis) from the different periods (x-axis) constitute top 100, 500, 1000 highest BC links; almost all 100 highest BC links existed before 1833, and the majority of top 500 and 1000 highest BC links existed before 1833. (Strano et al., 2012)

As shown in Figure 2.12, Masucci et al. (2013) found London's major roads existed before the studied period 1786 - 2010, and the increase of road length in recent 200 years were mainly from minor roads' growth. They concluded that the road network evolution had time sequences, in which major roads grew first and persist, then minor roads grew and subdivided the space between the major roads.

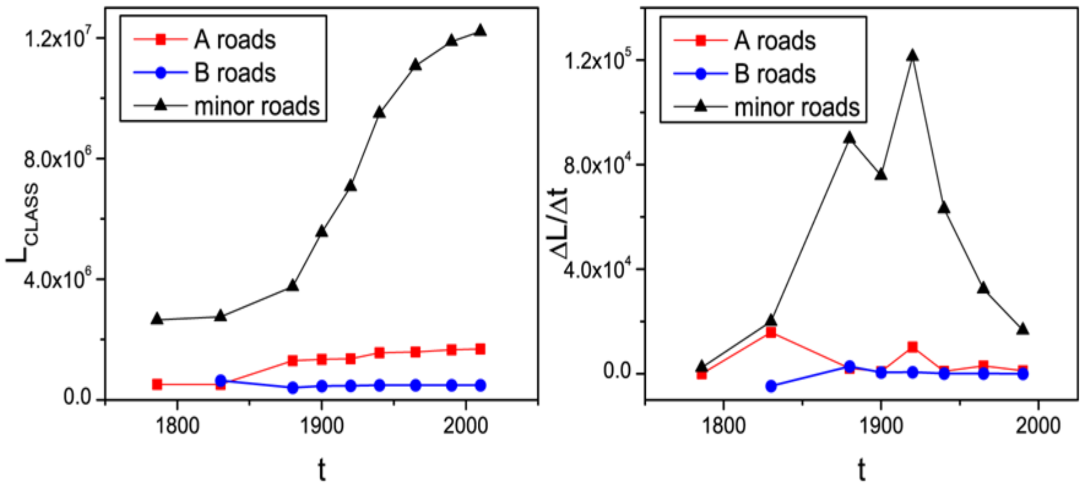



**Figure 2.12 The Backbone of Urban Road Networks – Growth of Major and Minor Roads in London Road Network**: The left plot shows total length of class A, B and minor roads; the x-axis represents time, and the y-axis represents road length. The right plot shows the change rate of the three categories of roads accordingly. Major roads had little increase during more than 200 years, while minor roads constituted the major growth. (Masucci et al., 2013)

### 2.4.3.1 The Backbone of Urban Road Networks Discussion

The observed RNE phenomenon – the backbone of urban road networks may be associated with the empirical finding of bimodal BC distribution, as reviewed in 2.4.1, 2.4.2. Though used to indicate the correlation between road segment importance and existence time, the backbone phenomenon has measured the correlation between link BC and existence time. The bimodal BC distribution has proposed that urban road networks consist of high BC components belong to an underlying spanning tree of the road networks and concentrate towards the barycentre of the networks as network density $\rho_e$ increases. Therefore, it appears that the correlation found between high BC and long-existing roads in the backbone phenomenon relates to broader correlations among network components that have high BC, belong to the underlying spanning tree, locate near the geographical centre, and exist for a long time in the network.

This correlation indicates that an inherent hierarchy does exist in urban road networks, which may relate to the road network hierarchy found in traffic concentration (Lämmer et al., 2006), road functional and operational classification (Xie and Levinson, 2007), and the continuity of streets (Marshall et al., 2018). Some networks components are more important than others, as shown by high BC, long existence time and geographical central locations. Moreover, this correlation indicates long-existing components are likely to be geographically central or lie on the underlying spanning tree of the network, which leads to their high BC values. Thus, the correlation between BC and existence time may require other factors, such as the underlying spanning tree structure and the geographical location, to explain. Also, the empirical findings of the backbone phenomenon suggest the evolution process of urban road networks may be described by two phases: the formation of major routes and the subdivision of space by minor routes.

Since the existing empirical studies have not considered the broader correlations between BC, existence time, the underlying spanning tree, and geographical locations, nor have they considered the network changing mechanism and process that led to the observation of the backbone phenomenon, two further research questions may be asked:

- Do network components that have high BC, belong to an underlying spanning tree, locate near the geographical centre, and long exist in urban road network correlate? What RNE mechanism does this reflect?
- How to the backbone of urban road networks form and change? What RNE mechanism does this reflect?

### 2.4.4 RNE Phenomenon - Densification and Exploration

Strano et al. (2012) proposed another RNE phenomenon – Densification and Exploration (DE). They proposed a measure - BC impact $\delta_{BC}(e)$ to characterise new links:

$$\delta_{BC}(e) = \frac{[\overline{BC}(G) - \overline{BC}(G \backslash e)]}{\overline{BC}(G)},$$

in which $\overline{BC}(G)$ denoted the average BC of network $G$, and $\overline{BC}(G \backslash e)$ denoted the average BC after removing link $e$ from $G$.

$\delta_{BC}(e)$ distribution at different historical periods along with the studied urban road network's development displayed a bimodal distribution with two well-defined peaks as in Figure 2.13 (d), categorising two types of new links. Exploration links associated mostly with dead-ends, and Densification links with bridging links of two previously existing links. Densification links was regarded as increasing the local density, and Exploration links as exploring the urbanisation front. DE was proposed to be two elementary urbanisation processes, with Densification being the first phase and Exploration being the second phase of an urbanisation cycle, as reflected by the visualisations in Figure 2.13 (a) – (c). The early stage of network development (a)-(b) witnessed both red exploration links and green densification links. The mature network development stage (c) had only green densification links; red exploration links stopped to occur.

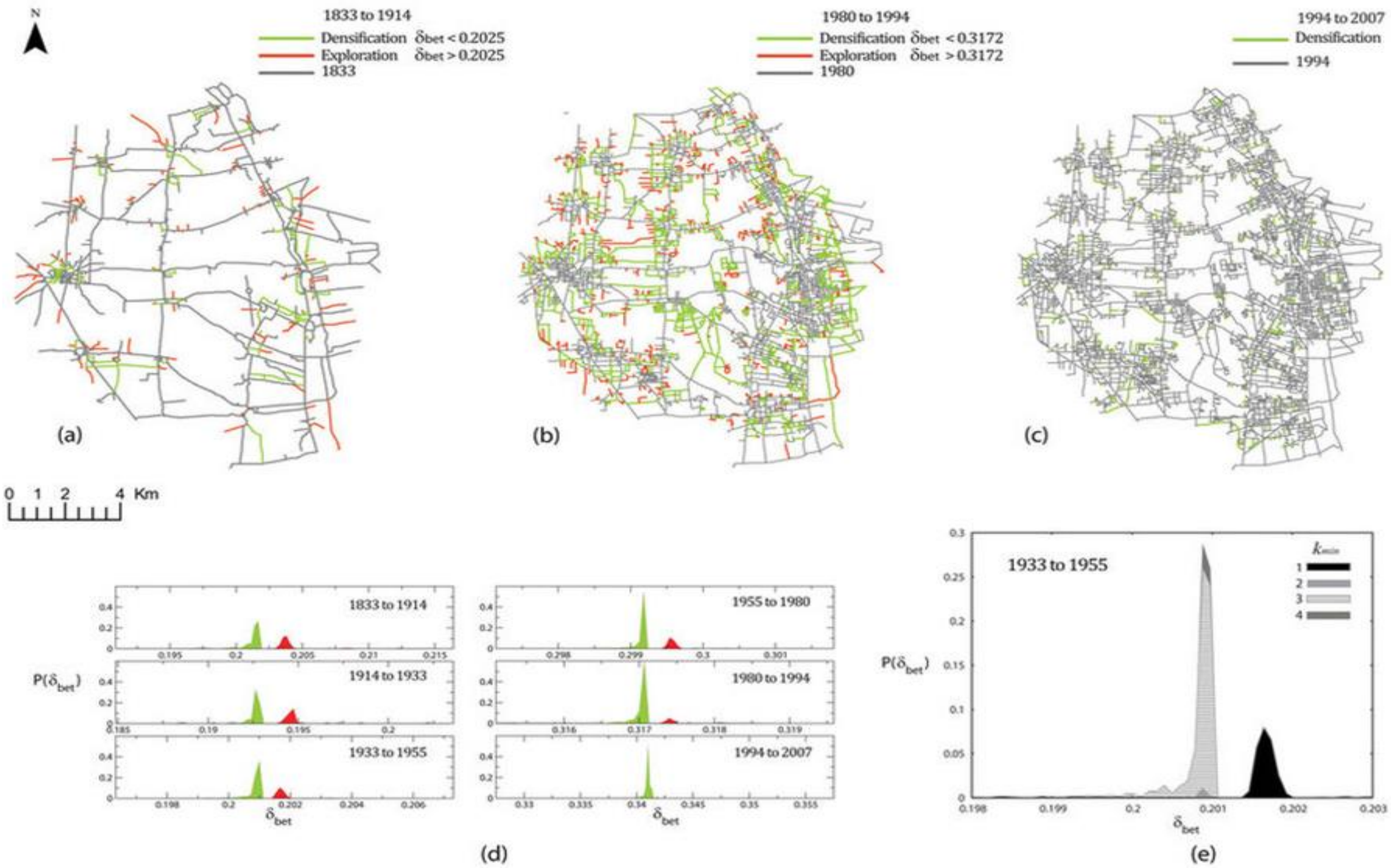



**Figure 2.13 Densification and Exploration in the Groane Road Network**: (a) - (c) map the Groane road network of three historical periods and colour the new links occurred in green and red according to densification and exploration (DE). (d) shows the BC impacts $\delta_{BC}(e)$ of new links added in six historical periods. The x-axis of each sub-plot represents $\delta_{BC}(e)$, and the y-axis represents probability density. New links' $\delta_{BC}(e)$ distributions had two peaks – green and red, which separated them into D and E links accordingly. The final period (1994 to 2007) did not have a red E peak anymore. (e) further shows compositions of the two peaks by the measure $k_{min}$ during the period (1933 to 1955). All links in the right E peak had $k_{min} = 1$ and were dead-ends, while all links in the left D peak had $k_{min} \geq 2$ and bridged two existing links before 1933. (Strano et al., 2012)

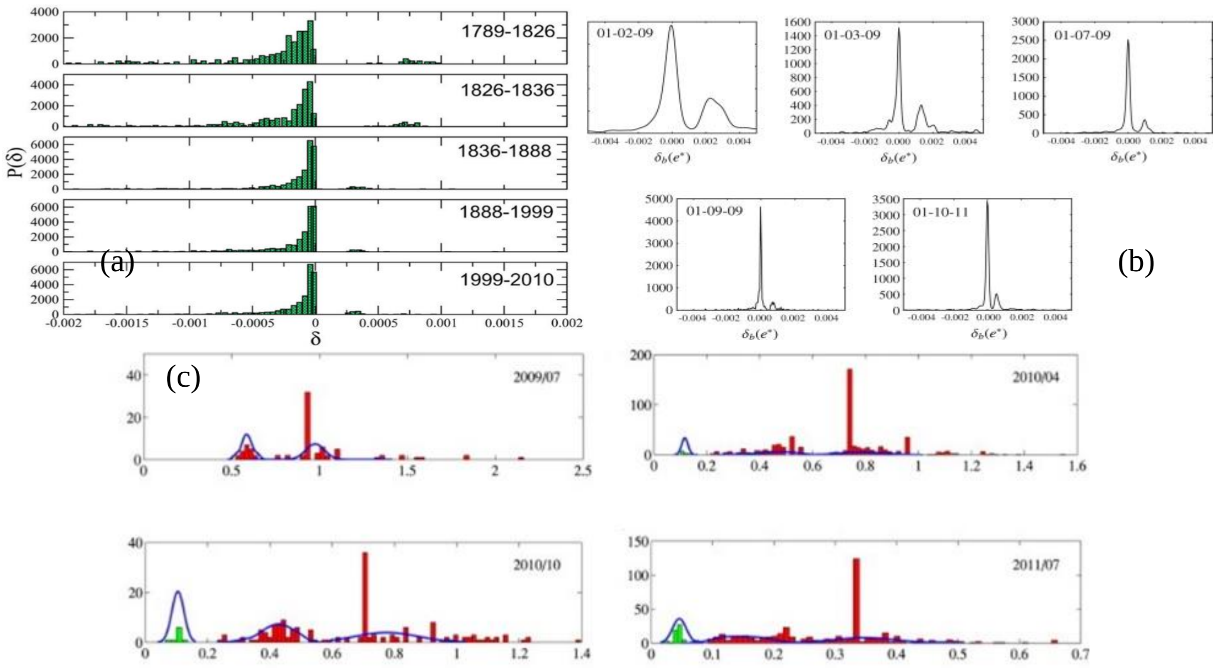



**Figure 2.14 Densification and Exploration in Spatial Networks**: (a)-(b) The x-axis of each sub-plot represents BC impact values, (c) The x-axis represents PageRank Centrality impact; (a)-(c) y-axis represents frequency. (a) The five panels show DE dynamics in five historical periods in the Paris road network. (Barthelemy et al., 2013) (b) The five plots show DE dynamics of the Maynooth's OpenStreetMap (OSM) in five periods starting from 02/2009 to 10/2011. (Corcoran and Mooney, 2013) (c) shows DE dynamics of the Beijing OSM calculated by PageRank centrality instead of BC (Zhao et al., 2015).

DE has been observed in other road networks and spatial networks. Barthelemy et al. (2013) confirmed DE in the Paris road network, as in Figure 2.14 (a). Another measure $E_i$ $i \in \{0,1,2\}$ was proposed to categorise new link, by the number of new nodes in new links' two end nodes. Corcoran et al. (2013) confirmed DE in three Irish cities' OpenStreetMap (OSM) dynamics as in Figure 2.14 (b). Zhao, P. et al. (2015) used PageRank node centrality instead of BC and confirmed DE in Beijing's OSM dynamics, as in Figure 2.14 (c).

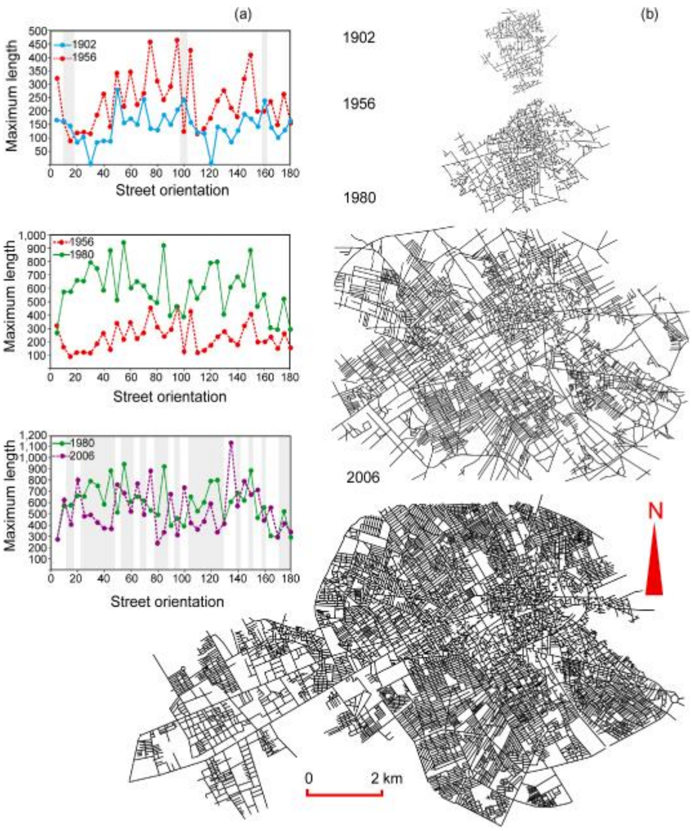



**Figure 2.15 Densification and Expansion**: column (a) shows changes of maximum link length $l_{max}$ in historical periods 1902-1956, 1956-1980, 1980-2006. The x-axis represents link orientations, which are azimuth angles in degree measured from the true North; the y-axis represents $l_{max}$ in meter. The top and middle subplots had almost all increased $l_{max}$, indicating dominant expansion of the network during these two periods. This result could be seen on the correspondent maps in column (b). The bottom subplot of column (a) had increased $l_{max}$ on some orientations and decreased $l_{max}$ on other orientations, indicating a mixture of densification and expansion happened during this period. (Mohajeri and Gudmundsson, 2014)

Instead of DE, Mohajeri and Gudmundsson (2014) proposed Densification and Expansion (DEx) as the two elementary processes to quantify urbanisation. They used the longest link length $l_{max}$ as the DEx measure, as in Figure 2.15: the decrease of $\max l$ indicated further dividing previous links – densification; the increase of $\max l$ indicated the addition of long new links at the periphery – expansion. They used DEx to described the evolution of Dundee (Gudmundsson and Mohajeri, 2013), Kerman, Khorramabad, Sheffield (Mohajeri et al., 2014) road networks. Further, DEx was related to the ecological effect of urbanisation and interpreted densification as preferred development and expansion as urban sprawl in the case of Geneva (Mohajeri et al., 2015).

Also, Patarasuk (2013) found the connectivity of Thailand's regional road network increased generally with the road network growth but not necessarily, because some new roads were dead-ends and did not improve road network's topological connectivity. Most of the new dead-end roads located in the agricultural land at the edges where two big cities in the region meet and extended into the hinterland.

#### 2.4.4.1 Densification and Exploration Discussion

Since its proposal as an RNE phenomenon, DE has been observed in many road networks and spatial networks. Two issues are worth further discussion: first, the meaning and interpretation of the measure BC impact $\delta_{BC}(e)$, and whether it reflects densification and exploration; second, the meaning and interpretation of the proposed RNE phenomenon DE and whether it reflects two elementary processes of RNE or urbanisation.

The many observations suggest DE may be a property shared by planar networks. A planar network has two possible new link connection patterns: a new link that is a dead-end or a new link that bridges two existing links. This reasoning agrees with the DE finding. Therefore, DE's mere existence may not be informative regarding whether road networks densify and explore, if it is a topological property of all planar networks and the only two possible connection patterns for new links. Densification has been expected to reflect the increase of urban density but has not measured the road network density explicitly; addition of new links bridging two existing links does not necessarily increase density. The same argument applies to exploration. Other than the identification of DE by BC impact $\delta_{BC}(e)$, more aspects shall be considered in characterising DE for more meaningful results, such as the spatial locations and temporal sequence of new links. In short, BC impact $\delta_{BC}(e)$ may quantify the two only possible connection patterns of planar network link addition; the mere existence of DE identified by $\delta_{BC}(e)$ may lack comprehensiveness to quantify densification and exploration processes and require further characterisation of spatial and temporal aspects.

Second, DE may represent elementary RNE processes, but the referred processes shall be further defined and related to urban processes. Existing DE definition has remained quantitative based on the new link's positive or negative influences on network BC, which may identify the two possible new link connection patterns and have no significance. On the other hand, DE can be associated with parallel urban processes, such as with infill and edge urban growth, which increase density and urban sprawl, respectively. Visually in the Groane road network, DE had spatial and temporal characteristics, e.g. Exploration links were often found at the fringe of the network and were not built as urbanisation proceeded to a certain extent. This reasoning has been confirmed in empirical findings of the Thailand regional road networks, in which new links were usually dead-ends that occurred at the fringe of urban areas. Therefore, provided that spatial and temporal characteristics were included in the definition and quantification, DE may describe potential RNE processes.

With these limitations identified, further research questions may be specified:

- Whether BC impact $\delta_{BC}(e)$, the DE measure, distinguishes dead-ends and bridging links, thus quantifies a topological property shared by planar networks when adding new links?

### 2.4.5 Betweenness Centrality Discussion

Among complex network centrality measures, BC has been the most widely applied to road network analysis and yielded the most informative results of the urban road network structure. Empirical research has reported BC to follow a bimodal distribution, consisting of high and low BC components from an underlying spanning tree and alternative loop paths, respectively. The bimodal BC distribution may only relate to road network's planarity and network density; the latter is measured by the number of links of the network against the number of links of a complete network on the same set of nodes. The BC distribution is likely to stay stable because the urban road network's density is likely to lie within a small range of values. If the network density increases, spatial correlation of high BC components is likely to increase and concentrate towards the barycentre of the network. Two proposed RNE phenomena in recent empirical RNE research have been constructed based on BC. The backbone of urban road networks has related roads' importance approximated by BC to their existence time and proposed long existing roads form a skeleton of major routes, and later network dynamics are the addition of minor routes that subdivides space in the skeleton. Densification and exploration (DE) have measured the change of network average BC caused by new links, distinguished two types of new links, and proposed these two types as representing different RNE or urbanisation processes – one increases the urban density, the other explores the urbanisation front.

Two limitations of existing empirical research on BC were identified. First, BC findings, including the BC distribution and dynamics, the backbone of urban road networks, and DE, are likely to be related. However, current research has not compared these findings horizontally to form a comprehensive picture of BC characteristics. This limitation may result from three issues: there has been disagreement in terms of the BC distribution; the empirical studies have focused on reporting the different distributions rather than reasoning the mechanisms and processes behind their formation; further investigations are required to understand the BC observations and implications. Correlations are likely to exist between network components that have high BC, belong to the underlying spanning tree structure, locate near the geographical centre, and long exist. This correlation may reflect the formation and dynamics of urban road networks. Urban road networks seem to first form a skeleton of major routes, then the minor routes; the major routes are likely to exist a long time in the network and have high centrality; the minor routes may perform densification or exploration.

The second limitation concerned BC's assumption in equating the high BC value to high road network structural importance. BC assumes the importance of network components, as well as the demand and flows on the network, can be approximated by the BC value, which is likely to require more empirical validation. This limitation lay beyond this study' research scope. This study regarded BC as an informative measure of the urban road network structure, because of the empirical evidence of BC's capacity in capturing major travel routes, as well as the correlations between BC and central spatial locations.

Following the empirical findings and limitations, further research questions may be asked:

- Does BC follow a bimodal distribution, consisting of high BC components from an underlying tree structure and low BC components from alternative loop paths in the road networks? Does network density control the BC distribution? How does the BC distribution emerge, and what RNE mechanism does this reflect?
- Do network components that have high BC, belong to an underlying spanning tree, locate near the geographical centre, and long exist in urban road network correlate? What RNE mechanism does this reflect? How the backbone of urban road networks form and change? What RNE mechanism does this reflect?
- Whether BC impact $\delta_{BC}(e)$, the DE measure, distinguishes dead-ends and bridging links, thus quantifies a topological property shared by planar networks when adding new links? What functions do the two types of new links perform and can this be inferred from their spatial and temporal characteristics? Can such characteristics be incorporated into identifying DE, which further reflects the RNE mechanism?

## 2.5 Chapter Conclusion

To synthesise an empirical understanding of urban road network structure and changes, 2.2 introduced the changing network science methods from characterising complex networks to spatial networks and from static structure to dynamic structure; 2.3 and 2.3.4.4 reviewed empirical findings of elementary urban road network components' characteristics and dynamics. This section concludes this literature review chapter's findings, which is a synthesised understanding of empirical urban road network evolution 2.5.1 and discusses the limitations of network science perspective empirical RNE research 2.5.2.

### 2.5.1 Synthesise an Empirical RNE Understanding

Regarding incremental growth, urban road networks seems to evolve with the addition and connection of elementary network components, during which macroscopic network characteristics and dynamics emerge.

Static node degree has been reported to exhibit a majority of $k_3$ nodes. Dynamics of $\langle k \rangle$ may increase, stay constant, or decrease, according to changes of $k_1$ and $k_4$ nodes proportions. Statically, link length $l$ has been reported to exhibit the lognormal distribution, which has been attributed to typical urban road networks' having very few very short or very long links, many medium links, and abundant short links. Dynamically, $l$ distribution has been reported to persist in being lognormal, with the peak concentrating because more short links are likely to be added as road network grows. Statically, block areas $A$ may exhibit power-law or lognormal distributions, depending on the density of the studied area. Dynamically, $\mathrm{P}(A)$ may persist in following power-law or lognormal distributions and may exhibit increased slope on the logarithmic scales because of more small blocks with urbanisation and large blocks' subdivision. Static BC has been reported to follow a bimodal distribution, separating high BC components from an underlying spanning tree within the road network and low BC components from alternative loop paths. Dynamically, BC has been proposed to be determined by the network density $\rho_e = \frac{|E|}{E_{DT}}$; BC hierarchy or ranks of network components are likely to stay stable if $\rho_e$ remains stable. BC is likely to concentrate towards the barycentre as $\rho_e$ increases. Correlations may exist between high BC and long existence time of road network components, which may result from broader correlations among the high BC, the underlying spanning tree's, the geographically central, and the long-existing components. Two types of new links may exist, causing different changes of the network average BC. These two types of new links are likely to be dead-ends and bridging links that connecting two previous existing links, which may perform different functions - Densification and exploration (DE). Urban road networks may first form a skeleton of major routes, followed by local development with the growth of minor network components.

This synthesised empirical RNE understanding included both the static and dynamic urban road network structures, characterised by elementary network components' characteristics and changes. Node degree characterised the road network's elementary connection patterns and changes. Link length characterised the filling of urban space by road network segments. Block area characterised the division and expansion of the covered urban space by road network. BC characterised the importance of network components and revealed the hierarchy among the urban locations. When combined, these characteristics quantified the urban road network structure and suggested the processes that lead to such a structure. This synthesised empirical RNE understanding provided a framework to characterise RNE, to examine simulation results in later chapters.

### 2.5.2 Empirical RNE Research Limitations

Empirical research using the spatial network characterisation has provided empirical evidence of RNE, with limitations in the meaning and interpretation of their measures and results, as well as in reflecting what urban knowledge has been created (Ducruet and Beauguitte, 2014).This chapter identified two limitations in the existing empirical RNE research.

First, empirical RNE findings have required further exploration because of insufficient horizontal comparison, consensus regarding the findings, as well as investigations of dynamic processes and mechanisms behind the empirical observations. The inconsistency partly came from the studied subjects. Each empirical RNE research studied one or a limited number of individual road networks. Since each road network was unique, differences always existed among urban road networks. Similarly, the choice of historical periods to study was subjective to each study. Also, this discrete nature to analyse a few network snapshots limited the generality of the findings as continuous RNE processes. Despite the uniqueness of different road networks, their historical paths, and the discrete nature of empirical studies that contributed to the inconsistency in findings and conclusions, empirical RNE research had different research scope and questions. The different research focuses created a barrier to piece together their results. Given similar subjects and research questions, empirical RNE studies again differed in data treatment and measurement, creating difficulty for cross-comparison of their results. Finally, there were debates over several road network characteristics, such as the link length, block areas BC distributions. However, empirical research focused on reporting the different findings rather than investigating the dynamic processes and mechanisms that led to the occurrence of different network characteristics.

Faced with the inconsistency in both findings and methods, this chapter started with elementary road network components' characteristics, which were more frequently studied than more sophisticated network characteristics and had more existing empirical results for cross-comparison. Also, this chapter emphasised on urban road network characteristics examined in the empirical RNE research that studied the changes in road networks. Through review and synthesis, this chapter put together a framework of RNE characterisation and characteristics.

Further understanding may be acquired with modelling and simulation, exploring the mechanisms behind the emergence of inconsistency in reported empirical findings. The empirical RNE findings suggest potential changing processes of urban road networks, which required further experiments to explore the relationships between the emergence of road network characteristics and network components' behaviour and interactions. Rather than accommodating the uniqueness of individual real-world road networks, modelling and simulation may study a general urban road network structure. Also, the changing processes of road network characteristics may be modelled, based on the growth of elementary components, to provide insights into the source of the inconsistency in empirical findings. Furthermore, modelling and simulation may study a continuous RNE process, thus transforming the discrete empirical understanding into continuous.

The second limitation of existing empirical RNE research has been the insufficient consideration of road networks' spatial structure, as shown in the limited discussions of both the road network spatial structure and its relationship with the urban system. Regarding the former, results of empirical RNE research suggest some network characteristics, such as the block areas, depended on the density and spatial distribution of urban road networks; others required representation and measurement of spatial characteristics, like the backbone of urban road networks and DE. However, existing empirical research has had limited measurements of the road network spatial structure, such as the spatial distribution and organization of road network components, in its methodology.

Regarding the second limitation, empirical RNE research has recognised that the road network structure was influenced by the urban system. Nevertheless, most of the empirical RNE research has quantified road networks' characteristics solely and did not consider the urban system at the same time. Many empirical RNE research has also equated road network to the urban system, overlooking the complex relationships between road network and the urban system. Urban road network resides and changes as a layer of the urban system. The urban road network should be distinguished from the urban system and urban spatial structure to be better integrated into them again. In doing so, it is necessary to understand both the spatial structure of both the urban road network and the urban system, as well as the relationships between them, to position the urban road network into the urban system.

In summary, this chapter addressed the initial research question 1.a in Chapter 1 section 1.4 to gather existing empirical knowledge on road network evolution and quantification, by piecing together and comparing existing empirical RNE research, which synthesised a framework of empirical RNE characteristics and characterisation. Table 2-1 summarised specified sub research questions regarding each elementary network characteristics and dynamics based on the synthesised understanding of empirical RNE findings and their inconsistency in this chapter at the end of each discussion section, which are to be explored with modelling and simulation of the dynamic RNE process in future chapters. Chapter 7 follows and addresses these sub-research questions with summarised findings in Table 7-1. Together, the specified sub research questions guide the simulation findings concluded in Chapter 10 section 10.1.2.

Furthermore, the characterisation of road network spatial structures and the integration of network science perspective RNE into the urban system have been limited; the next chapter reviews the road network structure in the context of the urban system.

**Table 2-1 Synthesised Existing Empirical RNE Understanding and Specified Further Research Questions**

| ***Synthesised existing empirical knowledge on road network evolution and quantification*** | ***Specified sub research questions to be explored in later chapters*** |
|---|---|
| **Node characteristics** 2.3.2.3<br>Empirical research has found a majority of $k_3$ nodes in urban road networks, reported inconsistent $\langle k \rangle$ dynamics and attributed $\langle k \rangle$ dynamics to the changing proportions of $k_1$ and $k_3$ nodes against $k_4$ nodes. | 7.2<br>• How do $k_1$, $k_3$ and $k_4$ nodes emerge respectively, and what RNE mechanisms does the emergence of different degree nodes reflect? Does node degree relate to organic and planned urban road dynamics? How do different $\langle k \rangle$ dynamics emerge, and why does $\langle k \rangle$ increase, decrease, or remain constant with time? What RNE mechanism does this reflect? |
| **Link characteristics** 2.3.3.2.2<br>Empirical findings of the link length $l$ distribution have shown inconsistency among several skewed distributions with a heavy tail, yet the latest findings have reported that $l$ followed a lognormal distribution. With the growth of the road network over time, more short and medium length new links were added, and $l$ persisted in following the lognormal distribution with a concentrating peak. | 7.3<br>• How does the lognormal $l$ distribution emerge in urban road networks and what RNE mechanism does this reflect?<br>• Does $l$ persist in following the lognormal distribution? How do new links influence $l$'s distribution? What RNE mechanism does it reflect? |
| **Block characteristics** 2.3.4.3<br>Empirical findings of urban blocks area probability distributions $P(A)$ have been inconsistent. However, the reported $P(A)$ shared the same characteristics for large $A$, which could be fitted on a log-log plot by a straight line. Mainly two $P(A)$ distributions have been reported: power-law and lognormal. | 7.4<br>• How do the lognormal or power-law $P(A)$ distributions emerge in urban road networks and what RNE mechanism does this reflect?<br>• How does $P(A)$ change - does it persist in following a lognormal or power-law distribution, and how do the characteristics of the distribution change? What RNE mechanism does this reflect? |
| **Betweenness Centrality** 2.4.3.1, 2.4.4.1, 2.4.5<br>Empirical research has reported BC to follow a bimodal distribution, consisting of high and low BC components from an underlying spanning tree and alternative loop paths, respectively. Two proposed RNE phenomena in recent empirical RNE research | 7.5<br>• Does BC follow a bimodal distribution, consisting of high BC components from an underlying tree structure and low BC components from alternative loop paths in the road networks? Does |

| | |
|---|---|
| have been constructed based on BC. The backbone of urban road networks: the backbone of urban road networks, densification and exploration (DE). | network density control the BC distribution? How does the BC distribution emerge, and what RNE mechanism does this reflect?<br>• Do network components that have high BC, belong to an underlying spanning tree, locate near the geographical centre, and long exist in urban road network correlate? What RNE mechanism does this reflect? How the backbone of urban road networks form and change? What RNE mechanism does this reflect?<br>• Whether BC impact $\delta_{BC}(e)$, the DE measure, distinguishes dead-ends and bridging links, thus quantifies a topological property shared by planar networks when adding new links? What functions do the two types of new links perform and can this be inferred from their spatial and temporal characteristics? Can such characteristics be incorporated into identifying DE, which further reflects the RNE mechanism? |

# Chapter 3 The Urban Spatial Structure of Road Network Evolution

## 3.1 Chapter Introduction

Focusing on quantifying topological and geometrical characteristics by analysing the network structure alone, network science perspective road network evolution (RNE) research has shown limitations in the characterisation and representation of the road network spatial structure in the context of the urban system. The spatial distribution and organisation of road network characteristics and dynamics have not been considered sufficiently. The urban road network structure resides and changes in the urban system; understanding RNE requires the integration of road network structure and dynamics into the urban system. However, existing empirical and modelling RNE research, if considered road network in the context of the urban system, has often equated the road network structure to the urban form, urban spatial structure or urban system, with limited discussions regarding the relationships of these concepts.

The urban spatial structure has established research history and theories; different disciplines address different layers and components of the urban system. The urban spatial structure has been described and characterised in terms of its factors like population distribution, physical built environment, commuting between work and residence, with these factors interrelated among themselves. Equating road network to the urban spatial structure, as existing empirical and modelling RNE research has done without discussions regarding their relationships, has increased the difficulty to disentangle the relationships among urban factors that may influence RNE and hindered the integration of network science perspective research into the urban system. The road network spatial structure and the urban spatial structure require both differentiation and integration to understand RNE in the context of the urban system.

Following the identified limitations, this chapter sets out with the following objectives:

- Review and synthesise existing knowledge on the spatial structure of urban road networks, urban spatial structure, and the relationship between them, to integrate RNE into the urban system.

Section 3.2 starts with the road network spatial structure, 3.3 reviews the urban spatial structure, leading to a framework of a layered urban system, in which road network spatial structure is distinguished from as well as integrated into the urban system. Following the framework of the layered urban system, 3.4 synthesises the relationship between the road network and the urban system as co-evolving, as represented by the co-evolution of population and urban road network.

| | |
|---|---|
| **3.2 Road Network Spatial Structure** | •3.2.1 Road Network Patterns<br>•3.2.2 Road Network Spatial Analysis<br>•3.2.3 Quantitative Road Network Classification |
| **3.3 Urban Spatial Structure** | •3.3.1 Economic Urban Spatial Structure<br>•3.3.2 Physical Urban Spatial Structure<br>•3.3.3 Functional Urban Spatial Structure |
| **3.4 Road Network in the Urban System** | •3.4.1 Road Network in the Urban System<br>•3.4.2 Urban Road Network and Population |

**Figure 3.1 Chapter 3 Structure**

## 3.2 The Spatial Structure of Urban Road Networks

As reviewed in Chapter 2, network science research has recognised that aspatial topological characterisation neglects the physical environment in which certain complex networks reside (Marshall et al., 2018). To address this issue, spatial networks have been proposed and studied, emphasising on the spatial embedding of complex networks, e.g. spatial locations and distance; however, the meaning of the applied network science measures and the new knowledge produced still require further understanding and interpretation regarding the spatial dimension of complex networks (Ducruet and Beauguitte, 2014). This limitation has been shown in the insufficient examination of urban road networks' spatial structure, their spatial distribution and organisation, in the network science perspective RNE research. Though existing empirical results have reported spatially inhomogeneous RNE processes, in-depth exploration of the corresponding spatial structures and behind emerging mechanisms has been limited.

The spatial structure of urban road networks has been characterised qualitatively, such as by the urban planning and design styles - gridiron, fragmented parallel, wrapped parallel, loops and lollipops, lollipops on a stick (Southworth and Ben-Joseph, 2013; Zhang et al., 2011) and has been classified implicitly with the urban form types – star, linear, grid, Baroque axial, lacework, inward closed, nested, and imagining (Lynch, 1984). This section divides existing quantitative research on the urban road network spatial structure into three categories: road network patterns 3.2.1, spatial analysis 3.2.2, and quantitative classification 3.2.2.

### 3.2.1 Road Network Patterns

Road network patterns are regularly repeated properties (Mackaness and Edwards, 2002) that represent the hierarchy and most central structure of road networks (Jiang and Claramunt, 2004a) and convey statically geographical processes (Mackaness, 1995). Road network patterns reviewed in this section included connection patterns and generalisation patterns.

Connection patterns are the dominant geometric connection structure inherent to the road networks. Haggett and Chorley (1969) classified planar geographic networks into linear, tree, circuit, and cellular by the existence of circuits in the network. Marshall (2004) identified local connection patterns - T, X junctions, blocks and dead-ends and global road network patterns - linear, tree, radial, cellular and hybrid. Xie and Levinson (2007) identified four connection patterns - ring, web, star, hub-and-spoke, as in Figure 3.2. Different connection patterns suggested structural differences of the road networks; for example, centrality was found to be more concentrated in road networks of the radial connection pattern than the grid pattern (Kisgyörgy, 2014). Connection patterns were associated with the travel behaviour, the distribution of work and residence, land-use and urban form (Xie and Levinson, 2007). For example, central business district (CBD) was correlated with dense grid connection patterns while the suburban residential area was associated with the tree connection pattern (Van Nes and ZhaoHui, 2009; Shi et al., 2013).

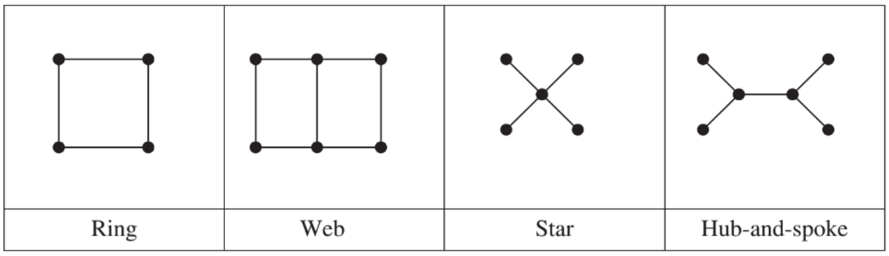



**Figure 3.2 Urban Road Network Patterns**: Xie and Levinson (2007) identified four typical connection patterns of urban road networks – ring, web, star, and hub-and-spoke.

Generalisation patterns select the core structure of road networks that retain their global structural property (Jiang and Claramunt, 2004a), from a geographic database to summarise a less detailed database or map (Touya, 2010). Liu et al. (2009) outlined three generalisation methods: semantic-based, stroke-based, and graph-based. The semantic-based method used road attributes such as the street name for selection (Jiang and Claramunt, 2004a). The stroke-based method transformed the road network into a set of linear elements, such as axial lines (Mackaness, 1995) and strokes (Thomson and Richardson, 1999), which chained road segments to retrieve continuity in the network. The graph-based method applied network characteristic measures such as centrality and connection patterns (Zhang, 2004; Heinzle et al., 2005) to extract the hierarchy of the network. Besides these approaches, road network attributes such as shape, orientation, connectivity, density and distribution were also used for generalisation (Mackaness and Edwards, 2002).

In summary, road network patterns have identified the structurally representative part of the urban road network spatial structure, such as the dominant connection patterns and the continuity hierarchy. Identified road network patterns may suggest specific road network spatial organisation and distribution, which have not been explicitly described. Road network patterns have been regarded as an inherent hierarchical structure, and the associated of road network patterns to the urban spatial structure has been limited.

### 3.2.2 Road Network Spatial Analysis

Road network spatial analysis combines the Geographic Information System (GIS) and the network concept and studies the geographic networks and the geography of networks (Borruso, 2003). The former extends the longstanding research effort on topological and geometric geographic network analysis to the GIS environment (Curtin, 2007; Curtin, 2017; Sovik, 2014). The generalised usage of GIS data ties road network and other layers of the urban system together by geographic location (Fischer, 2006). The primal representation of the road network is compatible with this GIS urban system representation (Boeing, 2019).

Spatial analysis on the geography of networks establishes the relationship between the urban road network and the urban locations and space. Road network is viewed as a framework of land-use and socio-economic activities (Borruso, 2005), a spatial domain alongside which events happen (Okabe and Sugihara, 2012), and a linear referencing system of location (Curtin, 2007). Connecting urban road network and the urban space, density has been used to study the spatial distribution of road networks, which further indicates the relationship between the road network and urban form, urban spatial structure.

Measuring road network density requires first the planar partition of space among geographical objects (Liu et al., 2009). Borruso (2003) proposed two methods to measure road density with road intersection point data. The first used a grid to partition the plane and measure the cell-wise road density; the second proposed a density estimator based on Kernel Density Estimation (KDE) which estimated point pattern intensity on a smoothed 3D continuous surface and avoided arbitrary space partitioning by the grid. Liu et al. (2009) proposed partitioning the plane using the Voronoi diagram of road segments and measured the tessellation-wise road density. Quinn and Fernández (2011) measured road density using concentric rings from the CBD centre. Road density on a larger scale, like on the national scale, was measured by administrative boundaries of cities (Zhang et al., 2015).


**Figure 3.3 Urban Road Network Density**: Quinn and Fernández (2011) calculated road network density by concentric rings from the CBD and found decreasing road density with the increasing distance to CBD.

The spatial distribution of road network density was associated with the urban spatial structure and regional economic development. Borruso (2003), Quinn and Fernández (2011) found decreasing road network density with the increasing distance to CBD. Chen et al. (2017) found Guangzhou's road density clustered in the historical city centre and CBD and reflected the realisation of city spatial form planning. Zhang et al. (2015) and Hu et al. (2018) found positive correlations between road density and regional economic development level.

In summary, spatial analysis combines the road network into the GIS urban system, in which urban road network is the framework of urban socio-economic activities and land-use. The distribution of road network density has shown correlations between the urban road network spatial structures and the urban spatial structure, such as in the decreasing road network density from the CBD, but have not established systematically theoretical and empirical relationships between them.

### 3.2.3 Quantitative Road Network Classification

New methods are emerging, which quantitatively classify the urban road network spatial structure without presuming road network patterns and spatial structures to be identified. The quantitative classification has paid attention to the processes behind the formation of urban road network spatial structures, such as centralisation and decentralisation, space division, clustering and dispersion, urban planning and design.

Quantitative classification, according to centralisation and decentralisation processes distinguished morphological or functional centre of the road network, e.g. high density or flow concentration part of the network. Samaniego and Moses (2008) investigated whether US urban road networks were analogous to the centralised biological vascular network, which had a single centre like the heart, as the origin and destination of all the flows. They proposed a centralised and a decentralised model; the former hypothesised a single centre which was the destination of all population, whereas the latter hypothesised population’s destinations were nearest centres. Empirical US urban road networks’ total lane miles scaled with a population similar to the decentralised model, and the travel distances scaled in between the centralised and decentralised models. Fialkowski and Bitner (2008) identified the centre and periphery of cities through block area distribution. Blocks area distributions had increasing block size from the dense urban centre to the sparse urban periphery, but exceptions like the Hawaii island had reversed large to small block sizes from the geographical centre to periphery because of the natural environment. Peiravian and Derrible (2015) demonstrated US urban road networks might be regarded as grid layouts tuned by monocentric density distributions.

Quantitative classification, according to space division processes regarded the urban road network spatial structure as fractal and self-similar. Jiang and Liu (2012) found block area distributions of the UK, France, and Germany road networks all followed heavy-tailed lognormal distributions, which had 80% of small blocks and 20% of large blocks. Such heavy-tailed distributions were thought as a result of recursive space division (Goodchild and Mark, 1987) by the urban road network, which generated fractal and self-similar structures across scales. Such space division process was also used to explain the power-law degree distribution in dual representation urban road networks (Kalapala et al., 2006; Zhang and Li, 2012).

Quantitative classification, according to clustering and dispersion processes identified morphological or functional clustering and dispersion in urban road networks. Functionally, Strano et al. (2018) identified the community in the road network, where a group of roads were more connected than with roads outside the group. Because of road network nodes’ limited connectivity, the community detection used the dual road network representation, in which long links had large node degree and formed communities, then transformed the identified communities in the dual representation back to the primal representation. Morphologically, Huynh et al. (2017) characterised the spatial distribution of public transport points, bus stops of 53 US cities, into regular, dispersed, and clustered. The regular spatial distribution displayed regular distance scales between points, which was attributed to underlying planned grid road networks. The dispersed spatial distribution maximised coverage area, in which the number of components was small compared to the coverage area increased by these components; while the clustered spatial distribution minimised coverage area, which contained a large number of components with relatively small coverage area. Public transport points are the events alongside the road network (Okabe and Sugihara, 2012) and delineate the road network; their spatial distributions indicate road networks' spatial distributions satisfy similar classifications.

Moosavi (2017) performed machine learning pattern recognition on one million road networks. Figure 3.4 shows a stripe that assembled a large number of road network miniature visualisations. Each point on the stripe was a road network visualisation. Road networks with the similar spatial structure were arranged nearby on the stripe. Together, these urban road network visualisations made up the change of colour shades on the stipe. Four sample road network spatial structures were shown. From left to right, the first sample's road networks had low density linear spatial structure; the second had monocentric radial spatial structure; the third had monocentric dense centres and sparse grid periphery; the fourth had dense polycentric spatial structure. This exhaustive machine learning study suggested the diversity of urban road network spatial structure; urban road networks are likely to display a spectrum of spatial structures.

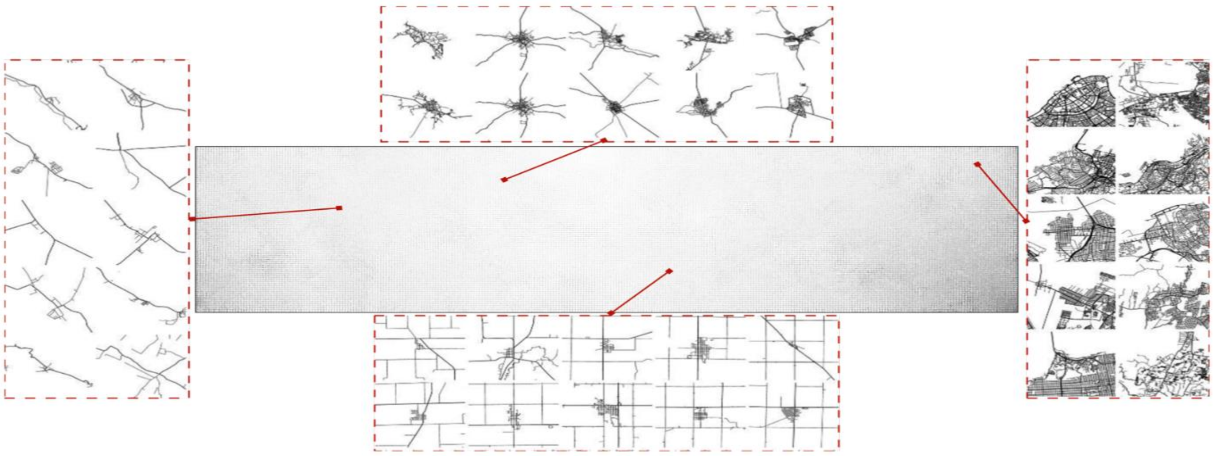


**Figure 3.4 Quantitative Road Network Spatial Structure Classification**: One million road networks displayed a spectrum of diverse spatial structures (Moosavi, 2017).

Quantitative classification by urban planning and design identified design features as the road network spatial structure. Figueiredo and Amorim (2007) classified urban road networks according to two dimensions, tree-ness to grid-ness and regular to irregular. Porta et al. (2014) separated road network spatial structures of different historical periods - ancient, medieval, renaissance, baroque, industrial, from that of modern planning paradigms - garden city, radiant city, new urbanism, by the length of the major street segment.

In summary, without presuming road network patterns and spatial structures to identify, quantitative characterisation found diverse road network spatial structures and demonstrated the spatial structure of urban road networks appear to be a spectrum, rather than a few clear-cut pattern types (Marshall, 2004; Huynh et al., 2017; Moosavi, 2017). This diverse spectrum of road network spatial structure may be characterised by the mechanisms and processes behind their formation and dynamics.

### 3.2.4 Road Network Spatial Structure Discussion

Network science's limitations regarding the understanding and interpretation of measures and results of complex networks' space dimension have been recognised. Chapter 2 identified inadequate representation and characterisation of the road network spatial structure in empirical RNE research, as well as the insufficient discussion regarding the relationship between the evolution of urban road network spatial structure and the urban system.

This section reviewed methods from transport and urban studies, which have studied the road network spatial structure as connection and generalisation patterns, used spatial analysis and other quantitative methods. Literature suggested an inherent hierarchy in road network spatial structure, as shown by dominant geometric connection patterns and continuity patterns. Positive correlations between road network density and the urban spatial structure suggested connections between the spatial structure of the road network and the urban system. The urban road network is perceived as a framework of the urban space along which socio-economic activities happen; the GIS urban system ties together road network, land-use and other layers by geographic location.

Especially, empirical studies (Huynh et al., 2017; Moosavi, 2017) have reported diverse road network spatial structures, suggesting that the spatial structure of urban road networks appears to be a spectrum, rather than a few fixed clear-cut types. This spectrum may be characterised by the processes behind the formation and dynamics of road network spatial structure. However, these empirical studies have been quantitative with limited qualitative theorisation. The processes identified, such as centralisation and decentralisation, clustering and dispersion, indicated relationships between the spatial structure of the road network and the urban system but have not specified. A framework to further explore the reported diverse road network spatial structure has yet to be established. Literature in the context of GIS urban system has treated the primal road network as the framework of the urban space; specific urban components that influence the road network spatial structure have yet to be specified. Further research questions may be asked:

- How to integrate road network spatial structure and dynamics into the urban system?

The literature on road network spatial structure has associated extensively with the urban spatial structure, borrowing theories and methods, but has not distinguished and discussed the relationship between the two explicitly. Following the specified question, the next section reviews the urban spatial structure, to synthesise a plausible approach to integrating road network spatial structure and dynamics into the urban system.

## 3.3 The Spatial Structure of the Urban System

Analysis of a transport system requires a representation of an urban system, to represent explicitly or implicitly socio-economic activities, transport network, and flows; representations of the urban system differ with different transport problems to address (Fielbaum et al., 2017). Clifton et al. (2008) compared various disciplines' perspectives on analysing the urban form. From a landscape ecology perspective, undeveloped areas are of interest rather than the urban areas and land cover types are measured instead of urban land-uses. The transport research perspective focuses on the transport efficiency and studies network configuration's impact on travel and accessibility provided by the transport network. Urban planning and design coordinate socio-economic activities at land-uses, accessibility, built environment to achieve urban living quality.

Concepts with intersecting contents have been used to refer to the urban system, as examples listed in Table 3-1. To identify a plausible approach to integrating road network spatial structure and dynamics into the urban system, this section builds up an understanding of the urban system through three levels of Urban Spatial Structure (USS): the economic USS 3.3.1, the physical USS 3.3.3, and the functional USS 3.3.3.

**Table 3-1 Layers and Components of the Urban System**

| The urban system | Socio-economic: population, employment, activities. | Land-uses | Physical Built Environment | Transport Network | Urban Planning and Design | Spatial Interactions |
|---|---|---|---|---|---|---|
| **Urban spatial structure** (Parr, 1985): Socio and economic organisation of a region, including<br>• Spatial concentration of population, employment, and infrastructure,<br>• Locational organisation of land-use and urban function,<br>• Networked social interactions and flows. | √ | √ | | | | √ |
| **Urban form** (Mackaness, 1995):<br>• Urban history,<br>• Population and activity,<br>• Built environment. | √ | | √ | | √ | |
| **Internal urban structure** (Heinzle et al., 2005):<br>• Land-uses,<br>• Mobility and spatial interactions. | | √ | | | | √ |
| **Urban pattern** (Marshall, 2005):<br>• Land-uses and distribution,<br>• Socio-economic distributions,<br>• Built environment and distribution,<br>• Physical form and pattern,<br>• Urban design type. | √ | √ | √ | √ | √ | |
| **Urban form and function** (Crooks et al., 2015):<br>• Physical form, including buildings, streets and other urban space components,<br>• Function: urban activities. | √ | | √ | | | √ |
| **Urban land-use** (Duranton and Puga, 2015):<br>• Land-uses,<br>• Transport land-uses. | | √ | | √ | | |

### 3.3.1 Economic Urban Spatial Structure

USS describes the regularities and irregularities over the urban space and seeks the urban nature through understanding how spatial structure and organisation of cities affect people's lives. From an urban economics perspective, USS mainly concerns the spatial organisation of population and employment. Evolution of this USS is perceived as driven by agglomeration economies, such as the scale of economy in which agglomeration of firms within a geographic area reduces production cost; meanwhile, positive and negative externalities interact, and all contribute to the formation and dynamics of USS. Processes along two dimensions characterise USS as in Figure 3.5: globally, concentration around the CBD leads to centralised spatial structure, the opposite leads to decentralised spatial structure; locally, concentration around subcentres leads to clustered polycentric spatial structure, and the opposite leads to dispersed and more regular spatial structure. (Anas et al., 1998)

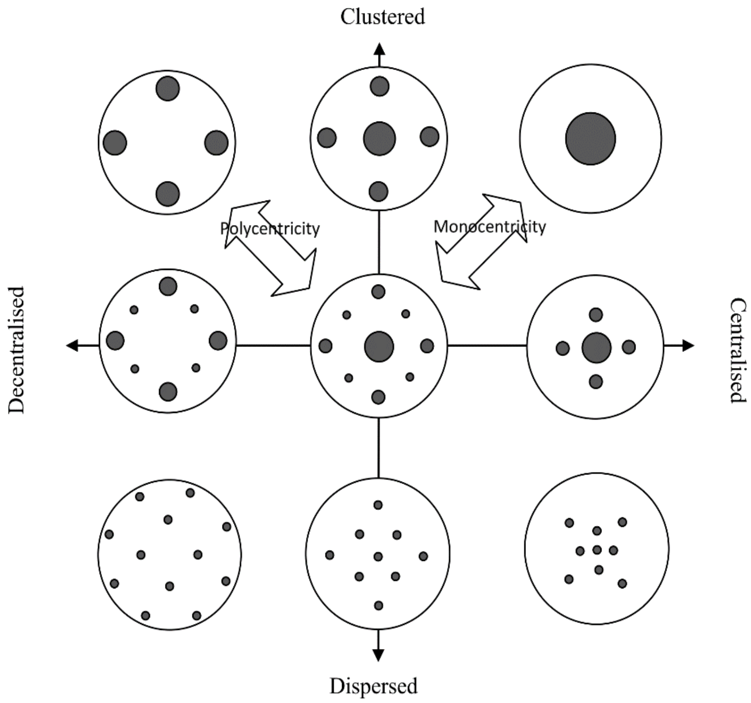



**Figure 3.5 Urban Spatial Structure and Characterisation**: Processes along two dimensions - centralised to decentralised (horizontal) and clustered to dispersed (vertical) characterise USS. (Smith, 2011)

Empirical research has found the transformation of real-world cities' spatial structures from monocentric to polycentric and dispersed (Gordon and Richardson, 1996), such as residence suburbanisation, employment sub-centring and dispersion. The monocentric city is explained by spatial decisions based on income, land rent and commuting cost, which leads to radial urban land-use and land price distribution from the CBD (Alonso, 1960). Trade-off between agglomeration's positive and negative effects drives the transition of the monocentric city: if subcentres overcome negative effects of the agglomeration such as high land price and congestion while maintaining the benefits, polycentric USS emerge; if the benefits of agglomeration fail to excel due to factors such as decreasing commuting cost, dispersed USS emerge (Lee, 2007).

Economic USS concerns the spatial distribution and organisation of urban population and their socio-economic activities. The population is a crucial component here. Decentralisation and dispersion of residence and employment lead to the widely observed transition from monocentric to polycentric and dispersed USS. Population density profile has been used to describe USS (Clark, 1951). Migration has been perceived to drive urban growth, and empirical population spatial distribution has been found as diverse and complex rather than singular and well-defined (Tatem, 2017).

In summary, the theoretical relationship based on individual spatial decisions, transport cost, and urban land-uses has been used to explain economic USS formation and dynamics. Processes of centralisation and decentralisation, clustering and dispersion, on the global and local scale respectively, characterise the economic USS. Economic USS has been the source of many concepts and measures used in describing the road network spatial structure as reviewed in 3.2. Existing research on road network spatial structure has borrowed greatly from economic USS, relating implicitly to the economic USS. Meanwhile, transport networks have not been explicitly considered in most economic USS studies, and understanding of the relationship between transport and USS has remained mostly theoretical.

### 3.3.2 Physical Urban Spatial Structure

Physical urban spatial structure in this section refers to the physical urban form - the spatial distribution and organisation of land-uses, infrastructure, transport and communication networks, and other elements of the physical built environment (Abrantes et al., 2017). The physical built environment can be decomposed into two types of space – access and place (Brelsford et al., 2018). Economic agglomeration encourages the spatial concentration of physical capital, such as buildings and infrastructure (Anas et al., 1998). At the same time, population and their socio-economic activities are constrained in the physical built environment (Batty and Kim, 1992); transport accessibility works as both centripetal and centrifugal forces in the centralisation and decentralisation, clustering and dispersion of USS (Smith, 2011). Because of the theoretical relationship between economic and physical USS and the increasing availability of physical USS data, empirical research has used the physical USS to approximate economic USS (Krehl et al., 2016). Nonetheless, deriving population density and the monocentric, polycentric and dispersed spatial structures replied on the physical urban area (Tsai, 2005). Physical urban density captured better the urbanisation than population density (Inostroza et al., 2013). Data transition from statistical socio-economic to physical enabled research of the temporal and spatial urban form on non-aggregate scales and research questions regarding how cities originate and change were explored from the physical USS perspective (Dietzel et al., 2005).

Physical urban growth patterns included infill and densification inside the urban boundary, expansion at the urban edge, and detached new development (Hoffhine Wilson et al., 2003), which led to the characterisation of physical USS as compact or sprawling (Johnson, 2001). Urban growth was regarded as an iterating process of coalescence and diffusion (Dietzel et al., 2005), which was globally constrained by the economic USS and transport network while locally driven by a set of enduring push and pull forces among categories of land-uses (Stanilov and Batty, 2011). Urban sprawl has been attributed to increasing income and decreasing commuting cost, inner city problems and residential preferences, planning and regulatory policies, with various leading factors for different world regions (Gouda et al., 2016).

Figure 3.6 shows four examples of empirical physical USS dynamics patterns. Schneider and Woodcock (2008) found cities from different world regions grew with the diverse population and physical urban growth patterns, e.g. infill, expansion, new development, at different urbanisation speed, and with varying levels of density. Empirical research found a homogeneous trend in real-world cities' physical USS in terms of increasing complexity, rather than following the dichotomy of becoming compact or sprawling (Darrel Jenerette and Potere, 2010). Physical USS's impact of travel behaviours has not been established as normative; compactness was associated with lower vehicle miles travelled and infrastructure construction costs but did not necessarily reduce travel time than sprawl (Ewing and Cervero, 2010; Ewing and Hamidi, 2015).

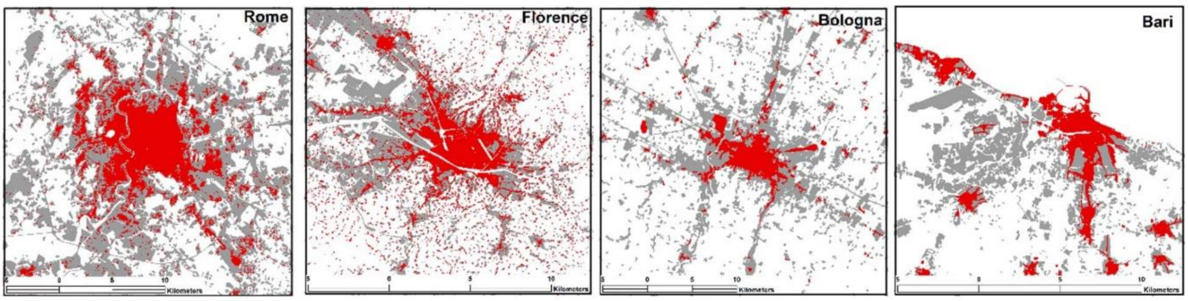



**Figure 3.6 Physical Urban Spatial Structure**: The panel shows four Italian cities' urbanised areas dynamics between the 1950s in red and 2000s in grey. (Romano et al., 2017)

In summary, after the socio-economic component, the physical built environment is a second component of USS, with essential layers - land-use and transport network. The physical USS has been perceived to aggregate because of population and their socio-economic activities while constraining the economic USS at the same time. Physical urban growth has been attributed to the existing economic USS, transport accessibility's centripetal and centrifugal forces, longstanding push and pull forces between land-uses, iterating coalescence and diffusion processes, which may combine to cause the complex physical USS and urban growth patterns.

### 3.3.3 Functional Urban Spatial Structure

USS extends from morphological to functional (Burger and Meijers, 2012), as demonstrated in Figure 3.7. Functional USS concerns spatial interactions underlying the arrangement of urban forms (Rodrigue et al., 2016) - the functional linkages (BERRY, 1968; Goddard, 1970). Functional USS has translated into the urban network, with nodes being urban centres and links being spatial interactions between centres (Salingaros, 2005; Dupuy, 2008). Commuting flows have been essential to study spatial interactions (Van der Laan, 1998; De Goei et al., 2010). Possible functional USS were identified: maximal disorder – dispersion of both residence and job, live-work mosaic – small residence and employment clusters, monocentric – concentration of employment at the centre, polycentric – concentration of employment at the centre and clustering of employment at subcentres, and hybrid of these structure; all generated different spatial interactions of commuting (Angel and Blei, 2016).

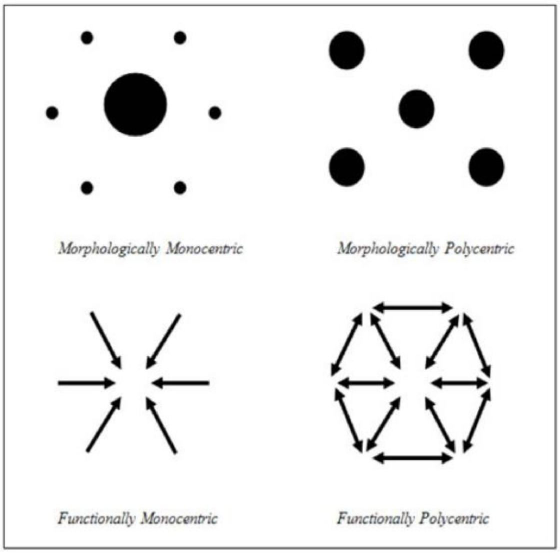



**Figure 3.7 Functional Urban Spatial Structure**: Functional USS considers spatial interactions between centres, sub-centres and the periphery, besides their distribution as considered in the morphological spatial structure. (Burger et al., 2014)

Increasing empirical analyses of mobility data created knowledge of urban activities and travel trajectories, from which meaningful locations, spatial and temporal flows have been retrieved (Guo et al., 2012). Complementing the morphological urban centre, subcentres, and boundary, functional counterparts were identified (Roth et al., 2011; Louail et al., 2014; Zhong et al., 2014; Liu, G. et al., 2015; Mu and Yeh, 2016). Transport demand (Guo et al., 2012) and land-use (Goddard, 1970; Toole et al., 2012) which resulted in the observed urban mobility could be derived from mobility data empirically. Urban mobility exhibited high spatial and temporal regularity, with individuals travelling characteristic distances and returning to a few frequent locations (Gonzalez et al., 2008).

In summary, it is the flows of people and commodity, or the strength of spatial interactions between urban locations that connect the economic and physical USS (Liu, X. et al., 2015). Urban flows have been perceived as the manifestation of the spatial interaction potentials between urban areas (BERRY, 1968).

### 3.3.4 Urban Spatial Structure Discussion

Through three USS levels, this section proposed a layered framework of the urban system, as illustrated in Figure 3.8. The urban system was perceived as overlaid layers, such as the USS, land-use, and transport layers. Land-use and transport corresponded with two types of urban space - place and access, constituted the physical USS and influenced the urban spatial structure as a whole. All layers had socio-economic, physical, and functional components, represented by population, built environment, and spatial interaction. In this framework, the urban road network resided on the transport layer and belonged to the physical built environment of the urban system, thus distinguishing the road network spatial structure from the USS as well as integrating RNE into the urban system.

Urban processes and patterns occurred on different urban system layers as Table 3-2 outlines, which together led to the form and spatial structure of the urban system. Economies and diseconomies of agglomeration have been regarded as driving the economic USS; the scale of economies pull population and socio-economic activities while diseconomies of agglomeration such as high land prices and congestion push. Centralisation and decentralisation emerge on the global scale, and clustering and dispersion emerge on the local scale, leading to observed monocentric, polycentric, and dispersed USS. Physical USS has been regarded as growing by iterating coalescence and diffusion, under the influences of attraction and repulsion among different land-use categories, as well as centripetal and centrifugal forces of transport accessibility, leading to urban form such as compact and sprawling. Functional USS has been regarded as realising spatial interactions, balancing demand and cost and leading to mobility patterns. Processes on different urban system layers are all likely to have push and pull forces on key components population, the physical built environment and spatial interaction. Spatial structures of different urban layers are likely to correlate.

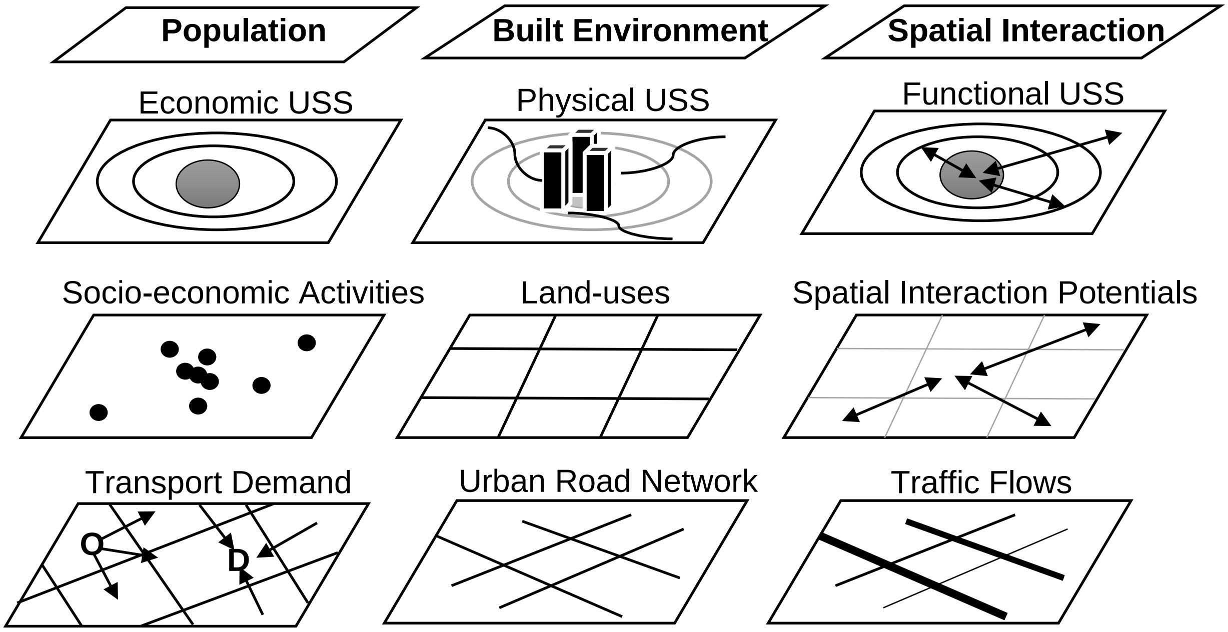



**Figure 3.8 A Layered Framework of the Urban System**: The urban system may be viewed in a framework of overlaid layers, such as the USS layer, land-use layer, transport layer. All layers have socio-economic, physical, and functional components, represented by population, built environment, and spatial interaction.

**Table 3-2 Processes and Patterns in the Urban system**

| ***Urban System*** | ***Process*** | ***Pattern*** |
|---|---|---|
| *Economic USS* | • Economies and diseconomies of agglomeration (Anas et al., 1998) | • Centralisation and decentralisation, clustering and dispersion;<br>• Monocentric, polycentric, dispersed urban spatial structure |
| *Physical USS* | • Coalescence and diffusion (Dietzel et al., 2005)<br>• Attraction and repulsion among land-use categories (Stanilov and Batty, 2011)<br>• Centripetal and centrifugal forces of transport accessibility (Smith, 2011) | • Infill, expansion, detached new development growth patterns;<br>• Compact and sprawling urban form;<br>• Linear urban development along the major transport routes |
| *Functional USS* | • Spatial interaction potentials (BERRY, 1968) | • Mobility patterns |

A shared theoretical understanding about the urban system has shown in urban and transport studies: population and their social interactions are the foundation of the urban system; social interactions require overcoming space through ways of communication including the transport system; construction of infrastructure such as the road network realises the demand for social interactions selectively. In such processes, urban spatial structure as a whole emerge. For example, the gravity model and social physics introduced the physical flow metaphor for spatial social interactions among population (Zipf, 1942; Stewart, 1950; BERRY, 1968); urban transport and geography have been modelled based on population's socio-economic activity, transport infrastructure, and land-use layers (Rodrigue et al., 2016); theoretical mobility research considered both potential and realised mobility (Kaufmann et al., 2004).

## 3.4 Road Network in the Urban System

As in the layered urban system synthesised in 3.3, the urban road network may be viewed as residing on the transport layer and belonging to the physical built environment of the urban system. Economic, physical, and functional urban spatial structures are likely to correlate, and push and pull forces present on all the urban system layers, together forming the urban spatial structure. Meanwhile, 3.2 reviewed that urban road networks have geometric connection patterns such as linear, star, ring, and web, continuity hierarchy, and density distributions; empirical quantitative pattern recognition has suggested urban road network spatial structure appears to be a spectrum, rather than a few clear-cut types. This section aims at connecting the spatial structure of the road network and the urban system.

### 3.4.1 Road Network and the Urban System

Being one primary source of geographic data, the urban road network has often been treated as part of the urban form and urban spatial structure; however, research that has considered the spatial structure of road network and the urban system independently while connecting the two with an explicit relationship has been limited.

Urban road networks have been reported to show high spatial correlations with economic, physical and functional urban spatial structure. Road network has been used as a linear space along which socio-economic activities happen, and activity intensity decays with the distance to the road network (Yu, 2017). Network centrality was found to correlate with urban areas of intense socio-economic activities (Shen and Karimi, 2016; Shen and Karimi, 2018). Road network density was found to correlate with the physical built environment (Hawbaker et al., 2005); physical urban density increased with decreasing distance to the road network (Garcia-López et al., 2015). As in Figure 3.9, Jia and Jiang (2010) used road network node number to approximate population, compared the growth of physical urban area against road node number, and categorised cities' USS into the sprawling, normal, and compact.

Road network separated different land-use categories (Agryzkov et al., 2014; Law, 2017); road network growth was found to correlate with employment and commercial development while railway correlates with residential development (Kasraian et al., 2016). Traffic flows on urban road segments were found to correlate positively with the network structure, which reflected functional USS (Wang et al., 2012; Zhou et al., 2015).

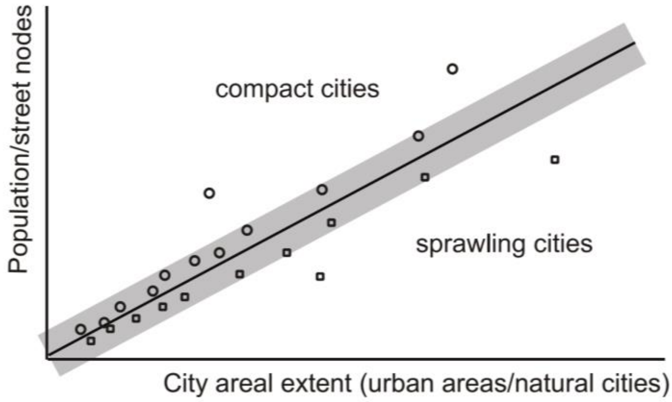



**Figure 3.9 Road Network and Urban Spatial Structure**: The x-axis represents the physical urban area; the y-axis represents number of road network nodes, circles represent cities. By comparing the growth of the physical urban area against road node number, cities within the grey bandwidth were categorised as normal, cities above were compact, and below were sprawling. (Jia and Jiang, 2010)

Road network spatial structure has been regarded as serving the urban spatial structure. Snellen et al. (2002) combined spatial patterns of the population and transport network to represent a multidimensional urban form. Spatial patterns of population included concentric, radial, polycentric, grid, and linear, and spatial patterns of transport network included linear, radial, ring, grid. Dutch cities were classified by the multidimensional urban form based on both population and transport network spatial patterns, e.g. cities with concentric population patterns and radial transport network. Grid transport networks were regarded as compatible with all population spatial patterns; radial transport networks were associated with concentric population patterns; ring transport networks were regarded as delineating the urban core. Wang et al. (2014) proposed a framework to understand transport network in the context of intraurban structure, relating road network centrality, land price, traffic flow by an inherent hierarchy in these urban components.

Transport network has been regarded as exerting both push and pull forces on the urban spatial structure (Smith, 2011). Transport accessibility could lead to spatial redistribution of population and socio-economic activities (Reggiani et al., 2011), such as in the land-use and transport interaction (Kasraian et al., 2016). Highway construction was found to correlate with residential decentralisation and suburbanisation (Baum-Snow, 2007; Garcia-López, 2012; Garcia-López et al., 2015) and employment decentralisation and sub-centring (Giuliano et al., 2012; Baum-Snow, 2014; Sánchez-Mateos et al., 2014). Population relocated to high transport accessibility areas (Kotavaara et al., 2011), as shown in the rapid land-use and population growth (Ji et al., 2014) and linear urban growth patterns (Inostroza et al., 2013; Krehl and Siedentop, 2019) alongside the road network.

In summary, empirical findings have reported positive spatial correlations between the road network and mutual influences between the two. Road network has been perceived to serve the urban system with road network spatial structure following the urban spatial structure, as shown by its correlations with economic, physical, and functional urban spatial structure. This correlation may result from the push and pull forces behind the urban spatial structure, as discussed in 3.3, including economies and diseconomies of agglomeration, attraction and repulsion among land-use categories. At the same time, the road network has also been perceived to perform push and pull forces that form and change the urban spatial structure. Transport accessibility may exert both centripetal and centrifugal forces in the spatial redistribution of population. Therefore, the evolution of road network spatial structure is likely to depend on and influence the evolution of the urban spatial structure; the relationship between urban road network and the urban system may be summarised as co-evolving.

### 3.4.2 Road Network and Population

As reviewed in 3.3.1, aggregation of population and their socio-economic activities generate the urban spatial structure, and the population density is often used to represent urban spatial structure. The co-evolution of population and road network may be a starting point to explore the co-evolution of the road network and the urban system and integrate RNE into the urban system. Relationships between population and urban road network can be viewed with three aspects: quantitative correlations, the relationship between population and road network spatial structure, and the relationship between population and road network connectivity.

Urban road networks and population have been found as positively correlated in quantity (Glover and Simon, 1975; Stamber et al., 2016; Meijer et al., 2018). As in Figure 3.10, Fu et al. (2016) reported positive correlations between road intersections and population density and attributed these correlations to infrastructure's nature to serve the population. Dynamically, urban road growth was reported to positively correlate with population growth (Duranton and Turner, 2008; Chi, 2010; Aljoufie et al., 2011). The positive correlation observed may be explained by the theory of urban roads' cost and benefit against urban density. As population density increased, the average cost of road construction decreased; assuming the benefit of roads is constant across densities, roads' benefit exceeded the cost at specific population density (Glover and Simon, 1975).

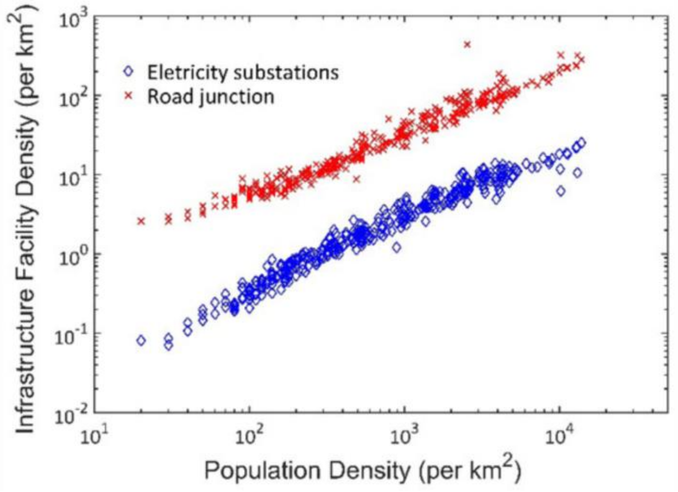



**Figure 3.10 Road Network and Population**: This plot demonstrates the positive correlations between infrastructure density and population density in England and Wales, in which red crosses represent road intersections. The x-axis represents population density; the y-axis represents infrastructure density; both axes are on the logarithmic scales. (Fu et al., 2016)

Another strand of theory and empirical findings associating the quantity of urban road infrastructure and the population is urban scaling, which has related urban properties to urban size. Empirical observations found social performance properties such as wealth creation and innovation increased superlinearly with the urban size, while infrastructure properties like road and electricity cable length increased sublinearly. This led to a theory bringing together population, transport infrastructure, and socio-economic welfare: the urban system depends on individuals' interactions, which are further realised through transport networks; and the system functions because socio-economic welfare created exceeds infrastructure costs (Bettencourt, 2013). Levinson (2012) confirmed the sublinear scaling between transport infrastructure properties and population size. Research that disagreed with the super- and sub-linear scaling found linear relationships between road length and other urban properties with urban size (Strano et al., 2017), and argued population and a single scaling equation were not enough to describe the urban system, instead urban systems' characteristics were in their diversity and heterogeneity (Arcaute et al., 2014).

Beyond quantitative correlations, the spatial structure of the road network and population have been associated because of the correlations between the road network and urban spatial structure at large. Following a monocentric spatial structure, road network and population density were found as both decreasing with distance to CBD (Quinn and Fernández, 2011). Beyond monocentric, the empirically reported a diverse spectrum of urban road network structures, as discussed in 3.2.3, which suggested the potential various population-road network spatial structures.

Finally, population density and road network connectivity have been associated. Peponis et al. (2007) found urban road densities, including node, link and other connectivity measurements, correlative positively with population density in Atlanta; they proposed that urban road network serves as the framework of population density and land-use changes. Levinson (2012) found US urban road networks' connectivity increased with population and inferred either large cities built highly connected road networks or highly connected road networks attracted more population. Maniadakis and Varoutas (2013) examined 100 1 $km^2$ square Greek urban road network samples and found network length, connectivity, efficiency increased with population density. Tsiotas and Polyzos (2017) examined four Greek cities' road networks and found road network characteristics including BC, total length, and shortest path length, increased with socio-economic factors including population, employment and commuting. On the other hand, Weber (2016) examined 160 US cities' highway networks and found low correlations between highway network topological connectivity and urban population. Abundo et al. (2013) studied the complexity of 200 largest world cities' road networks and proposed the upper limit of the complexity of road networks might prevent population growth.

In summary, empirical findings have reported correlations between population and the urban road network in quantity, spatial structure, and network characteristics. Meanwhile, empirical findings have shown inconsistency regarding the correlation between population density and urban road network connectivity and have not discussed the mechanisms that gave rise to these empirical findings. Also, current research have not related the diverse road network spatial structures with the co-evolution of the road network and the urban system.

Further research questions may be asked:

- What population-urban road network co-evolution mechanism do the correlations between population and urban road network in terms of quantity and spatial structure, and network characteristics reflect? Does road network connectivity relate to population?
- What road network spatial structure may arise during the co-evolution of road network and population? Can this spatial structure be characterised by processes of global centralisation and decentralisation and local clustering and dispersion?

## 3.5 Chapter Conclusion

### 3.5.1 Synthesise an Urban Road Network Spatial Structure Understanding

This chapter filled in the gap identified in Chapter 2 regarding the lack of representation and characterisation of road network spatial structure and dynamics in the network science perspective RNE studies. Section 3.2 reviewed road network spatial structure and found road network spatial structure is likely a spectrum rather than a few fixed clear-cut types. 3.3 reviewed USS and proposed a layered framework of the urban system 3.3.4. Based on this framework, the road network resides on the transport layer and belongs to the built environment of the urban system, thus enabling the integration of network structure and dynamics into the urban system.

The co-evolution of population and road network may be a starting point to explore the co-evolution of the road network and the urban system. Population and socio-economic activities are the foundation of the urban system; the urban road network serves population's spatial interaction demand. Correlations between urban population and road network have been reported in terms of quantity, spatial structure and network connectivity 3.4.1, 3.4.2. These correlations supported the theoretical hypothesis of the population and road network co-evolution, which may lead to the emergence of the diverse road network and urban spatial structure. The road network spatial structure spectrum may be characterised by the processes behind their emergence, such as global centralisation and decentralisation and local clustering and dispersion. Further, such diverse road network spatial structures indicate potential push and pull forces across urban system layers that drive the road network and population co-evolution, such as economies and diseconomies of agglomeration of the economic urban spatial structure, coalescence and diffusion in urban growth, attraction and repulsion among land-use categories, large and small spatial Interaction potentials.

### 3.5.2 Urban Road Network Spatial Structure Research Limitations

This chapter identified the following limitations in current studies of the urban road network spatial structure.

First, the characterisation of road network spatial structure has been limited in existing research. Road network spatial structure has been studied by geometric connection patterns and continuity hierarchy, spatial analysis, and quantitative classification. Though existing research has borrowed concepts and measures from the urban spatial structure, few have tried to characterise road network spatial structure by processes such as centralisation, decentralisation, clustering, and dispersion, which have been used to characterise the urban spatial structure, as discussed in 3.2.4.

Second, studies of the USS have lacked considerations of transport networks, and vice versa. Previous transport network analysis pointed out the necessity and difficulty to represent and analyse detailed transport networks and USS together. Representing the road network and population as two inter-dependent layers and analysing their relationships may contribute to this issue, as proposed in 3.3.4.

Third, though empirical correlations have been observed between urban road network and population in terms of their quantities, spatial structure, and network characteristics, exploration of the mechanisms behind urban road network and population co-evolution that led to these correlations have been insufficient, as discussed in 3.4.2.

These gaps constituted further research questions specified in this chapter, as in sections 3.2.4 and 3.4.2. Future chapters follow the proposed layered framework of the urban system, propose methods to characterise the road network spatial structure, and a co-evolution mechanism of the urban road network and population, to integrate RNE into the urban system.

# Chapter 4 Modelling the Urban Road Network Evolution

## 4.1 Chapter Introduction

Modelling of the evolution of transport networks dates back to quantitative geography, which introduced graph theory to analyse transport networks. Sequential changes of network topology and geometry were identified as transport networks' evolution processes, such as node-connecting sequences, space-filling sequences, and space-partitioning sequences (Haggett and Chorley, 1969). Prominent models included Taaffe et al. (1963)’s transport expansion phases in underdeveloped regions from scattered ports to interconnected ports and inland penetration lines, as well as Garrison and Marble (1965)’s transport network development prediction model which hypothesised connections among nearest neighbouring nodes. Graph theory introduced Network Design Problems (NDPs) which optimised to connect a set of points (Johnson et al., 1978); NDPs were applied to treat transport network formation and dynamics as an optimisation process. In the 1960s and 70s, transport demand modelling prevailed and shifted the research focus to transport systems’ function and performance; research interests in topological and geometrical transport network structure stagnated (Ducruet and Lugo, 2013). Meanwhile, transport NDPs, which designed addition and expansion of transport networks, developed a bi-level structure, incorporating lower-level transport demand modelling and upper-level socio-economic welfare optimisation (Yang and H. Bell, 1998). The theoretical foundation on which transport demand modelling relied developed from early location theories to social physics, macro and micro urban economics, then to the decentralised behavioural decision making - complexity of urban systems was recognised and modelled, including the evolution of these systems (Batty, 2009). Along with the development in complexity research, network science in the 1990s have been revived research interests in the network structure of transport networks; and the evolution of transport networks has been modelled from the network science perspective (Xie and Levinson, 2011).

Though having this extensive research background, RNE modelling which has emphasised explicitly on the urban road network structure and dynamics have been few. Based on the layered urban system framework summarised in the previous chapter, this chapter reviews related models according to their modelled layers and components of the urban system as illustrated in Figure 4.1. First, models that have considered only dynamics of the road network alone are reviewed in 4.2. Then, models that have considered Road Network Dynamics in the urban system are reviewed in 4.3. 4.4 synthesises a modelling RNE understanding which addresses the research question of existing modelling RNE knowledge in Chapter 1 and identifies modelling and simulation as a suitable approach to explore RNE and provide insights into empirical RNE findings.

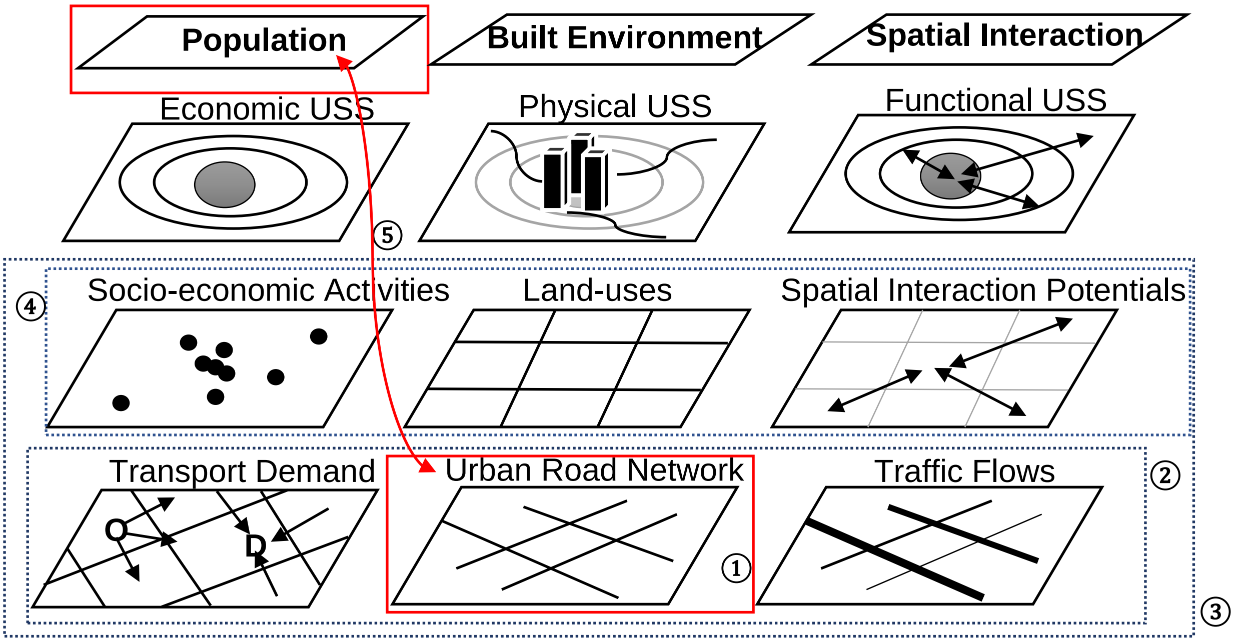



**Figure 4.1 Chapter 4 Structure**: RNE related models that have considered the dynamics of road network alone - ① Section 4.2 Spatial Network Models 4.2.1.1, Planar Network Models 4.2.1.2, Proximity Graph Models 4.2.2, GNMs of Urban road networks 4.2.3. RNE related models that have considered the dynamics of road network in the urban system - ② Section 4.3.1 Transport Demand Modelling and Network Evolution; ③ Section 4.3.2 Land-use and Transport Network Interaction (LUTI) and the Network Evolution; ④ Section 4.3.3 Urban Dynamics and the Transport Network ; ⑤ Section 4.3.4 Generative Network Models of the Urban Road Network in the Urban System.

## 4.2 Modelling RNE: Consider the Urban Road Network Alone

This section reviews previous RNE modelling research, which has considered the urban road network structure alone, from spatial graph 4.2.1.1, planar graph 4.2.1.2, proximity graph 4.2.2, and generative network models of urban road networks 4.2.3. 4.2.4 summarised the section.

### 4.2.1 Spatial and Planar Network Models

As reviewed in Chapter 2, network science has regarded the urban road network as spatial and planar, and spatiality and planarity constrain the primal road structure from exhibiting small-world and scale-free complex network topological characteristics. Thus, spatial network and planar network generations have been used to model the evolution of urban road networks.

#### 4.2.1.1 Spatial Network Models

Gastner and Newman (2006b) compared the Internet, an airline network, and the US interstate highway network and found that road network differed from the other two by small link length, large diameter (the largest number of links along shortest paths between any two nodes), and low node degree. They hypothesised that spatial networks balanced two preferences, a short Euclidean or network distance (number of links along the path connecting two nodes). Given a set of nodes with spatial positions, they proposed a model to optimise the node connection by balancing the generated network's preference between Euclidean distance and network distance. Simulation results showed when the Euclidean distance was preferred, the simulated network had a structure similar to the road network; and when the network distance was preferred, the hub-and-spoke structure emerged. The Gastner and Newman model solved a network design problem (NDP) originated from graph theory, in the context of network science. NDPs aim at finding an optimal way to connect a set of nodes; the optimisation might minimise network length, which would join the nodes into a minimal spanning tree (MST) (Johnson et al., 1978).

Schweitzer et al. (1997) proposed an NDP road network optimisation model. They hypothesised that road networks optimised by two contradicting criteria: the first minimised construction costs, thus minimising connections and the total link length; the second minimised detour, thus minimising the shortest path length between any two nodes. The two criteria could not be achieved at the same time: the first criteria alone would result in an MST; the second criteria alone would result in a complete network. Real road networks lay between the two extremes; they proposed the optimisation model that balanced cost and detour. They acknowledged that their model did not consider transport properties of road networks, like link flows and capacity; costs only considered link length, neglecting link width; detour considered link length, instead of travel time and cost. The simulation started from a complete network of a set of nodes and optimised at each time step cost and detour to add or delete links. Simulated networks were examined using a potential function that measured the balance of cost and detour. Figure 4.2 shows how the simulated network changed during the optimisation process.

The previous two models were static – connecting a given set of nodes to generate networks. Xulvi-Brunet and Sokolov (2007) proposed a dynamic model of spatial network growth. They hypothesised that the spatial network structure resulted from two mechanisms: spatial interactions, which depended on node attractiveness, and inhomogeneous node spatial distribution. The attractiveness of nodes related to node degree – higher degree indicated higher attractiveness. At the same time, node attractiveness was local information, constrained within a geographical distance. Based on this hypothesis, the proposed model iterated adding nodes and links at each time step: new nodes were designed to locate more likely near existing nodes; then new nodes preferred to connect to high degree existing nodes within a geographical distance; besides, existing nodes might also form connections. Simulated networks were examined by complex network topological characterisation measures: node degree distribution, average path length, and clustering coefficient. The simulated networks ranged from “strong geographical” to “weak geographical”. The cost of geographical link length constrained strong geographical spatial networks; the primal urban road network was an example of such networks. Weak geographical networks included airline networks and the Internet, to which geographical distance was not a strong constraint; long-distance links might form between attractive nodes for spatial interaction. The inhomogeneous spatial distribution of new nodes – preference for spatial closeness to the existing network contributed to clustering and hierarchy in the simulated networks.

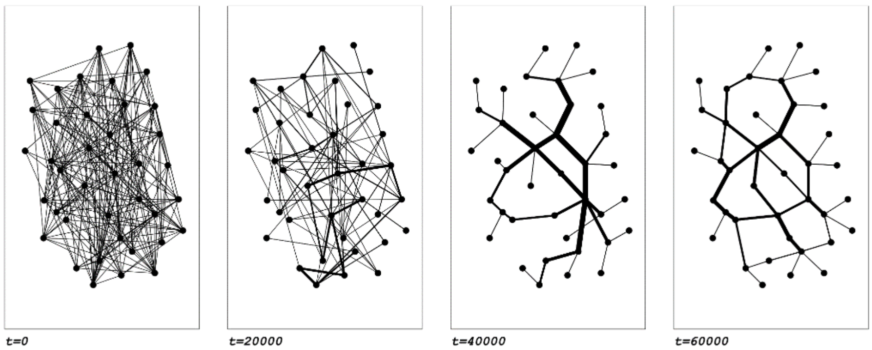



**Figure 4.2 Spatial Network Models**: The four plots show changes of an initial complete network (left) to an optimised network (right), following a fixed parameter to balance cost and detour at each time step. Thickness of the links represents betweenness centrality, which suggested link usages. (Schweitzer et al., 1997)

In summary, spatial network models have modelled the spatial network structure and dynamics according to the spatiality, embedding nodes in the space and associating link lengths with costs. Link Connection processes of reviewed models have considered the cost of link length as a primary factor to model the spatial network structure, ranging from “strong geographical” to “weak geographical”. Strong geographical constraints of link length generated short links and long average paths, leading to the planarity of urban road networks. Weak geographical networks may show small-world and scale-free properties despite the spatiality. Apart from link length, efficiency has often been considered in Link Connection as well; the Gastner and Newman model and the Schweitzer et al. model both considered the number of links along connected paths. In urban road networks, this reflects the number of turns on a path. High efficiency is likely to require short-cuts between node pairs, leading to the circuitous structure.

Node Addition processes of reviewed models have considered the role of node spatial distribution in generating the spatial inhomogeneity of the spatial network structure. New nodes were assumed to be randomly distributed or prefer spatial closeness to the existing network. Statically, the Gastner and Newman model and the Schweitzer et al. model both assumed optimisation mechanisms behind road network formation, while dynamically the Xulvi-Brunet and Sokolov model grew spatial networks by iterative addition of nodes and links.

#### 4.2.1.2 Planar Network Models

Masucci et al. (2009) proposed a static and a growing random planar graph model, as well as a growing grid model to compare with the London road network. To generate a random planar network, a given set of nodes were connected while maintaining planarity: random node pairs within a certain Euclidean distance were selected and connected if obeying planarity until reaching a certain level of Link Connections. To model a growing random planar network, iterative Node Addition and Link Connection were performed while maintaining planarity. At each time step, the model chose one random node of the existing network and drew from it a link if obeying planarity; at every few steps, random node pairs within a certain Euclidean distance were selected to form cycles if obeying planarity. Simulated networks like that in Figure 4.3 were examined by measures: node density from the geographical centre, node degree, block perimeter and area, and closeness centrality. Compared to random planar graph counterparts, the London road network was characterised by a longer tail of density distribution at the periphery, similar link length distribution at the centre but smaller at the periphery, a lower range of node degrees, a broader range of block perimeters and areas. This finding related to London’s high level of urbanisation at the periphery; and the random planar graphs, on the other hand, are sparse at the periphery. The closeness centrality which measured the total length of shortest paths between node pairs, lay between static and growing planar networks, suggesting the level of easiness to reach nodes in the network. Based on these results, the authors concluded that the London urban road network’s characteristics were not trivial outcomes of its planarity.

In summary, the planar network models, both static and dynamic, did not necessarily generate the urban road network structure. Growing planar networks could exhibit small-world and scale-free properties (Haslett and Brede, 2015), differing topologically from urban road networks.

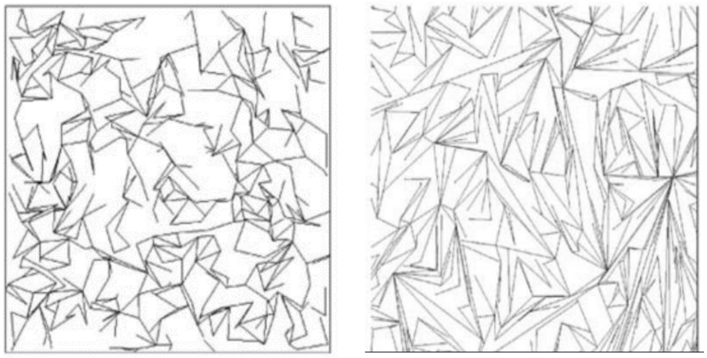


**Figure 4.3 Planar Network Models**: The two plots show local views of simulated networks by the static (left) and growing (right) random planar graph models respectively. (Masucci et al., 2009)

#### 4.2.1.3 Spatial and Planar Network Models Discussion

Models and simulation results reviewed in this section showed that neither modelling spatiality nor planarity guaranteed the generation of the urban road network structure, which suggests mechanisms beyond the spatial and planar network generation. At the same time, the modelling of spatial and planar networks has been meaningful to the modelling of urban road networks, since the primal urban road network structure is spatial and planar.

Both spatial and planar network models have recognised that static network structure results from a dynamic formation and changing process and used an iterative formation process to model this dynamic process. Growth models have been proposed for both spatial and planar networks to model characteristics beyond static models. Second, both spatial and planar network growth models have iterated Node Addition and Link Connection. Modelling spatiality has considered nodes' spatial embedding in Node Addition. Inhomogeneous node distribution has been regarded as leading to the inherent spatial inhomogeneity. Modelling spatiality has considered the link length cost in Link Connection, leading to strong and weak geographical networks. Modelling planarity has considered the maintenance of planarity along with the iteration of Node Addition and Link Connection. Third, the spatial and planar network models have emphasised the comparison with complex networks; thus, simulation results have been examined by complex network topological characterisation measures. Some results have linked urban road network characteristics to spatiality and planarity:

- Urban road networks have been reported to have lower node degree range, similar link length distribution, and follow the power-law distribution, compared to the modelled random planar graph, suggesting spatial and planar constraints.

### 4.2.2 Proximity Graph Models

The last section concluded that spatiality and planarity could not guarantee the generation of urban road network structure. Meanwhile, a type of networks – proximity graphs, have demonstrated the possibility to model primal urban road network structure. Proximity graphs refer to a family of networks defined using some concept of “closeness” or “neighbourhood”; Relative Neighbourhood Graph (RNG) is a prominent member, from which the concept of “neighbourhood” is generalised, bringing this family of networks together (Toussaint, 2002; Jaromczyk and Toussaint, 1992).

RNG was proposed in the 1970s for pattern recognition in computer science (Toussaint, 1980). Figure 4.4 illustrates the definition of RNG. To decide whether to connect two nodes $v_i$ and $v_j$ in a given set of nodes, two circles are drawn with a radius equal the distance $d_{ij}$ between $v_i$ and $v_j$, centring at $v_i$ and $v_j$ respectively. The intersection of these two circles - the lune, determines the proximity neighbourhood of $v_i$ and $v_j$. If there is no other node in this proximity neighbourhood, $v_i$ and $v_j$ are RNG neighbours and connected. Mathematically, given a finite set of nodes, RNG of the set is defined as the network $\mathrm{G} = (\mathrm{V}, \mathrm{E})$, in which $\mathrm{V}$ represents a set of $\mathrm{n}$ nodes, and $\mathrm{E}$ represents a set of $\mathrm{m}$ links; there exists a link $e_{ij}$ with weight $d_{ij}$ if and only if $d_{ij} \leq \max\,(d_{ik}, d_{jk})$, $v_k \in V$, and $k \neq i$, $k \neq j$ (Toussaint, 2014). Namely, there is no third node in $\mathrm{V}$, which was closer to both $v_i$ and $v_j$.

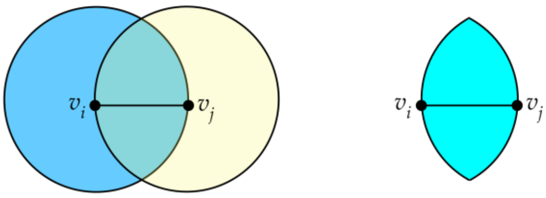



**Figure 4.4 Relative Neighbourhood Graph**: The two plots illustrate the definition of RNG neighbourhood of nodes $v_i$ and $v_j$. $v_i$ and $v_j$ are RNG neighbours, if the lune (right) of two circles drawn with radius equals the distance $d_{ij}$ between $v_i$ and $v_j$, centring at $v_i$ and $v_j$ respectively (left), is empty. (Toussaint, 2014)

Apart from RNG, other proximity graphs include Reciprocal pairs (RP), Nearest Neighbourhood Graph (NNG), Minimal Spanning Tree (MST), Gabriel Graph (GG), and Delaunay Triangulation (DT), as shown in Figure 4.5. From RP to DT, the size of proximity neighbourhood defined in each of these networks decreased, showing in the increasing connectivity of the networks, and their relationships: $\mathrm{RP} \subseteq \mathrm{NNG} \subseteq \mathrm{MST} \subseteq \mathrm{RNG} \subseteq \mathrm{GG} \subseteq \mathrm{DT}$. Watanabe (2008) found link lengths from RP to DT all had peaked distributions, with link length increasing with connectivity. He then compared GG, RNG, DT on regular node spatial distributions – triangle, square, and hexagon grids. RNG had shortest paths similar to rectilinear distances between nodes, DT’s shortest paths resembled Euclidean distances, and GG's lay in between them. He further interpreted these characteristics in terms of travel distance and efficiency of these proximity graphs when treated as transport networks.

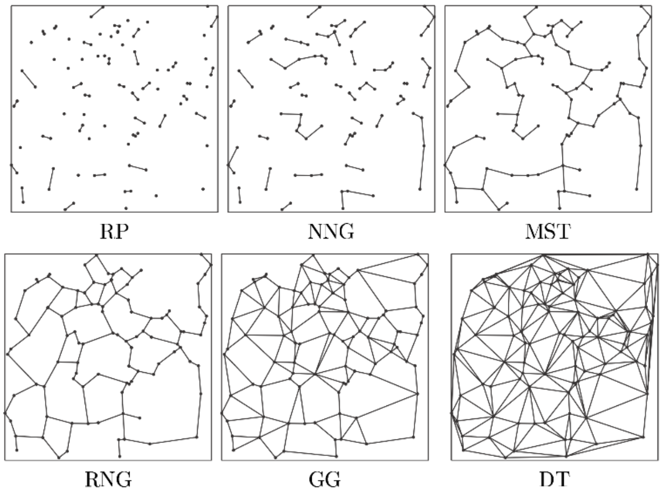



**Figure 4.5 Proximity Graphs**: The two panels include members of the proximity graphs family - Reciprocal pairs (RP), Nearest Neighbourhood Graph (NNG), RNG, Minimal Spanning Tree (MST), Gabriel Graph (GG), and Delaunay Triangulation (DT); $\mathrm{RP} \subseteq \mathrm{NNG} \subseteq \mathrm{MST} \subseteq \mathrm{RNG} \subseteq \mathrm{GG} \subseteq \mathrm{DT}$. (Watanabe, 2008)

Watanabe (2010) compared RNG and several US cities' urban road networks. He hypothesised that the proximity relationships between urban road network intersections decided network connect patterns and constructed RNGs based on empirical spatial distributions of US urban road network nodes. Generated networks were examined by the ratio between tree and grid, density, and link correspondence to the original urban road networks. The generated network based on the Denver road network nodes displayed the highest link correspondence to the original road network, which was explained by the Denver road network's high proportion of grid structure. Therefore, the author concluded that RNG could model the grid structure in urban road networks.

Following a similar approach, Osaragi and Hiraga (2014) compared β-skeleton networks and the Tokyo road network. β-skeletons use a single parameter β to describe a group of proximity graphs. Two nodes $v_i$ and $v_j$ are connected if the lune between two discs with radius $\beta d_{ij}/2$, centring at $\left(\left(1-\frac{\beta}{2}\right)i, \frac{\beta}{2}j\right)$ and $\left(\frac{\beta}{2}i, \left(1-\frac{\beta}{2}\right)j\right)$ has no third node, $\beta \geq 1.0$. $i$ and $j$ are the coordinates of $v_i$ and $v_j$. $\beta < 1$ leads to non-planar networks, and $\beta \geq 2.0$ leads to disconnected networks; $\beta = 1$ equals GG, and $\beta = 2.0$ equals RNG (Adamatzky, 2013a). Osaragi and Hiraga constructed β-skeletons on Tokyo road network's intersections and compared the generated networks with the real-world counterpart, as shown in Figure 4.6. Constructed networks with $\beta \in [1.0, 1.5]$ had the highest link correspondence with the Tokyo road network; these networks also had similar efficiency to the real-road network. Further, they pointed out that β-skeletons exhibited lower similarity with urban road networks when applied to low density or mountainous areas.

The previous two proximity graph models were static and connected a given set of nodes, e.g. real-world urban road networks' intersection positions. Adamatzky (2013b) proposed a growing β-skeleton model. β-skeleton networks' connectivity decreases with β; the network structure is not stable unless node spatial distribution is regular. To grow connected β-skeleton networks with stable β, the proposed model iterated Node Addition and Link Connection. In particular, Node Addition required new nodes to satisfy two criteria: first, new nodes lay outside the neighbourhoods of existing nodes; second, the network remained connected after adding the new nodes. Simulated networks transformed from having a grid structure to a tree structure when simulated with increasing β.

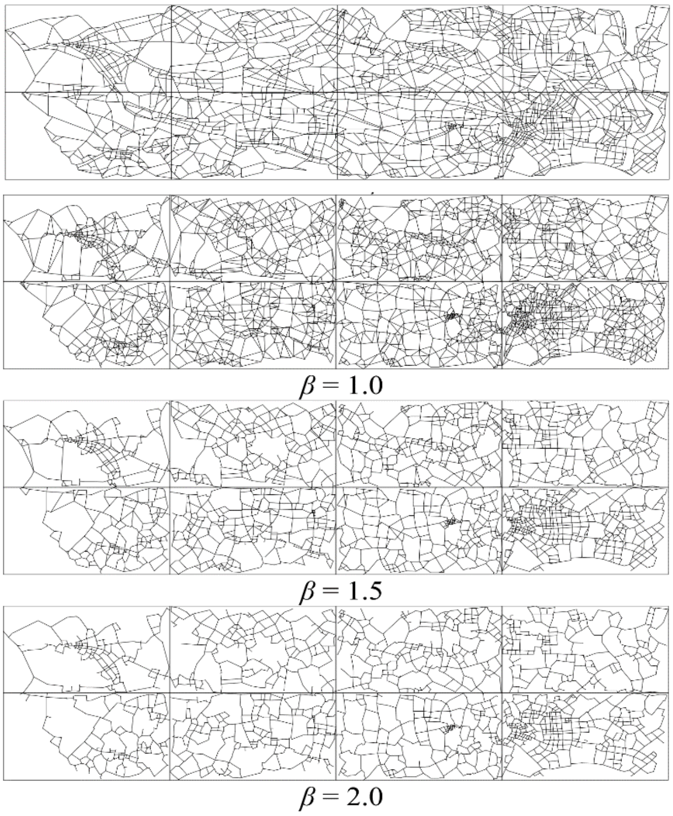



**Figure 4.6 β-skeleton networks**: The four panels compare the Tokyo road network (top) and constructed β-skeleton networks on the spatial distribution of Tokyo road network nodes with $\beta = 1.0$, $1.5$, and $2.0$. (Osaragi and Hiraga, 2014)

#### 4.2.2.1 Proximity Graph Models Discussion

Network structure like MST and DT have been used to compare and approximate urban road networks since quantitative geographical network analysis in the 1960s. The cost of link length and efficiency have been two essential mechanisms to model the Link Connection of spatial networks as discussed in 4.2.1. Strong constraint of link length cost led to the minimally connected MST, while strong preference for efficiency led to maximumly connected DT. Meanwhile, only cost and efficiency mechanisms did not guarantee the generation of primal urban road network structure. The models reviewed in this section have shown, MST and DT belong to the family of proximity graph networks, which specify local geometric proximity relationships of network nodes, beyond globally minimising or maximising cost and efficiency.

The proximity graph models have differed from spatial and planar network models in this additional consideration of local proximity relationships in the Link Connection. Previous models have found that RNG could reconstruct network structures with high link correspondence on real road network nodes. This empirical finding suggested that RNG may play an essential role in modelling the rectilinear connection in urban road networks. Previous models have also found β-skeleton networks $\beta \in [1.0, 1.5]$ had the highest link correspondence with real urban road networks, indicating this single parameter β may model a broad spectrum of urban road network structures. In short, existing proximity graph network models suggested the consideration of local proximity relationships beyond cost and efficiency in Link Connection, which the spatial and planar network models lacked, may enable the generation of the primal urban road network structure.

Existing proximity graph models of urban road networks have been static, limiting the current research to the analyses of proximity graph realisations on real road network nodes. Nevertheless, the computer science community have developed dynamic growing proximity graph models, which iterated Node Addition and Link Connection processes as well. Further research questions may be specified:

- Can proximity relationships from the proximity graph networks be used to model the dynamic process of RNE? Further, can proximity relationships controlled by β be used to model RNE?
- What are the influences of link length cost, network efficiency and proximity relationship between nodes on the urban road network structure, and do the local proximity relationship lead to the differences of urban road networks from other spatial and planar networks?

### 4.2.3 Generative Network Models of Urban Road Networks

Generative network models (GNMs) hypothesise network evolution mechanisms and generate network structure, accordingly, thus offering theories of the formation and dynamics of networks. To be more detailed, GNMs implement hypothetical generative mechanisms; the emergence of simulated network structure similar to real networks manifests, though not proves, the generative mechanism are plausible as evolutionary mechanisms behind complex network formation and dynamics (Newman, 2010). A prominent GNM is the Barabási-Albert (BA) model. Observing that many complex networks' node degree distribution exhibits power-law decay – the scale-free property, Barabási and Albert (1999) proposed a hypothetical generative mechanism that real complex networks developed with two features: growth and node degree preferential attachment. Scale-free property emerged from implementing this mechanism; hence, growth and preferential attachment of the BA model became plausible mechanisms behind complex networks' scale-free property.

Spatial network models have generated spatiality in the networks using mechanisms related to the cost of link length; planar network models have generated planarity using mechanisms to maintain planarity during network growth 4.2.1. Proximity graph models have generated networks with mechanisms of proximity relationships between network nodes 4.2.2. Though compared with and used to approximate urban road networks, none of these models has generated the primal urban road network structure. Thus, the primal urban road network structure required other design in generative mechanisms (Courtat et al., 2011). Barthélemy and Flammini (2008) pointed out though GNMs have been successful in modelling complex networks, their application in urban road networks has been limited. This section reviews four generative models that have generated the primal urban road network structure, which are summarised in Table 4-1.

#### 4.2.3.1 Generative Network Model of Leaf Venation Patterns

Runions et al. (2005) proposed two GNMs of leaf venation patterns, to generate leaf venation networks with or without loops. The leaf venation pattern was represented as a network with a set of nodes representing small vein segments and a set of links connecting adjacent vein nodes. A second sub-system modelled was a set of points representing hormone sources.

The generative mechanisms were based on biological theories regarding hormone control of vein morphology. The generative mechanism modelled the following process of leaf venation growth: veins grew towards hormone sources embedded in leaf blade by laying new vein nodes, hormone sources occurred and disappeared according to their proximity relationships with veins and other hormone sources, and both vein and hormone sources' development were further influenced by lead blade growth. To generate leaf venation network with cycles, the generative mechanism further designed: hormone sources attracted the closest vein node as well as all the vein nodes in their Relative Neighbourhood Graph (RNG) proximity neighbourhood to create cycles. Veins grew towards hormone sources that attracted them; new hormone sources occurred at distance $b_v$, $b_s$ away from existing vein nodes and hormone sources accordingly.

Assumptions made beyond the theoretical hypotheses included hormone sources emerge at random locations that satisfy $b_v$, $b_s$. The initial network condition was specified by user input. Parameters used to control the modelled system included $b_v$, $b_s$, and $\rho$, which controlled the number of hormone sources per time step. The model was validated visually by the generated leaf venation patterns, as in Figure 4.7.

**Figure 4.7 Generative Network Model of Leaf Venation Patterns**: The three plots show the sensitivity test of parameter $\rho$, the number of new hormone source per time step, as $\rho$ increases from the left to right (Runions et al., 2005).

#### 4.2.3.2 Generative Network Model of Urban Street Patterns

Based on the GNM of leaf venation patterns, Barthélemy and Flammini (2008) proposed a GNM of urban street patterns. The modelled sub-systems consisted of a set of nodes - urban centres which are new land-use locations, and a road network to connect the centres with nodes representing small road segments and links connecting adjacent road nodes. Observing similarity in empirical network characteristics, this model hypothesised general mechanism existed behind urban road evolution - local optimality: urban road network connected locally, in the most efficient way using minimum road length. In the implementation, urban centres were added with time and attracted the nearest road as well as other close roads in their RNG proximity neighbourhood. Assumptions made beyond theoretical hypotheses included exogenously given positions of new centres, a unit square simulation area, a time framework with new urban centres added slower than road growth, specified initial and termination conditions.

Network characteristics examined of the simulated networks include the ratio between the node and link number $e = \frac{E}{N}$, total link length $L_{tot}$, form factor $\varphi = \frac{4A}{\pi D^2}$, and block perimeter $p$. As in Figure 4.8, average network characteristics of 1000 simulations were plotted: $L_{tot} \sim N^{1/2}$; $\varphi$ peaked around 0.6 and in the range [0.4,0.7]; block area distribution $P(A)$ followed an exponential distribution. By controlling the distribution of new urban centres to follow an exponential decay from the geographical centre of the simulation area, generated urban road network's $\mathrm{P(A)} \sim \mathrm{A}^{\alpha}$ followed a power-law distribution with $\alpha = 1.9$, as in Figure 4.9. After this, characteristics of the simulated networks agreed with Lämmer et al. (2006)'s empirical results of German road networks, which was reviewed in Chapter 2 section 2.3.4.

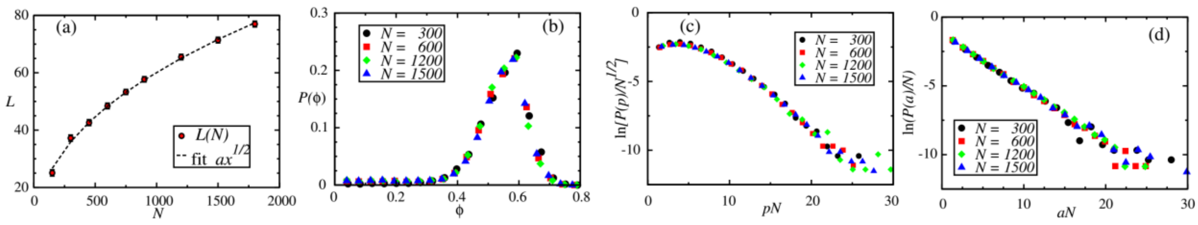


**Figure 4.8 Generative Network Model of Urban Street Patterns**: Simulation network characteristics (a) total link length $\mathrm{L_{tot}} \sim N^{1/2}$ followed a power-law distribution. The x-axis represents node number $N$, and the y-axis represents $\mathrm{L_{tot}}$. Red dots represent values of $\mathrm{L_{tot}}$ at different node number and was fitted by the dashed line, showing a power-law fit. (b)-(d) Blue circles, red squares, green diamonds, and blue triangles represent simulated network characteristics at node number $N = 300, 600, 1200, 1500$, respectively. (b) Form factor $\varphi$ peaked at 0.6, and belonged to a range [0.4,0.7]. The x-axis represents form factor $\varphi$, and the y-axis represents probability $P(\varphi)$. (c) Block perimeter $\mathrm{p}$ followed an exponential distribution. The x-axis represents $\mathrm{p}$ rescaled using node number $N$, and the y-axis represents probability $P(\mathrm{p})$ rescaled using $N^{1/2}$ and on a logarithmic scale. (d) Block area distribution $\mathrm{P(a)}$ followed an exponential distribution. The x-axis represents block areas $a$ rescaled using node number $N$, and the y-axis represents probability $P(\mathrm{a})$ rescaled using $N$ and on a logarithmic scale. (Barthélemy and Flammini, 2008)

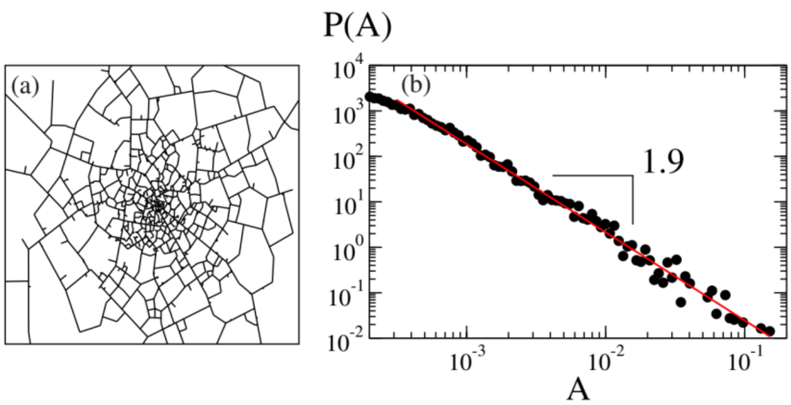


**Figure 4.9 Generative Network Model of Urban Street Patterns – Node Spatial Distribution Following Exponential Decay**: Plot (a) shows a simulated network given urban centres following an exponential spatial distribution. Plot (b) shows block area distribution $\mathrm{P(A)} \sim \mathrm{A}^{\alpha}$ followed a power-law distribution, with $\alpha = 1.9$. The x-axis represents block areas $A$, and the y-axis represents probability $P(A)$. (Barthélemy and Flammini, 2008)

#### 4.2.3.3 Generative Network Model of City Graph

Courtat et al. (2011) proposed a GNM to generate morphology of a city represented by its streets. The modelled network $\mathrm{C(t)} = [(\mathrm{V(t)}, \mathrm{E(t)}), \mathrm{H(t)}]$ consisted of $\mathrm{G} = (\mathrm{V}, \mathrm{E})$

– a spatial geometrical network with the set of nodes $\mathrm{V}$ and the set of links $\mathrm{E}$. A hypergraph $\mathrm{H}$, on top of $\mathrm{G}$, in which as many as degree $\mathrm{k}_2$ nodes could be added to each link, recovering the city's streets from $\mathrm{G}$. The network was historically dependent, as all components were function of time $\mathrm{t}$.

The model hypothesised that a city developed locally through division and extension of space through constrained development like a shell and could be represented by infinite small street segments. The generative mechanism was implemented as the following. New urban settlements were added to the simulated city area according to a potential attraction field depending on the existing network; the settlements then connected to the existing network to the set of points which were orthogonal projections of new settlements on $\mathrm{C}$ while keeping the network planar and satisfying RNG proximity.

Parameters influencing the simulated network structure included $P_e$ which controlled the extent to obey the attraction potential field, β which controlled local geometry in choosing new node position, ω which controlled the extent to obey the Link Connection choices, and $f_{ext}$ which controlled the extent of network sprawling. As in Figure 4.10, ω influenced the network structure to vary from circuitous to treelike from top to bottom rows. $P_e$ reflected the extent of unplanned to planning growth, from left to right columns; planned networks obeyed to global node position choices.

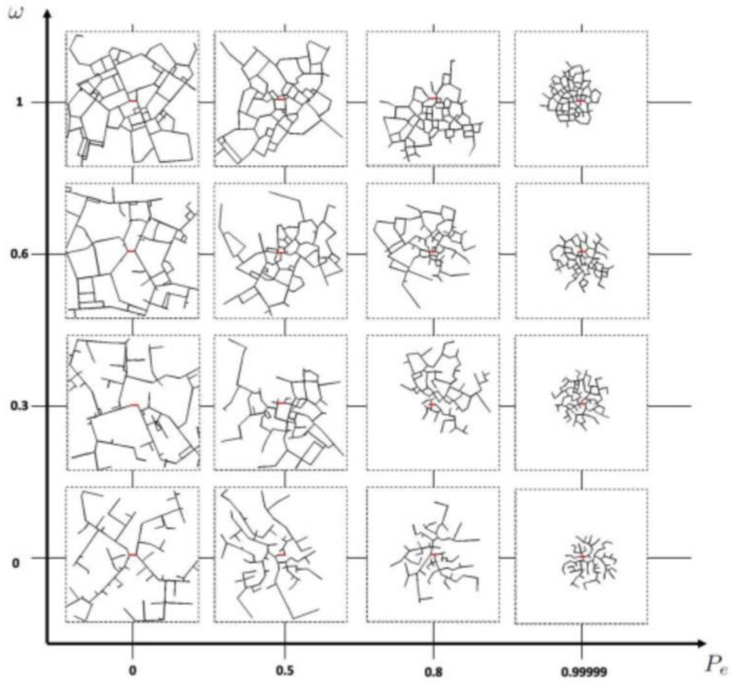



**Figure 4.10 Generative Network Model of City Graph**: These sixteen plots show the influences of parameters $P_e$ – the extent to obey attraction potential field and ω – the extent to obey Link Connection choices on simulated networks. The combinations of $P_e = 0, 0.5, 0.8, 0.99999$ on the x-axis, and $\omega = 0, 0.3, 0.6, 1$ on the y-axis were tested. (Courtat et al., 2011)

Examined network characteristics included Organic ratio $r_N$ – the proportion of degree $k_1$ and $k_3$ nodes, Meshedness coefficient $\mathrm{M}$ – the extent of a planar network from a tree $\mathrm{M} = 0$ to a complete planar network $\mathrm{M} = 1$, Topological distance $d^{topo}$ – the number of turns from a street to another, Anisotropy $\mathrm{A}$ – the distribution of angles between streets, and link length distribution. The simulated networks showed $r_N \approx 1$, similar $\mathrm{A}$, $\mathrm{M}$ depending $(P_e, \omega)$ as in Figure 4.10, small $d^{topo}$, and lognormal distribution of link length.

#### 4.2.3.4 Generative Network Model of Centre Competition

Rui et al. (2013) proposed a GNM of self-organised urban street networks; they proposed a centre competition mechanism in Node Addition. The modelled road network consisted of a set of nodes representing urban centres and a set of links representing road segments.

The generative mechanism hypothesised: new centres were chosen among candidates according to maximum or minimum utility value, which was the sum of node degree within radius $\mathrm{r}$ to a candidate node. New nodes first connected to one point on the existing network balancing distance and node degree; new nodes then connected to points on the existing network satisfying RNG proximity with a probability $\mathrm{P}_l$.

Parameters of the model included: $\alpha$ balanced the importance between distance and node degree in Link Connection, $\mathrm{P}_l$ which controlled the extent of connections between new node and RNG proximity points in Link Connection, $\mathrm{r}$ which was the radius controlling the neighbouring area to measure candidate utility, and the number of new node candidates per time step. $\alpha$ introduced consideration of node degree, or the Link Connection would connect the new node to the nearest point on the existing network like previous GNMs *4.2.3.1 – 4.2.3.3*. $\mathrm{P}_l$ was like $\omega$ in *4.2.3.3*, leading to treelike or circuitous structure. $\mathrm{r}$ affected Node Addition by defining the area to calculate candidates' utility. As in Figure 4.11, $\mathrm{r} = 0$ in the plot (a) means the area is 0, disabling the competition mechanism, and the simulated network has homogeneous node distribution. As $\mathrm{r}$ increased, the simulated network changed from having several small clusters to having one whole compact cluster.

The examined simulated network characteristics included Organic ratio $r_N$, Meshedness coefficient $\mathrm{M}$, total topological link length $\mathrm{L}_{topo}$, total geometrical link length $\mathrm{L}_{tot}$, Efficiency $\mathrm{E}$ which compared the Euclidean distance to network distance, Topological efficiency $\mathrm{E}_{topo}$, Fraction of dominant sectors which measured the ratio of sectors having dominant number of centres, Gini index of BC, Block distribution $\mathrm{P(A)}$, and BC distribution. $r_N$ decreased with $\alpha$ and $\mathrm{P}_l$, while $\mathrm{M}$ increased. Both $\mathrm{L}_{topo}$ and $\mathrm{L}_{tot}$ increased with $\mathrm{P}_l$, while $\mathrm{L}_{tot}$ increased and $\mathrm{L}_{topo}$ decreases with $\alpha$. $\mathrm{E}$

reached the highest value with a medium $P_l$; larger $P_l$ led to decrease of $E$. $E_{topo}$ increased with $\alpha$. The fraction of dominant sectors decreased with $r$. BC Gini index increased first to the maximum value, then decreased with $r$. $P(A)$ was very sensitive to centre spatial distribution; uniform centre distribution at $r = 0$ led to exponential $P(A)$ distribution; $r = 0.25$ resulted in power-law $P(A) \sim A^{\alpha}, \alpha = 2.5$; and $r = 0.05$ led to most heterogeneous block areas following $P(A) \sim A^{\alpha}, \alpha = 1.05$. Finally, BC exhibited exponential distribution.

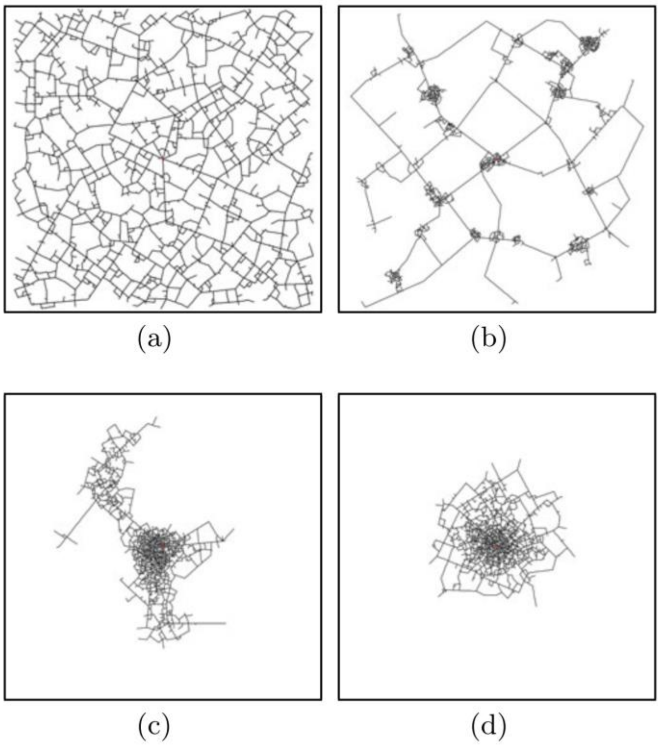


**Figure 4.11 Generative Network Model of Centre Competition**: The four plots show the influences of parameter $r$, increasing from 0, 0.025, 0.075, to 0.25 (a)-(d). (Rui et al., 2013)

#### 4.2.3.5 Generative Network Models of Urban Road Networks Discussion

GNMs of urban road networks have combined considerations of spatiality, planarity, and proximity relations, and generated primal urban road network structures dynamically. These models have followed the network science approach to grow networks by the iterations of two processes – Node Addition and Link Connection. Generative mechanisms have been designed to direct Node Addition and Link Connection. Spatiality was modelled as spatial network models in 4.2.1.1: nodes' spatial locations were meaningful in Node Addition; Link Connection used the cost of link length – connecting the new nodes to their nearest points on the existing network. Link Connection also considered efficiency – creating cycles between new nodes and the existing network besides the shortest connections. Planarity was modelled as planar network models in 4.2.1.2: planarity was maintained in Link Connection.

These models have further considered the proximity relationship in Link Connection besides cost and efficiency, as in the proximity graph models 4.2.2, which was key to the generation of primal urban road network structures. These models contributed to model proximity graph models dynamically, instead of connecting a given set of nodes. Last but not the least, these models have examined broadly simulated networks' characteristics and compared to real urban road networks, which have not been done in the studies of spatial, planar, and proximity graph network models.

Meanwhile, the previous GNMs of urban road networks have had the following limitations.

First, though having generated the primal urban road network structure and validated the simulated network structure by comparing empirical counterparts, the modelled network structures were not all primal urban road networks. The GNM of urban street patterns 4.2.3.2 followed the GNM of leaf venation patterns 4.2.3.1 and modelled two sub-systems: a set of urban centres that attracted road growth, and a network to connected urban centres with nodes representing small road segments and links connecting adjacent nodes. The GNM of city graph 4.2.3.3 modelled a primal urban road network, with nodes representing intersections and links representing road segments, as well as a hypergraph representing streets. However, this network represented a city, thus equating the urban road network structure to the urban system. The GNM of centre competition 4.2.3.4 modelled a primal urban road network; the nodes represented urban centres. Therefore, existing GNMs of urban road networks have either modelled an urban network in which nodes were urban centres or a primal urban road network that represented a city. If these models have not modelled a primal urban road network, their simulated networks should not have been compared to or validated by one. If these models have modelled primal urban road networks, they needed to clarify the relationships between the urban road network and the urban system.

Second, previous GNMs of urban road networks have not compared the Link Connection mechanism horizontally or analysed its impact on the generation of primal urban road network structure. These models shared a similarity in Link Connection: new nodes were all connected to the closest point on the existing network as well as RNG neighbours. However, each model has described this process differently and heuristically, without explaining the working mechanism behind. The GNM of urban street patterns 4.2.3.2 described that roads grew towards the urban centres and connected first according to a local optimisation principle to minimise the cost of link length connection locally, then connected to RNG neighbours. The GNM of city graph 4.2.3.3 described new nodes connected to an intersection of a few point sets: the “visible points” – points on the existing network that maintain planarity after the connection, the orthogonal projection of new nodes on the existing network, and the RNG neighbours. The GNM of centre competition 4.2.3.4 followed The GNM of urban street patterns.

As reviewed in 4.2.2, RNG is a member of the proximity graph family, and its structure has been thought as similar to the urban road network because it could model the grid structure in urban road networks. Moreover, other proximity graphs may share a similar structure to urban road networks, too, such as β-skeletons with $\beta = 1.0$ to $2.0$. The proximity relationships examined between nodes in Link Connection have determined the connection patterns of these networks. The existing GNMs of urban road networks have not related to the proximity graph models 4.2.2. They have not related the Link Connection process to the proximity relationship. For example, why Link Connection that connected to new nodes’ nearest point and RNG neighbours on the existing network could generate the primal urban road network structure. Other proximity relationships have not been explored either, like that of the β-skeletons, which may be equally effective in generating the urban road network structure besides the RNG proximity relationship.

Third, previous GNMs of urban road networks have put more emphasis on reproducing empirical urban road network statistics, rather than modelling the dynamic RNE process. The generation of network structures that were statistically similar to empirical urban road networks did not guarantee the proposed generative mechanisms were behind the urban road network evolution, because different processes might result in the same pattern and different generative mechanisms might lead to the same network structure.

Fortunately, GNMs enable the observation of the continuous simulated network dynamics as well. Statistical similarity in how simulated networks and empirical urban road networks change, namely the dynamic network structure, may increase the credibility of the generative mechanism. Nevertheless, previous models have not compared their results with the empirical RNE findings. As reviewed in Chapter 2, increasing empirical RNE research has quantified the dynamics of real-world urban road networks through network snapshots of historical periods. These quantified empirical RNE characteristics and processes may be compared with the simulated network dynamics using GNMs. The capacity of a GNM in simulating plausible network dynamics, besides static network structure, may increase the model and its generative mechanism’s credibility to model RNE. Further simulation experiments may explore the processes and mechanisms behind the occurrence of empirical RNE observations, thus provide insights into the inconsistent and conflicting results.

Finally, GNMs of urban road networks reviewed in this section have only considered the urban network structure, without integrating RNE into the urban system. This limitation has shown in the Node Addition process. Spatial network models 4.2.1.1 demonstrated spatial distribution of nodes determined the spatial distribution and organisation of simulated networks to a great extent. The GNM of urban street patterns 4.2.3.2 assumed new nodes' locations to follow a random and exponential distribution. The GNM of city graph 4.2.3.3 assumed a potential field to calculate spatial locations' attractiveness to new nodes according to the existing network's spatial distribution. The GNM of centre competition 4.2.3.4 assumed a utility function to calculate spatial locations' attractiveness to new nodes according to total node degree within a certain distance, namely according to existing network's spatial distribution and topological characteristics. Therefore, all reviewed models in this section have considered the urban road network structure alone. However, the road network resides and changes in the urban system; it is reasonable to expect urban factors significantly influence RNE. For example, as reviewed in Chapter 3, empirical evidence has reported positive correlations between the road network and the urban spatial structure. GNMs of urban road networks in the urban system are reviewed in section 4.3.4.

### 4.2.4 Modelling RNE: Consider the Urban Road Network Alone Summary

This section followed spatial, planar, proximity graph network models' applications in modelling urban road networks and narrowed down to a small group of GNMs, which generated the primal urban road network structure. Selected simulation results of these models were put together in Figure 4.12, with summarised generative mechanisms. This progression of modelling effort led to the generation of the urban road network structure. GNMs of urban road networks have merged generative mechanisms of the three other models, generated the primal urban road network structure, and may model the dynamic RNE process.

The reviewed models in this section have modelled the urban road network component of the urban system, as shown in Figure 4.1, which differed them from alternative RNE modelling approaches. The next section reviews modelling effort that has combined the urban road network with other layers and components of the urban system, demonstrating how RNE could be modelled according to different urban system aspects of focus.

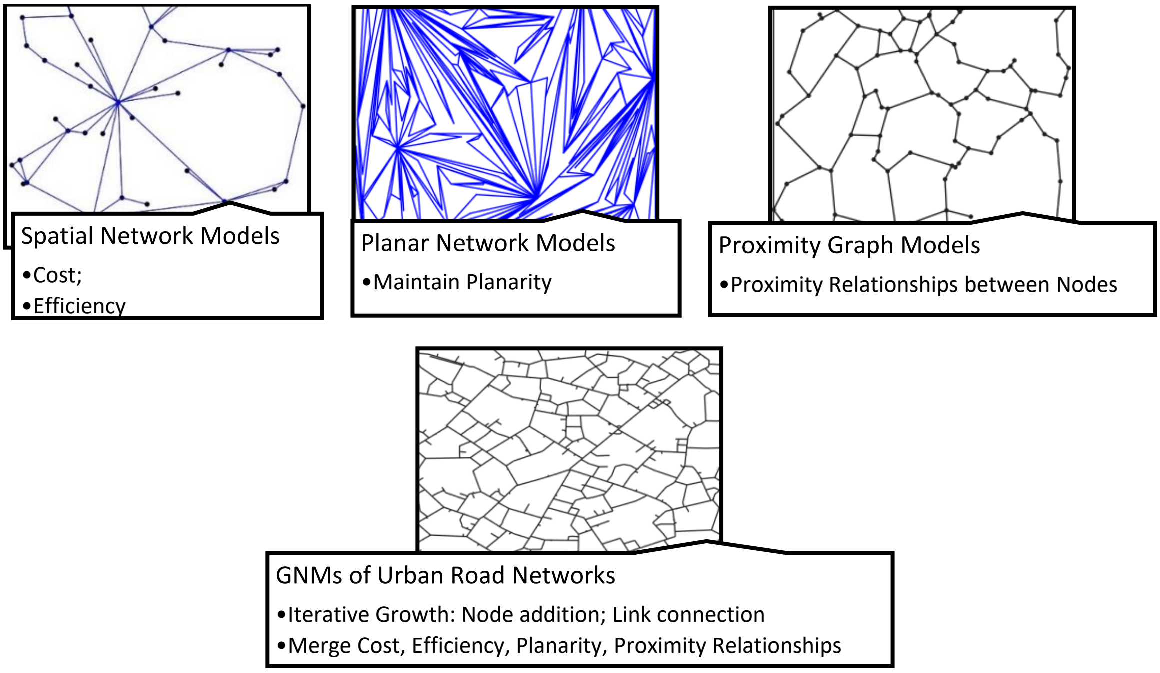



**Figure 4.12 Modelling RNE: Consider the Urban Road Network Alone**

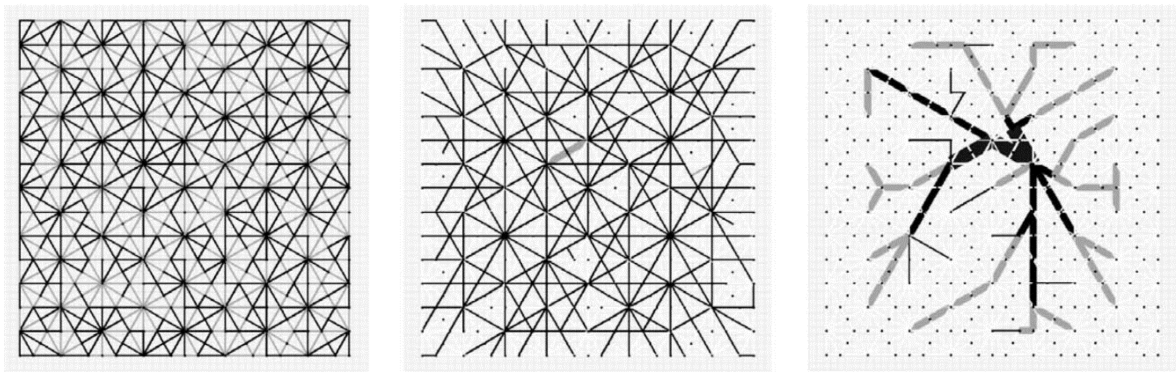
**Summary**: The top panel selects simulated networks of spatial (Gastner and Newman, 2006b), planar (Haslett and Brede, 2015), proximity graph (Watanabe, 2010) network models, respectively. The lower panel shows simulated networks of GNMs of Urban road networks (Barthélemy and Flammini, 2008).

## 4.3 Modelling RNE: Consider the Urban Road Network in the Urban System

### 4.3.1 Transport Demand Modelling and Network Evolution

Based on the observation that urban road networks are hierarchical, Levinson and Yerra (2006) proposed this inherent hierarchy came from road networks' self-organisation, rather than the central planning. They proposed an agent-based model consisting of four sub-models for RNE. The model assumed uniform land-use and population distributions to avoid the influence from the land-use hierarchy on an urban road network. Land-use and road network were modelled as two connected layers. The road network was assumed to have a grid layout and given initial speed levels. The first transport demand sub-model followed the traditional four-stage transport demand forecasting, which loads populations' transport demand onto the urban road network and calculated traffic flows. With the link speed, flows and length, the second revenue sub-model calculated revenue of links. The third cost sub-model used link flows to calculate maintenance costs. Finally, an investment sub-model determined whether links should be upgraded or degraded based on their revenue and maintenance costs. This modelled process of RNE iterated until equilibrium was reached or could not be reached.

Xie and Levinson (2009) continued exploring urban road networks' self-organisation, and proposed a degeneration RNE process, as in Figure 4.13. Following the process of travel flow forecasting, revenue, cost, and investment in the previous model, this model added a degeneration step, in which the least used links were abandoned. The capacity of this model to generate typical urban road structure like ring, web, tree and circuit from different initial conditions, network structure, and decision rules, was used to demonstrate the plausibility of road networks' self-organisation hypothesis. The topological structure of simulated networks was measured, including network connectivity, network density, the entropy of link speed, Gini index of link traffic volume, and connection patterns of ring, web, tree and circuit.



Iteration 0 Iteration 500 Iteration 1000

**Figure 4.13 Transport Demand Modelling and Network Evolution**: The three plots show the evolution process of a simulated road network from an initial condition of an asymmetric hexagon to a hub-and-spoke network (Xie and Levinson, 2009).

Instead of self-organisation, de Martinis et al. (2014) and Pagliara et al. (2016) proposed a dynamic retail structure model based transport demand RNE model. They perceived the RNE process as links upgrading according to the flow-capacity ratio, which suggested the congestion level. The model consisted of a hierarchy of zones, and roads connected nearby zones' centroids. Link flows were acquired using transport demand modelling, then used to select links for the upgrade. However, the modelled road network structure was restricted to be of "illustrative purpose".

#### 4.3.1.1 Transport Demand Modelling and Network Evolution Discussion

As shown in Figure 4.1, models reviewed in this section have combined transport demand modelling and road network evolution on the transport layer of the urban system, modelling the transport generation from origins and destinations; the traffic flows resulted from transport demand direct the development of road networks. These models have explored the self-organisation of urban road networks, with the RNE hypothesis that road networks emerged from local individual economic decisions, merging traditional transport demand forecasting with complexity theory.

These models have focused on urban road networks' transport properties: the urban road network modelled was link-centric, in which links had differentiated functional properties and operational performance (Xie and Levinson, 2007). These models have included a significant level of road network functional details, like link speed and flows, road construction time scales, which made them highly compatible with transport planning. They were applied to real road networks to simulate alternative policy scenarios like road expansion, road construction, budget constraints, and selections of possible new links, helping policy decision-making (Levinson et al., 2012).

However, with the high level of realisticity and applicability come these models' complexity and inflexibility. The incorporated transport demand model has a profound theoretical and modelling framework, which made these models less flexible in terms of exploring urban road networks' network characteristics and dynamics. For example, the modelled RNE processes have been restricted within the transport demand modelling framework, following a sophisticated process of reaching transport demand equilibrium. Consequently, it was challenging to experiment RNE by coupling with various urban system factors, because of the difficulty in introducing new factors into the profound transport demand modelling framework. The time scope accorded with the planning horizon but was limited in terms of exploring long-term dynamics.

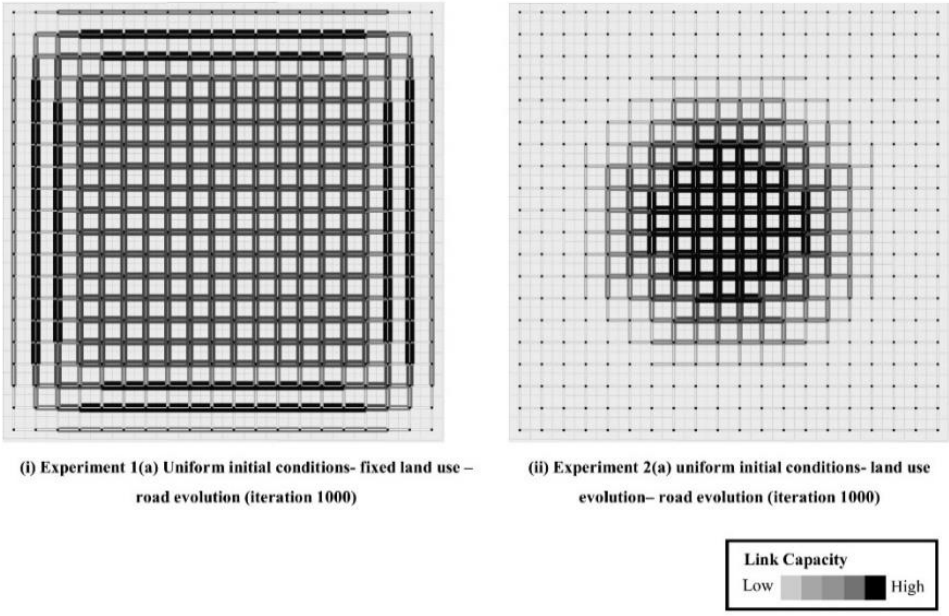
### 4.3.2 Land-use and Transport Network Interaction (LUTI) and the Network Evolution

Transport and land-use are considered to have reciprocal influences on each other (Kelly, 1994), which forms a Land-use and Transport Interaction (LUTI) feedback loop consisting of four parts. The spatial distribution of land-uses determines spatial locations of socio-economic activities; socio-economic activities requires transport infrastructure to fulfil the demand for spatial interactions; the spatial distribution of transport infrastructure determines the accessibility for spatial interactions; accessibility, in turn, influences spatial decisions for land-use locations (Wegener and Fürst, 2004).

On this theoretical foundation, most LUTI models couple a land-use component with a transport demand model; the latter assigns transport demand to and determines traffic flows on the transport network. Then, accessibility is imported to decide the locations of socio-economic activities; for instance, families are assumed to prefer high accessibility to work and shopping, while businesses are assumed to prefer high accessibility to the labour market. Provided by the transport network, accessibility is calculated by travel time and cost, projecting transport's influences, such as congestion, onto accessibility and the locations of socio-economic activities. (Iacono et al., 2008)

Levinson et al. (2007) proposed a co-evolution model of land-use and the urban road network. This model followed the LUTI feedback loop: changes in land-use led to changing travel patterns and determined flows on the transport network; changing flows led to the improvement of the transport network and accessibility; the changed accessibility then led to land-use relocation. In particular, this model explored the influences of land-use's hierarchy on the urban road network hierarchy, using four sub-models. Land-use was modelled as a grid layer with land-use cells; the urban road network was modelled as a grid layer on top of the land-use, connecting centroids of transport analysis zones which were the land-use cells.

The first sub-model was a transport demand model, loading population and employment information and transport demand onto the urban road network. The second sub-model then balanced revenue and maintenance costs of individual links based on link flows calculated in the first sub-model and decided the investment of individual links locally. The third sub-model calculated the accessibility of transport analysis zones or the land-use cells. Finally, a land-use model remade spatial decisions of land-use locations according to accessibility provided by the road network, while maintaining the total population and employment. In making the spatial decisions, the population were assumed to prefer high accessibility to work and low accessibility to other population; businesses were assumed to prefer high accessibility to both population and other businesses.




(i) Experiment 1(a) Uniform initial conditions- fixed land use – road evolution (iteration 1000)

(ii) Experiment 2(a) uniform initial conditions- land use evolution– road evolution (iteration 1000)

**Figure 4.14 Land-use and Transport Network Interaction (LUTI) and Network Evolution**: Simulated land-use and urban road network with assumed fixed land-use (left) and evolved land-use with the road network (right). The grid land-use layer lay beneath the grid road network layer, with the road network connected centroids of land-use cells. The thickness of road network links represents the link capacity. (Levinson et al., 2007)

Two simulation experiments were conducted, as shown in Figure 4.14: the first simulated urban road network evolution under fixed land-uses, and the second simulated the co-evolution of land-uses and the urban road network. Simulation results demonstrated that road network exhibited a higher level of the hierarchy, i.e. more concentrated link capacity when co-evolved with land-use than under fixed land-use. Simulation results were examined by a Gini index measuring agglomeration of land-use and link capacity, and a clustering degree that measured distances from land-use cell centroids to the centre of the simulation area.

Other than hierarchy in urban road network during the co-evolution of land-use and transport network, Levinson and Huang (2012) further explored the reciprocal land-use and transport relationship’s influence on road network’s connection patterns. They hypothesised a decentralised LUTI mechanism: land values increased with accessibility, and road building resulted from individual landowners’ pursuit of interests to increase land values through increasing accessibility. The model consisted of a grid land-use layer and a grid road network on top. The Land-use layer differentiated central and non-central cells for commercial and non-commercial land-uses; accessibility to different land-uses varied land cell values; different owners owned land-use cells. Road network was assumed to grow only rectilinearly to connect adjacent land-use cell centroids; individual landowners built roads provided the interest in gaining accessibility exceeds the cost of road construction. Figure 4.15 shows (a) a simulated road network grew from an initial no roads condition, (b) to early development of a tree structure, (c) with emerging circuits, and finally (d) to a network with circuit structure around the centre and dead-ends at the periphery, demonstrating accessibility to central commercial land-uses' incentive on Road Network Dynamics. Treeness and circuitness were examined to characterise the evolution of simulated road networks.

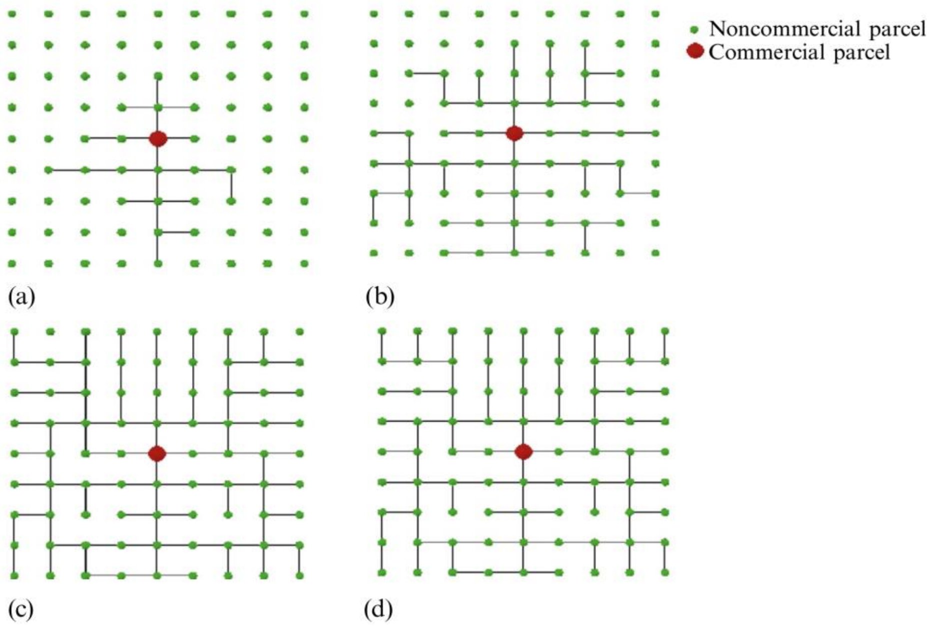



**Figure 4.15 Decentralised Land-use and Transport Network Interaction (LUTI) and Network Evolution** : (a)-(d) show the simulated growth of an urban road network under a mechanism of decentralised land-use and transport interaction. Nodes represent centroids of land-use cells underneath the road network, which might be commercial (red) and non-commercial (green). Road network connected adjacent land cell centroids. (Levinson and Huang, 2012)

#### 4.3.2.1 LUTI and the Network Evolution Discussion

LUTI models involve both land-use and transport layers, as illustrated in Figure 4.1, and perceive the RNE process as a step in the feedback relationship between land-use and transport. Transport factors essential to LUTI models revolve around transport demand modelling, including trip length, trip frequency, mode choice (Wegener and Fürst, 2004). However, the characteristics and dynamics of the urban road network structure have been rarely considered. This limitation has been attributed to the fact that LUTI models were often quite complex, being all-encompassing, operational and data-oriented, and their results were less reproducible, with components relationships hard to disentangle, and no emphasis on the emergence of macroscopic system characteristics (Levinson et al., 2007). The co-evolution model of land-use and urban road network proposed by Levinson et al. (2007) demonstrated the possibility to integrate RNE into a LUTI framework. The Levinson and Huang (2012) model did not include a full LUTI cycle and land-use dynamics but grasped its key components – land-use, transport network, and accessibility. This design enabled a more flexible model that was capable of exploring in more depth emerging road network characteristics, other than the spatial distributions of land-use and road network studied by the previous model.

Nevertheless, the LUTI theoretical and modelling framework has provided a well-established perspective to think about and model the urban system (Renner et al., 2014), as well as the relationship between urban road network and the urban system.

### 4.3.3 Urban Dynamics and the Transport Network Evolution

Urban modelling began with the initiative to test urban theories scientifically, with early urban theories like location theory which branched into social physics, macro and micro urban economics; economic-based urban models from the 1960s assumed self-equilibrium of land-uses and activities and urban movements in analogy to gravity and potential field; in the 1970s and 80s, the bottom-up decentralised dynamic models took off (Batty, 2009). Li and Gong (2016) summarised urban modelling developed from macro to micro and from static to dynamic. The micro and dynamic urban models, like Cellular Automata (CA) and Agent-Based Models (ABMs) agreed with the complex theory and modelled the emergence of macroscopic urban system characteristics and phenomena, arising from microscopic urban system components' behaviours and interactions. Though not in great numbers, attempts have been made to include transport network dynamics into some most prominent urban dynamic models. This section reviews urban dynamic models including fractal 4.3.3.1, ABM 4.3.3.2, CA 4.3.3.3, and space syntax 4.3.3.4 models that have incorporated explicitly urban Road Network Dynamics.

#### 4.3.3.1 Fractal Urban and the Transport Network Evolution

Batty et al. (1989) pointed out urban models at the time were built mostly around economic theories and assumed inherently specific urban spatial structure, without considering the formation of urban form. They introduced the Diffusion-Limited Aggregation (DLA) process from physics to model urban population's spatial growth, leading to fractal urban form. The model assumed an urban centre, according to which new population locations were added and connected. The simulation results were dendritic clusters, which exhibited fractal structure and similar macroscopic urban scaling relations. This model pioneered in relating the growth process of urban form to urban system's macroscopic characteristics, thus manifested modelling dynamics of urban form could offer insights into understanding the urban system at large.

Acknowledging DLA was essentially a physics process and did not realistically represent microscopic urban growth, Andersson et al. (2002) proposed urban growth result fundamentally from human behaviours, and proposed a model in which the locations of new urbanisations were chosen according to a spatial interaction potential field based on land-uses. Gastner and Newman (2006a) proposed a generative network model which was capable of generating similar dendritic structure as the DLA model. They modelled distribution networks, in which nodes represented distribution centres like transport stations, and links represented distribution lines. The model assumed a centre, according to which new nodes and links were added; it also assumed random locations of new nodes. Simulated distribution networks either minimised the cost of link length or maximised efficiency to the centre at each time step. As shown in Figure 4.16, simulated networks from both mechanisms had a dendritic structure; however, the former covered much less area compared to the latter, which was measured by the fractal dimension. The similar simulated networks of the network science model and the DLA model suggests their connection.

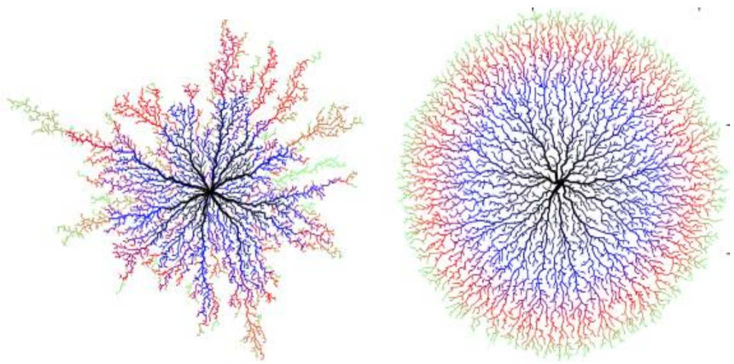


**Figure 4.16 Fractal Urban and Transport Network Evolution**: These two plots show simulated distribution networks by minimising the cost of link length (left) and maximising efficiency (right), both having dendritic structure. (Gastner and Newman, 2006a)

#### 4.3.3.2 Agent-Based Models and the Transport Network Evolution

Helbing et al. (1997) proposed an agent-based model (ABM) to study the formation of pedestrian trails in urban green areas in order to understand their topological structure and whether optimal trails could be predicted for urban planning. ABMs represent individual and elementary system components which have behaviours through time and space; these models generate emergent spatial and temporal patterns from bottom up (Batty, 2009). The model consisted of individual agents that represented pedestrians and an adaptive landscape. Pedestrians' movements depended on destinations and existing trails. Pedestrians' walking on the landscape created trials, which further influenced their movements. Simulation results found a completely connected trail network between origins and destinations only emerged when all other existing trails were equally comfortable; emerged trail networks minimally connected if pedestrians preferred using existing trails.

Acknowledging ABM’s potential usage on transport networks, Zanin and Véjar (2009) used an ABM to model the emergence of transport networks. Pedestrians’ movements depended on their destinations and neighbouring landscape. Pedestrians’ movements gradually changed the landscape into transport network paths. Figure 4.17 shows the simulated transport network evolved from a random initial state (a) with agents moving along various paths to a final state (d) with agents moving along major paths of the network.

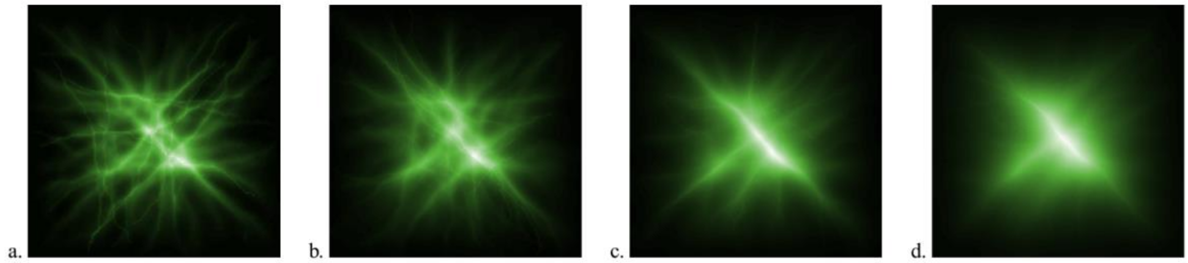



**Figure 4.17 Agent-based model of Urban and Transport Network Evolution**: (a)-(d) show the evolving process of a transport network result from agents’ movements. (Zanin and Véjar, 2009)

Further, Schweitzer and Nanumyan (2016) used ABM to model the co-evolution of the transport network and the urban system. They pointed out the two systems and their dynamics cannot be considered separately and employed two sub-ABMs to model the two systems and their feedback relationships on an adaptive landscape. They proposed the co-evolution of the transport network and the urban system are two iterative processes: access space and occupy space. The first sub-ABM created trails to model the dynamics of the transport network; the second aggregated to occupy space for land-uses and activities. The two sub-ABMs were connected with feedback relationships in which transport demand from the latter stimulates more network infrastructure in the former and increases of network infrastructure stimulates the aggregation of new land-uses and activities in the latter.

#### 4.3.3.3 Cellular Automate of Urban and the Transport Network Evolution

White and Engelen (1993) introduced a Cellular Automata (CA) model to simulate the spatial and temporal dynamics of urban land-use spatial structure. CA uses an array of grid cells, which have discrete states that are determined by neighbouring cells; cell states change under transition rules. The authors proposed a 50*50 CA grid. Cells had four possible states: vacant, housing, industrial, and commercial. At every time step, a certain number of cells changed states under designed transition rules; simulation terminated until clusters emerged. The simulated land-use spatial structure was examined in terms of their fractal dimension and found a similar fractal structure to real cities.

Yamins et al. (2003) pointed out insufficient discussion of CA's usage on transport networks, and the potential of combining CA of transport network dynamics with general CA models of urban dynamics. They proposed urban road networks evolve by two iterative processes in the context of urban growth. From an initial homogeneous CA grid with cells of potential states – unbuilt, built, and transport infrastructure, the first step chose new locations of land-uses among unconnected cells according to transport potential of an area – the total amount of unconnected cells. The second step connected the new location with roads by comparing the cost between building across or around the existing dense built area. By controlling the cost of building roads in dense urban areas in the second step, the model was able to simulate urban road network structure including radiating roads from an urban centre, beltways, and homogeneous irregular non-planned roads.

The Yamins et al. model modelled land-uses and urban road network using the same CA grid. Semboloni (2000) on the other hand, modelled land-use and urban road network co-evolution using two interconnected layers - a CA land-use grid of Delaunay Triangulation (DT), and an urban road network connecting centroids of the DT cells. Their model iterated two processes of urban growth as well. The first chose new locations of land-use cells to be connected, which involved the generation of new DT cells and transformation of DT cell land-use states among unbuilt, built for housing, built for service activities, and temporarily unoccupied. The second connected centroids of the new land-use cells using two mechanisms – the new cell centroid might connect to the existing road network with long links while maintaining planarity, and the new cell centroids might connect orthogonally to the existing road network with short links. Figure 4.18 shows the simulated urban area and road network growth; the simulated urban area's fractal structure was examined.

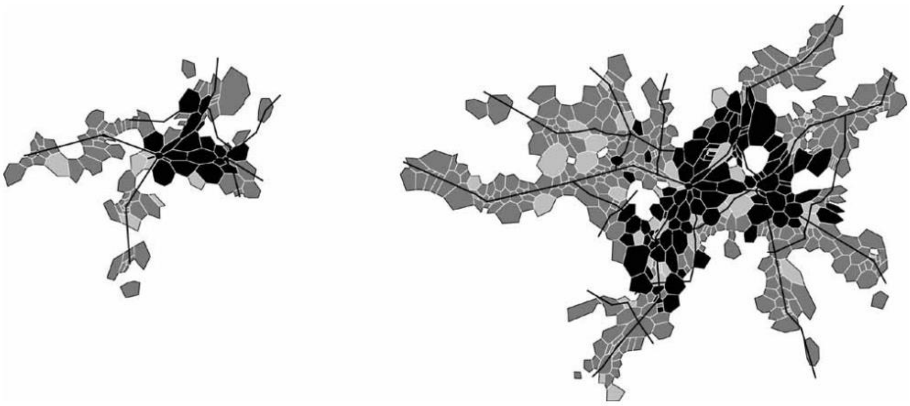


**Figure 4.18 Cellular Automata of Urban and Transport Network Evolution**: The two plots show simulated growth of an urban area and its road network by a Cellular Automata (CA) model. Land-uses were represented by a growing Delaunay triangulation (DT), and a growing road network connects the centroids of DT cells. DT cells had four states: unbuilt, temporarily unoccupied, built for housing, and built for service activities, in correspondence with white, light grey, dark grey, and black DT cells in the plots. (Semboloni, 2000)

Though separately and explicitly modelled, the urban road network in Semboloni model had inherent geometric dependence on the DT land-use layer, since it connected land-use cells' centroids. The modelled road network structure depends on land-uses, instead of having a reciprocal relationship. Raimbault et al. (2014) proposed a hybrid model consisted of a CA land-uses dynamic sub-model and a network dynamic sub-model.

The CA land-use grid had cells with status empty or occupied that could change with time; a subset of cells was assumed as urban centres where socio-economic activities might happen. The dynamic road network consisted of nodes that were land-use cells and links that were roads. The modelled co-evolution of urban land-uses and road network iterated two processes: building new land-use cells and building new roads to connect the new cells. Four characteristics of a cell were considered in choosing new cells to build and connect with roads: density around it, its Euclidean distance to the nearest roads, its network distance to the nearest centre, and its accessibility to different activities at centres. These four characteristics were assigned weights, which summed as the cell's land value, to control their influences on the co-evolution process. At each time step, all cells' land values were updated; among cells with highest values, a fixed number of cells were chosen to be built; and among the built new cells, the ones with a distance larger than a threshold from existing road network were connected orthogonally to the nearest road segments. As in Figure 4.19, the simulated land-uses and road network exhibited a broad range of forms, including human settlements types outlined by Le Corbusier - rural, linear, and radial-concentric, which were generated by large preferences for low density, short distances to road, and short distance to centre respectively. The simulated structure was further examined by four categories of measures: morphology by density distribution, network performance by network efficiency, functional accessibility by accessibility to activities, and economic performance by a segregation index.

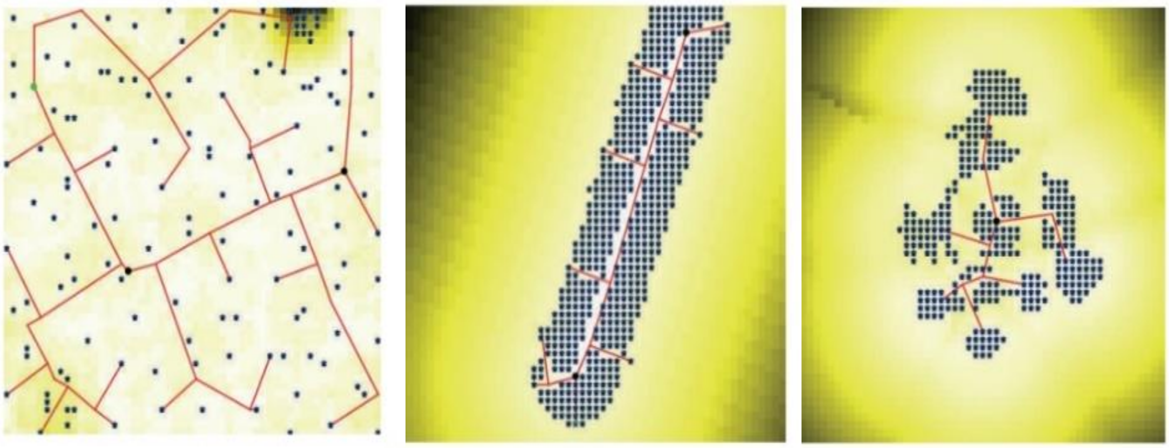


**Figure 4.19 Hybrid Cellular Automata and Network Model of Urban and Transport Network Evolution**: The three plots show generated urban settlement types rural (left), linear (middle), and radial-concentric (right); black points represent land-uses, red lines represented roads. (Raimbault et al., 2014)

#### 4.3.3.4 Urban Design and the Transport Network Evolution

Generative modelling and simulation effort from the urban design perspective calls for attention to the local level urban fabric transformation besides the aggregated urban dynamics addressed by macroscopic urban models (Al_Sayed et al., 2012). Space syntax seeks the relations between spatial structure and the social structure behind, and proposes to describe, analyse, and model space as a discrete system, using elementary generators and structure that capture social logic; buildings and streets are the two urban form components of focus (Hillier and Hanson, 1989).

Erickson and Lloyd-Jones (1997) proposed urban development iterates two processes – the local level informally planned and the global level planned development and proposed an urban growth model of buildings and streets. Following space syntax of fixed building and street spatial relationship, they modelled small and informal village settlements. As shown in Figure 4.20, this model was capable of generating the detailed urban form, including streets and buildings.

Marshall and Sutton (2014) explored the possibilities of generating street-based urban layouts and proposed street-based rules to grow the urban layout in a structured way without a fixed plan. The proposed street-based rules used road design codes, including hierarchy, connectivity and frontage constraints. The proposed model could anticipate effects of rules in the street design manuals.

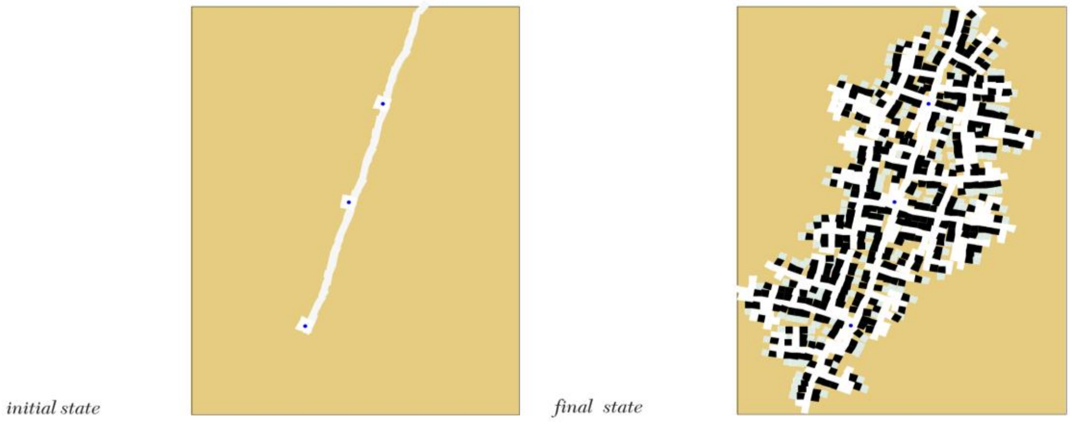



**Figure 4.20 Urban Design and Transport Network Evolution**: The two plots show initial and final states of a generative Space syntax model of urban settlements. The white cells represent roads and blacks cells represent buildings. (Erickson and Lloyd-Jones, 1997)

### 4.3.3.5 Urban Dynamics and the Transport Network Evolution Discussion

This section reviewed four types of urban dynamics models, chosen for their effort in combining urban road network dynamics. Figure 4.21 illustrated these models' typical simulation results.

Fractal models 4.3.3.1 have filled in the gap in previous urban theories and models in pre-assuming the urban form by modelling the growth of the urban form and showed insights of the urban system might be gained by modelling the formation and dynamics of urban form. ABMs 4.3.3.2 have demonstrated the emergence of system characteristics from individual agents' behaviours and interactions. CA models 4.3.3.3 have shown arises of spatial structure from autonomous transitions of individual cells. Urban design models 4.3.3.4 have generated specific urban form using elementary generators. All these models were compatible with the complexity theory, by modelling the emergence of macroscopic system characteristics from simple system components' microscopic behaviours and interactions.

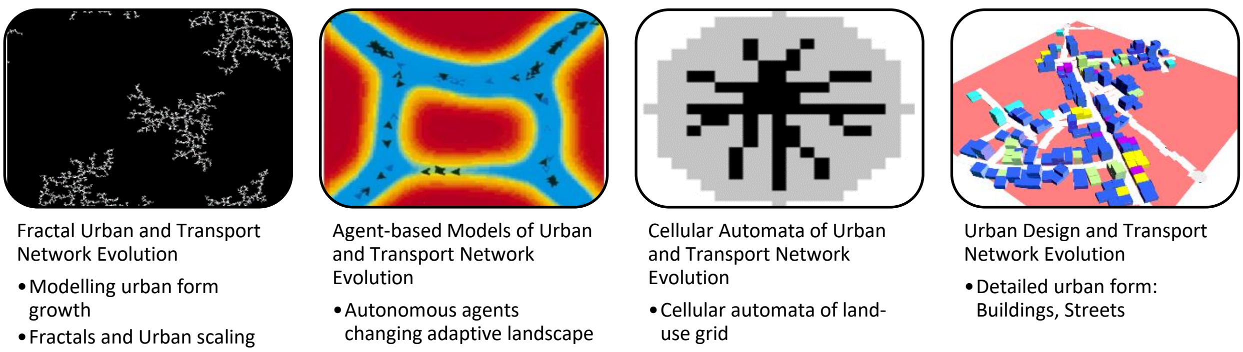



**Figure 4.21 Urban Dynamics Coupled with Transport Network Dynamics Summary**: The four plots select representative simulation results of 4.3.3.1 fractal (Andersson et al., 2002), 4.3.3.2 agent-based (Helbing et al., 1997), 4.3.3.3 cellular-automata (Yamins et al., 2003), 4.3.3.4 urban design (Erickson and Lloyd-Jones, 1997) models reviewed in this section.

The models reviewed in this section have demonstrated how the urban land-uses and dynamics might be modelled on various scales, as well as how the urban road network might be integrated into the micro and dynamic urban modelling. Fractal models have implemented an incremental dendritic structure and viewed RNE as part of the aggregate urban form growth. ABMs have modelled an adaptive landscape which changed through agents' movements; RNE has been viewed as part of the landscape's adaption - differentiate into land-use and transport network areas. CA models have constructed on a grid land-use layer which divided an urban area into parcels; RNE has been coupled on top of the land-use grid. Urban design models have used detailed urban form generators, buildings and streets, as well as their spatial relations; RNE has been viewed as an inherent part of urban form formation and dynamics.

On the other hand, these models of urban dynamics have mainly focused on the land-use layer, as illustrated in Figure 4.1. Fractal models concerned the fractal structure of urban form; ABMs and CA concerned the dynamics of a land-use plane, on which transport network was a subset of land-uses; and space syntax models concerned design aspects of detailed urban form. None of these models has aimed to model the primal urban road network structure and dynamics nor have they examined network characteristics in simulation results. Hybrid CA models (Raimbault et al., 2014; Wu et al., 2016) that modelled road network and land-use explicitly and separately were the few exceptions. Still, the primary goal was on land-use dynamics, and the road network modelled only connected urban centres, instead of evolving as an independent urban road network. As Raimbault (2016) concluded from a systematic review on urban and transport network evolution models, models considering both urban and transport network dynamics have been still rare, due to diverging disciplinary research interests.

### 4.3.4 Generative Network Models of the Urban Road Network in the Urban System

Section 4.2 concluded that network evolution can be modelled by two iterative processes – Node Addition and Link Connection. Link Connection formed elementary network connection patterns. Node Addition influenced the network spatial structure, through directing node spatial distribution. Thus, Node Addition is the primary mechanism through which mutual influences and interactions between urban road network and the urban system may be modelled. When considering the network alone as in 4.2.3, Node Addition was assumed to follow random or given distributions.

This section reviewed Generate Network Models (GNMs) of urban road networks in the context of the urban system, extending GNMs from 4.2.3 which consider the road network alone. Table 4-1 summarised these models and simulation results.

#### 4.3.4.1 GNM of the Population Density - Road Network Topology Co-evolution

Barthélemy and Flammini (2009) observed positive correlations between empirical population density and transport networks and hypothesised a co-evolution mechanism of population density and urban road network: urban road network evolves to serve increasing population density; the consequentially increased accessibility attracts population; the increased population density leads to high land-use price that limits the area growth. They proposed a GNM to explore the dynamics of population density spatial distribution and road network topological structure in their co-evolution. The modelled co-evolution iterated over Node Addition and Link Connection: Link addition was the same as in 4.2.3.2; the co-evolution mechanism of this model differed from the former by the Node Addition mechanism.

The modelled structure represented a city that consisted of nodes – land-use and activity locations, and links - roads. The modelled urban area was divided into sectors, each having different potential to attract new nodes, based on existing population and roads in the sector. The land price of a sector was an increasing function of population density. Transport cost of a sector was a decreasing function of Betweenness Centrality (BC). The Node Addition mechanism chose a sector to locate new land-use and activity locations by balancing price and transport cost of a sector. Link Connection then followed to connect new nodes to the existing network.

The simulation results, as shown in Figure 4.22, exhibited a more extensive range of structure, compared to that of previous models Figure 4.9. By controlling the preference for low land-use price or transport cost in Node Addition, this model was capable of generating exponential decay of population distribution from the centre. The simulated structure was examined by node density distribution.

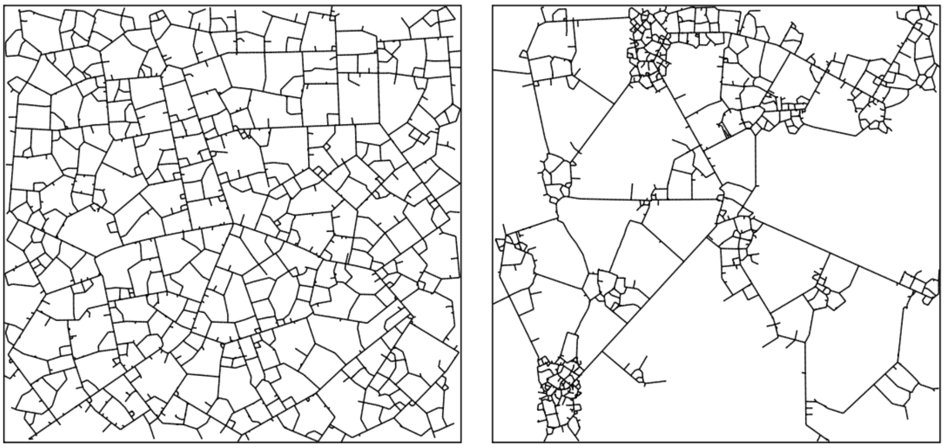


**Figure 4.22 GNM of Population Density and Urban Road Network Co-evolution**: The two plots show two simulated structure with different spatial distributions by varying the preference for low land-use cost or transport price. (Barthélemy and Flammini, 2009)

#### 4.3.4.2 GNM of the Shanghai Pudong Road Network Growth

Yang et al. (2011) applied a GNM to predict the growth of the Shanghai Pudong road network. The model iterated two processes as well, Node Addition and Link Connection. In Node Addition, the model first predicted the growth of new node number from base year to target year by regression based on base year's road network density. Spatial locations of the new nodes on sectors of the studied area were then chosen by considering population density, tax revenue, road network density and clustering coefficient of a sector. After Node Addition, Link Connection connected the new nodes to the existing road network according to the same Link Connection mechanism as in the previous model 4.2.3.2. Calibrated by historical GIS and socio-economic data from 1995 to 2007, the model was able to simulate the growth of Pudong road network from 2000 to 2004 and 2004 to 2007 as shown in Figure 4.23, within 20% differences from the real growth in terms of total link length, road network density, average shortest path length, and BC.

a 2000 b 2004 c 2007

**Figure 4.23 GNM of Shanghai Pudong Road Network Growth**: The three plots show simulated Pudong road network growth from 2000 to 2007. (Yang et al., 2011)

#### 4.3.4.3 GNM of the Population-Driven Urban Road Network Evolution

Zhao, F. et al. (2015) hypothesised human settlements evolve under two mechanisms - accessibility-seeking and space-seeking: the former refers to the preference for communities with high population, the latter refers to the random exploration of communities. Following this mechanism, they proposed a GNM of population-driven road network evolution. The model consisted of two layers – the city and the road network; the city was divided into sectors with assigned land-uses; road network had nodes representing communities with specific population and links representing roads. The model iterated two processes of Node Addition and Link Connection. In Node Addition, the space-seeking mechanism added new nodes to sectors whose population exceeded capacity. Then Link Connection connected new nodes to the existing network by balancing the accessibility-seeking mechanism's preference to connect to nodes in the network with a large population, and a cost mechanism for minimum link length. Compared to other GNMs of urban road network reviewed in this section and 4.2.3, the simulated network here, as shown in Figure 4.24, exhibited star structure as a result of the population driven mechanism: since new nodes had accessibility-seeking behaviours, they preferred to connect to existing nodes with high population. The simulated structure was further examined by degree distribution, BC, circuitness and treeness, and coverage of the area.

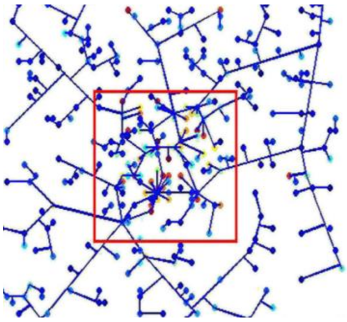


**Figure 4.24 GNM of Population-Driven Urban Road Network Evolution**: This plot shows the simulated network under the population-driven mechanism. The red box highlights the formation of star structure due to new nodes' preference to connect to existing nodes with high population in Link Connection. Colours of the nodes represented the size of the population at nodes, increasing from blue to red. (Zhao, F. et al., 2015)

#### 4.3.4.4 Generative Network Models of the Urban Road Network in the Urban System Discussion

In comparison to GNMs in 4.2.3 that have modelled the urban road network alone, the GNMs reviewed in this section have attempted to integrate the network science perspective RNE into the urban system. The population density - road network topology co-evolution model 4.3.4.1 used LUTI and urban economic theories and designed the co-evolution mechanism using a feedback LUTI relationship between land-use, transport network and accessibility, and urban economic location theory formulation of utility, income, rent, and transport cost. These urban theories were translated into network evolution mechanism to direct the iterative processes of Node Addition and Link Connection. The GNM of Shanghai Pudong road network 4.3.4.2, on the other hand, carried out the integration by calibrating the proposed GNM statistically using empirical GIS and socio-economic data. The GNM of population-driven urban road network evolution was based on human settlement theories. These different designs to combine the road network and the urban system have manifested the flexibility of the GNM to explore RNE.

The studies reviewed in this section have combined the urban road network component and the population component of the urban system, as illustrated in Figure 4.1.

Compared to alternative RNE modelling approaches, such as transport demand, LUTI, and urban dynamics models, as reviewed in previous sections 4.3.1, 4.3.2, 4.3.3, GNMs reviewed in this section emphasised on the urban road network structure explicitly. Simulated network characteristics were examined in detail. The population density - road network topology co-evolution model considered total link length, block shapes, perimeters, areas and density distribution. The GNM of Shanghai Pudong road network examined total link length, road network density, average shortest path length, and BC. The GNM of population-driven urban road network evolution examined degree distribution, BC, circuitness and treeness, and coverage of the area. The consideration of the urban system has distinguished them from models in previous sections 4.3.1, 4.3.2, 4.3.3, which have emphasised other aspects of the urban system.

Meanwhile, GNMs reviewed in this section exhibited the following limitations. They inherited limitations from the GNMs that have considered the road network structure alone, as pointed out of 4.2.3.5. These models lacked horizontal comparison of the Link Connection mechanism and did not model the dynamic RNE process. Further, two limitations were notable.

First, population and urban road network were modelled by one network, with nodes representing urban centres and links representing roads. For instance, the population density-road network topology co-evolution model implemented two layers: a land-use layer divided into grid cells and a network layer with nodes representing population locations and links representing roads. Under its population-road network co-evolution mechanism, nodes of the network layer served as the indicator of population density and land price of a land-use cell; links of the network layer served as the indicator of accessibility and transport cost; together nodes and links decided the potential to add new nodes of a land-use cell. Two sub-systems population and urban road network were modelled using one network; thus, population and road network were related even without the co-evolution mechanism, being one network's nodes and links. This modelling choice undermined the model's capacity of connecting the co-evolution mechanism and simulated population and road network structure since the simulated structure was not only influenced by the co-evolution mechanism but also by the built-in network connectivity. The GNM of population-driven urban road network evolution used a similar design, implementing a land-use grid layer and a network with nodes representing population concentrated communities and links representing roads. As reviewed in Chapter 3 section 3.3.3, the modelled network structure with nodes representing population concentration locations and links representing roads may be an urban network, rather than a primal urban road network. However, both models validated the simulated structure using primal urban road networks. If previous models intended to model urban networks, their results should not be validated against primal urban road networks' characteristics. Otherwise, node should represent road intersections and links should represent road segments, as in a primal road network representation, and different representation of the road network and the urban system should be proposed.

Second, the result examination of these studies have not considered the spatial structure of the urban road network and its relationship to the urban system sufficiently. The population density-road network topology co-evolution model examined the simulated structure as urban spatial structure, by examining population spatial distribution, namely its simulated networks' node spatial distribution. The GNM of population-driven urban road network evolution examined the simulated structure as an urban road network. Since two sub-systems were modelled, result examination may look into both simulated sub-systems' structure respectively, as well as their relationship. However, existing studies have examined only one sub-system, urban road network or population, which possibly resulted from the modelling choice of population and urban road network as one network. Provided concepts such as urban road network, road network spatial structure, urban spatial structure and urban system were distinguished, and road network and population were appropriated represented and modelled, modelling and simulation using the GNM may contribute more to understand the co-evolution of road network and the urban system.

### 4.3.5 Modelling RNE in the Urban System Summary

This section reviewed modelling approaches to urban road network dynamics in the urban system. The reviewed various RNE modelling approaches differed by the addressed urban system layers and components, as illustrated in Figure 4.1.

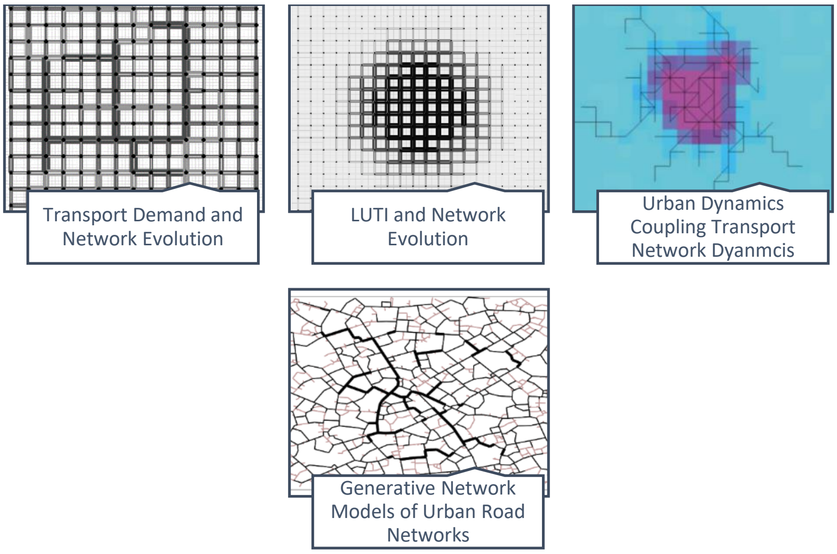



**Figure 4.25 Modelling RNE in the Urban System Summary**: The upper panel selects simulation results from modelling approaches – transport demand modelling 4.3.1, Land-use and Transport Interaction (LUTI) 4.3.2, urban dynamics modelling 4.3.3, that explicitly included urban road network dynamics, from left to right (Levinson and Yerra, 2006; Levinson et al., 2007; Wu et al., 2016) accordingly. The bottom panel shows a simulation result (Barthélemy and Flammini, 2009) of a Generative Network Model (GNM).

The transport demand modelling approach 4.3.1 has focused on the transport layer of the urban system, integrating urban road network and the urban system by considering transport demand between origins and destinations satisfied by the urban road network. These models have emphasised transport function and performance, calculate urban road network's transport properties such as link flow, speed and capacity. The well-established transport demand modelling framework has limited their flexibility to model long term dynamics of the urban road network structure. The LUTI modelling approach 4.3.2 has combined urban road network and the urban system through the theoretical feedback relationships between the transport and the land-use system. The road network structure has not been not the focus of LUTI models, though a few models as reviewed have started to incorporate transport network dynamics into the LUTI framework. Urban dynamic models 4.3.3 lay on the land-use layer of the urban system; this approach has combined urban road network and the urban system through modelling fractal urban form 4.3.3.1, modelling urban road network as part of an adaptive landscape changed by agents 4.3.3.2, as part of or a layer on top of a cellular automata grid 4.3.3.3, and as a space syntax generator 4.3.3.4. Hybrid CA, combining a land-use dynamics layer and a network dynamics layer, has achieved promising integration of the two. Still, inclusions of transport network dynamics have been limited, as these models focused on land-use dynamics, instead of urban road network characteristics. The upper panel of Figure 4.25 selected representative simulation results of these modelling approaches accordingly.

The network science perspective GNMs have attempted to integrated RNE into the urban system. Instead of modelling the transport layer, the land-use layer, or the LUTI relationship, this approach has focused on dynamics of the urban road network structure and combined it with dynamics of key urban system factors, such as the population. Given its focus on the road network structure and dynamics, GNMs is a suitable tool to explore the evolution of urban road network in the urban system. GNM and RNE may be integrated into the urban system through the co-evolution of population and the urban road network.

**Table 4-1 Generative Network Models of Urban Road Networks**

| **GNMs** | **Modelled Systems** | **Generative Mechanisms**<br>(N) Node Addition; (L) Link Connection. | **Assumptions, Parameters** | **Simulation Results and Examination**<br>(t) topological; (g) geometrical; (p) spatial; (s) static; (d) dynamic. | | | |
|---|---|---|---|---|---|---|---|
| | **Modelling the Urban Road Network Evolution Alone** | | | **Node** | **Link** | **Block** | **Centrality** |
| **Urban street patterns**(Barthélemy and Flammini, 2008)**4.2.3.2** | 1. Urban centres: A set of points;<br>2. Road network: A network consists of nodes – small road segments, and links – connecting adjacent nodes. | New urban centres added; (N) Urban road network first connects urban centres in the locally most efficient way using minimum road length, then connects urban centres locally to Relative Neighbourhood Graph (RNG) neighbouring points on the existing network. (L) | 1. Unit square simulation area.<br>2. Time framework of urban centres addition and road growth.<br>3. Specified initial and termination conditions.<br>4. Node Addition assumes new centre positions. | Node/link ratio $e \approx 1.3$. (t) (s) | Total link length $L_{tot} \sim \lvert V \rvert^{1/2}$. (g) (s) | Form factor $\varphi \in [0.4, 0.7]$. (g) (s)<br>Block perimeter $p$: exponential distribution. (g) (s)<br>Block area $P(A)$: exponential distribution, new nodes added at random locations; - power-law distribution $P(A) \sim A^{\alpha}, \alpha = 1.9$, new nodes added according to exponential distribution. (g) (s) | - |
| **City graph** (Courtat et al., 2011)**4.2.3.3** | A network representing a city, consists of: Nodes – Road network intersections; Links – Road segments;<br>A Hypergraph – Streets. | New urban settlements added according to a potential field based on existing network; (N) New settlements connected to the existing network to the intersection of point sets: orthogonal projections of new settlements on existing network, points maintaining planarity, RNG neighbors. (L) | As 1-3 above.<br>4. $P_e$ - the extent to obeys attraction potential field - Node Addition.<br>5. $\beta$ - local geometry in choosing new node position - Node Addition.<br>6. $\omega$ - the extent to obey connection choices - Link Connection.<br>7. $f_{ext}$ - the extent of network sprawling - Node Addition. | Organic ratio $r_N \approx 1$. (t) (s) | Anisotropy $A$: similar across simulated networks. (g) (s)<br>Meshedness coefficient $M$: depends on $(P_e, \omega)$. (t) (s)<br>Topological distance $d^{topo}$. (t) (s)<br>Link length: lognormal distribution. (g) (s) | - | - |
| **Centre competition** (Rui et al., 2013)**4.2.3.4** | A network consists of Nodes – Intersections and Urban centres;<br>Links – Road segments. | New centres chosen among candidates, according to utility value - the sum of node degree within radius $r$. (N) New nodes first connected to the existing network balancing distance and node degree; then connected to RNG neighbors with a probability $P_l$. (L) | As 1-3 above.<br>4. $\alpha$ - preference of distance or node degree - Link Connection.<br>5. $P_l$ - the extent to connect RNG neighbors - Link Connection.<br>6. $r$ - radius to measure candidate utility - Node Addition. | Organic ratio $r_N$: decreases with $\alpha$, $P_l$. (t) (s)<br>Fraction of dominant sectors: decreases with $r$. (p) (s) | Meshedness coefficient $M$: increases with $\alpha$, $P_l$. (t) (s)<br>Total topological link length $L_{topo}$: increase with $P_l$, decreases with $\alpha$. (t) (s)<br>Total geometrical link length $L_{tot}$: increase with $P_l$, $\alpha$. (g) (s)<br>Efficiency $E$: highest value with a medium $P_l$. (g) (s) | Block distribution $P(A)$: uniform centre distribution at $r = 0$ - exponential distribution; $r = 0.25$ - power-law $P(A) \sim A^{\alpha}, \alpha = 2.5$; $r = 0.05$ - most heterogeneous block areas, $P(A) \sim A^{\alpha}, \alpha = 1.05$. (g) (s) | BC Gini index: increases, then decreases as $r$ increases. (tg) (s)<br>BC distribution: exponential distribution. (tg) (s) |

| | | | | | |
|---|---|---|---|---|---|
| | | | 7. The number of new node candidates per time step - Node Addition. | Topological efficiency $E_{topo}$: increases with $\alpha$. (t) (s) | |
| **Modelling Urban Road Network Evolution in the Urban system** | | | | **Road network Characteristics** | **Urban system Characteristics** |
| **Co-evolution of Population density and Road network topology** (Barthélemy and Flammini, 2009)**4.3.4.1** | 1. A Land-use layer, divided into sectors.<br>2. A network representing a city, consists of: Nodes – Urban centres of land-use and activity locations; Links – Roads. | Sector chosen for new centres' locations by balancing price (population density) and transport cost (BC) of a sector. (N)<br>New centres connected as the Urban street patterns Model 4.2.3.2. (L) | As 1-3 above.<br>4. $\lambda$: Relative weights between density and BC.<br>5. $\beta$: the extent generative mechanism is obeyed. | - | Spatial distribution of centres: uniform – small $\lambda$; clustered – large $\lambda$. (p) (s)<br>Fraction of dominant sectors: decreases with $\lambda$; decreasing speed decreases with $\beta$. (p) (s)<br>Population density from the centre: uniform – small $\lambda$; exponential decay – large $\lambda$. (p) (s) |
| **Shanghai Pudong Road Network Growth** (Yang et al., 2011) **4.3.4.2** | An urban road network, consists of: Nodes – Intersections; Links – road Segments. | Predicted the growth of new node number by regression based on base year's road network density; spatial locations of the new nodes chosen by considering population density, tax revenue, road network density and clustering coefficient of a sector. (N)<br>New nodes connected as the Urban street patterns Model 4.2.3.2. (L) | - | Total link length: within 20% difference compared to the empirical growth. (g) (s)<br>Road network density: as above. (g) (s)<br>Average shortest path length: as above. (g) (s)<br>BC: as above. (tg) (s) | - |
| **Population-Driven Urban Road Network Evolution** (Zhao, F. et al., 2015) **4.3.4.3** | 1. A Land-use layer, divided into sectors.<br>2. A network, consists of: Nodes – Communities of population concentration; Links – Roads. | A space-seeking mechanism add new nodes to sectors whose population exceeded capacity. (N)<br>Connected new nodes by balancing the accessibility-seeking mechanism's preference to connect to nodes in the network with high population, and a cost mechanism for minimum link length. (L) | As 1-3 above.<br>4. $\beta_1$: preference for low cost of link length.<br>5. $\beta_2$: preference for high population density. | Degree distribution: range increases with $\beta_2$. (t) (s)<br>Average node degree: decreases with iterations. (t) (d)<br>BC: decreases with iterations; BC concentration increases with $\beta_2$. (tg) (s)<br>Circuitness/ treeness: circuitness increases with $\beta_2$. (t) (s)<br>Coverage of the area: increases with iterations. (p) (d) | - |

## 4.4 Chapter Conclusion

### 4.4.1 Synthesise a Modelling RNE Understanding

This chapter reviewed RNE related modelling effort according to modelled layers and components of the urban system and positioned GNM in a broad RNE modelling research background. This chapter separated models considering the road network alone 4.2 and models considering road network in the urban system 4.3. The latter category can be further divided according to the urban layers and factors modelled. Compared to potential RNE modelling approaches that have focused on the transport demand 4.3.1, urban dynamics 4.3.3, and LUTI 4.3.2, GNMs 4.3.4 emphasised on the urban road network structure and dynamics explicitly, with comparable simulation results to the increasing empirical RNE findings. Also, GNMs have shown flexibility to couple with urban factors and theories, as discussed in 4.3.5. Thus, the RNE modelling approach choice shall be made by the urban factors and layers of interest.

GNMs have generated macroscopic network structure by modelling the microscopic generative mechanism. GNMs model network evolution through iterating Node Addition and Link Connection. Empirical RNE characteristics, as reviewed in Chapter 2, have shown potential parallels with the network generation process; thus, GNMs may be used to model the dynamic RNE processes, beyond network generation. Link Connection directed elementary connection patterns of the network. Node Addition directed simulated network's spatial structure. Urban system's influences on RNE have been designed into GNM mainly through Node Addition onto road network spatial distribution and organisation. Previous GNMs have modelled the co-evolution of population and urban road network.

Table 4-1 summarised previous GNMs and their simulation results. Previous studies have generated urban road network characteristics and examined road network characteristics such as the block area distribution. Meanwhile, previous studies have lacked consistency in the simulated network structure examination framework and have not examined dynamic RNE characteristics sufficiently. Though previous studies have recognised the positive correlation between population and urban road network and proposed co-evolution mechanisms, representation of both population and urban road network has been limited, and simulation results have not been examined in terms of road network spatial structure and regarding the mutual influences between population and road network on each other's characteristics. Further research questions can be specified regarding existing GNMs that have modelled the urban road network structure alone 4.2.3:

- What is the working mechanism of previous GNMs of urban road networks in generating urban road network structure? Can previous RNE models' generative mechanisms be generalised?
    - Can their generative mechanisms be generalised – merging cost, efficiency, and proximity relationships to model the spatial and planar urban road network structure?
    - Whether proximity relationships from proximity graphs other than RNG, like β-skeletons play a role in modelling RNE?
- Can GNMs model the dynamic RNE process?
    - What is the relationship between the simulated static and dynamic network structure and the generative mechanism, without considering the urban system?
    - Are the simulated networks' dynamic structure comparable to the dynamic RNE process? Can this be examined using the framework of elementary network component - node, link, block characteristics?

In terms of GNMs that have modelled RNE in the urban system 4.3.4, further research questions can be specified as:

- How to integrate GNM of urban road network evolution into the urban system?
    - What representation of both the road network and the urban system is suitable to model the co-evolution of road network and population?
    - What population-urban road network co-evolution mechanism do the correlations between population and urban road network in terms of quantity and spatial structure, as well as by the mutual influences between the road network and the urban system reflect?
- What road network spatial structure may arise during the co-evolution of road network and population? How do the simulated road network and population relate?
    - Can this spatial structure be characterised by processes of global centralisation and decentralisation and local clustering and dispersion?

### 4.4.2 Modelling RNE Research Limitations

This chapter identified four limitations in previous GNMs of urban road networks, as discussed in 4.2.3.5, 4.3.4.4. First, previous GNMs have not compared or generalised the Link Connection mechanism in the urban road network structure generation. Second, previous studies have put more emphasis on reproducing empirical urban road network statistics, rather than modelling the dynamic RNE process, and have not integrated empirical RNE studies into simulation result examination. Third, the representation of both the road network and the urban system has been insufficient. Forth, previous studies have not examined the simulation results regarding the spatial structure of urban road networks or its relationship to the urban system sufficiently. With these limitations identified, the next chapter proposes the methodology of this study, a framework of RNE modelling and simulation.

# Chapter 5 Methodology

## 5.1 Chapter Introduction

Modelling the evolution of urban road networks lies in a research background with intertwined urban and transport theories and methods development,  as outlined in Table 5-1, which led to a network science approach. Road network evolves along with the urban system; hard-to-predict system characteristics emerge. Complexity theory in which simple components follow local rules rather than central control, provides a powerful tool to explore this evolution process. It does not presume a city resulting from particular historical development path, socio-economic condition and natural environment, or a global optimising goal to achieve economic equilibrium or minimise transport cost but had the flexibility to integrate with established transport and urban theories while exploring complex emerging system characteristics and processes. Network science studies the transport network structure explicitly, setting a feasible scope to explore network evolution and connecting research effort from the quantitative geography network analysis to the complex system modelling and simulation.

**Table 5-1 Research Background - Modelling the Evolution of Urban Road Networks**

| | Theories and Methods |
|---|---|
| *19th Century - Early 20th Century* | • **Location Theory**: How economic activities locate? (e.g. von Thünen's Isolated state theory, Central place theory)<br>• **Human Ecology**: Sociology of internal urban structure. (e.g. Concentric Model) |
| *1940s* | • **Social Physics**: Quantify social theories (e.g. Spatial Interaction/Gravity Models) |
| *1950s* | • **Transport Demand Forecasting**: (e.g. Detroit Metropolitan Area Traffic Study, Chicago Area Transport Study)<br>• **Quantitative Geography**: Network analysis using graph theory; Sequential network development models. |
| *1960s* | • **Urban Economics**: Economics of internal urban structure. (e.g. Alonso's Monocentric City)<br>• **Land Use Transport Interaction (LUTI)**: Urban development modelling framework (e.g. Lowry's Pittsburgh Model)<br>• **Urban Morphology**: Analyse urban form. (e.g. the Conzenian School)<br>• **Urban Design**: Design ideal urban form. (e.g. Lynch's Image of City)<br>• **Historical Geography**: History of urban form. (e.g. Mumford's City in History) |
| *1970s* | • **Urban Modelling and Simulation**: Switch to bottom-up dynamic models (e.g. Tobler's urban growth model of Detroit) |
| *1980s* | • **Space Syntax**: Describe, analyse, generate urban form.<br>• **Spatial Analysis**: GIS data and analysis. |
| *1990s - Present* | • **New Science of Cities**: Study cities as complex systems. (e.g. fractal urban form, cellular automata models, agent-based models)<br>• **Network Science**: Describe, analyse, model complex networks. |

Following this approach, this chapter proposes a modelling and simulation framework of Road Network Evolution (RNE), as summarised in Figure 5.1. So far, empirical RNE research has accumulated a considerable number of empirical findings, and modelling RNE research have proposed Generative Network Models (GNMs) to generate network structure that shared empirical urban road network characteristics. However, empirical RNE findings required further understanding regarding inconsistency and mechanisms behind the emergence of observed RNE characteristics. GNMs of urban road networks required further exploration regarding the generality of network generative mechanisms, model design, and simulation results examination. Modelling and simulation was an appropriate methodology for the current stage of RNE research. Rather than making predictions or directing data collection, modelling and simulation served as a suitable tool to forward RNE understanding and extend existing empirical and modelling findings.

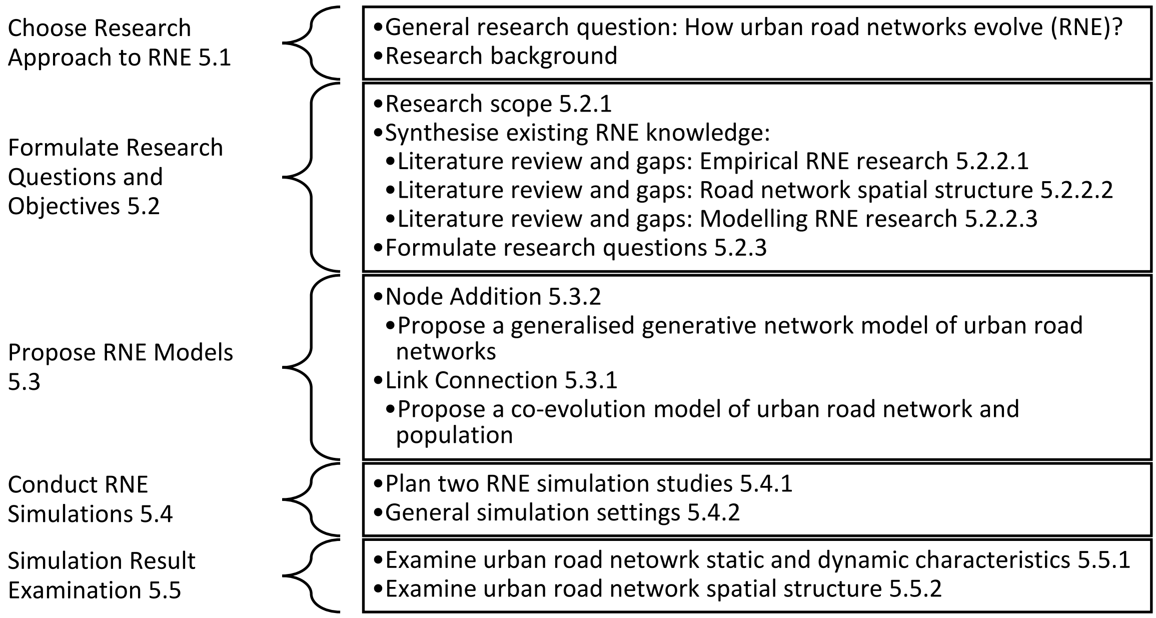



**Figure 5.1 Methodology – An RNE Modelling and Simulation Framework**

## 5.2 Formulate Research Questions and Objectives: RNE Modelling and Simulation using Generative Network Models

### 5.2.1 Research Scope

From a network science perspective, the network structure was described by network characteristics examined; the evolution of networks was reflected in the emergence of network characteristics. Networks had both static and dynamic structure; the former referred to network characteristics at a point in time, the latter referred to changes of network characteristics with time. The evolution of networks was studied through a series of network snapshots, by analysing the static structure of each snapshot and the dynamic structure between snapshots. Co-evolution of complex systems meant the evolution of one system depended partially or totally on related systems; the evolution of one system influenced the evolution of related systems and the environment.

Within this scope, urban road network structure in this thesis was limited to the discussion of selected network characteristics; and the evolution of urban road networks referred to the changes of these network characteristics, reflected in both static network structure at a snapshot and dynamic structure between snapshots. Road network and the urban system were regarded to co-evolve, as the two systems had feedback relationships and mutual influences on each other's development.

### 5.2.2 Synthesise the Existing RNE Knowledge

Within the research scope, existing knowledge regarding how urban road networks evolved, both empirical and modelling, required syntheses.

#### 5.2.2.1 Empirical RNE Research

From the literature review in Chapter 2, an empirical RNE understanding was synthesised based on elementary road network components' topological and geometrical characteristics and dynamics. First, the urban road network was considered as a complex system consisting of elementary components nodes, links, and blocks; emerging macroscopic road network characteristics arose from the behaviours and interaction of individual components. Second, the framework followed the network science approach to characterise complex network evolution. The static structure was studied by analysing an urban road network at one point in time; the dynamic structure was studied based on snapshots of networks over time tracing the trajectories of network characteristics. Third, the framework used spatial network characterisation with both topological and geometrical measures. Finally, empirical RNE research represented the urban road network structure explicitly using the primal representation, instead of aggregated statistical measurements, ideal networks, or road networks on the other scales like regional road networks. This synthesis framework maximised the utilisation of existing empirical results since elementary network component characteristics were most frequently studied and could be compared across studies. Table 5-3 summarised the synthesised RNE measurements and empirical understanding.

Static node degree has been reported to exhibit a majority of $k_3$ nodes, dynamics of $\langle k \rangle$ increased, stayed constant, or decreased according to changes of $k_1$ and $k_4$ node proportions. Statically, link length $l$ exhibited lognormal distributions, because typical urban road networks had few very short or very long links, many medium-length links, and abundant short links. Dynamically, $l$ distribution persisted in being lognormal, with the peak concentrating because more short links were added as road network grew. Statically, block areas $A$ exhibited power-law or lognormal distributions depending on the density level of the studied area. Dynamically, $A$ persisted in following power-law or lognormal distributions and exhibited increased slope on the logarithmic scales because of increasing small blocks with large blocks' subdivision. Static BC separated high BC components from an underlying spanning tree within the road network and low BC components which formed loops in the network. Dynamically, BC depended on network density $\rho_e = \frac{|E|}{E_{DT}}$; BC hierarchy or ranks in network components remained stable if network density remained stable while BC concentrated towards the barycentre as network density increased. Correlations existed between BC and the existence time of road network components, which might further reveal correlations among the high BC components, the underlying spanning tree components, the geographically central components, and the long-existing components. Two types of new links were added to the road network, causing differences in the change of network average BC; these two types of new links – dead-ends and bridging links, may perform different functions and represent two RNE processes – Densification and exploration (DE). Overall, empirical research has pictured a dynamic RNE process of stable connections, iterative space division, first forming a skeleton of major paths, then filling in the space with minor paths, with elementary components characteristics and dynamics.

Regarding the incremental growth of road networks, associations could be made between the microscopic growth of network components and the macroscopic road network characteristics and dynamics. Growth of road networks happened locally by elementary network components; urban road networks evolved with the addition and connection of elementary network components. Empirical RNE research has provided directions to relate elementary network dynamics to macroscopic network characteristics. Theoretical hypotheses of RNE mechanisms could be proposed when these elementary urban road network components' characteristics and changing processes were put together.

Gaps identified during this synthesis of existing empirical RNE research included:

- The need to further understand empirical findings, because of the inconsistency in results and the lack of consideration of processes and mechanisms behind empirical observations;

- The limitation in studied network structures' generality, since RNE mechanisms have been proposed based on individual urban road networks at a few discrete historical moments;
- Insufficient characterisation of urban road network's spatial structure and consideration of road network structure in the context of the urban system.

#### 5.2.2.2 Urban Road Network Spatial Structure Research

Spatial structure referred to the spatial distribution and organisation of urban road networks. Attention paid to road network's spatial structure in the network science approach has been insufficient, though the spatial distribution of network components has been recognised to influence network characteristics like the block area distribution. Existing research on urban road network spatial structure, as reviewed in Chapter 3, included road network patterns, spatial analysis, and quantitative classification. Road network patterns have studied dominant geometric connection patterns such as linear, star, hub-and-spoke, ring, cellular, as well as continuity hierarchy patterns based on street names or strokes. Spatial analysis has studied the geography of urban road networks and the networked geography, using measures such as density. The quantitative classification has not assumed fixed types of road network spatial structure and found diverse empirical urban road network spatial structures resulted from various formation processes.

The spatial structure of urban road networks was likely to be a spectrum, rather than a few discrete types. Like the urban spatial structure, processes behind the formation of road network spatial structure - centralisation to decentralisation on the global scale, clustering to dispersion on the local scale, may be used characterise the road network spatial structure. Studying RNE in the context of urban system required the representation of the urban system, which could be thought as overlaid layers. Urban road network resided on the transport layer and belonged to the physical urban spatial structure. The spatial structure of urban road network has been reported to correlate with the economic, physical, and functional urban spatial structure; both road network and the urban system were likely to be driven by push and pull forces across different urban layers - urban road network and the urban system co-evolved. The population has been used to represent the urban spatial structure; correlations between population and road network in density, spatial structure, connectivity have been reported. The co-evolution of population and urban road network was an appropriate starting point to understand the co-evolution of the road network and the urban system.

Gaps identified during the synthesis of urban network spatial structure included:

- Insufficient representation of both the road network and the urban system;

- Insufficient network characterisation and understanding of processes and mechanisms behind empirical observations of the urban road network spatial structure;
- The need to further understand empirical findings regarding the inconsistency in correlation results and relationships between urban road network and population.

#### 5.2.2.3 Modelling RNE Research

RNE related modelling could be viewed according to the research scope - considering road network alone or road network in the urban system, and according to the urban layers and components involved. GNMs generated macroscopic network structure from microscopic network components' behaviours and interactions, iteratively through local changes of Node Addition – adding new nodes and Link Connection – connecting new nodes to the existing network. Modelling RNE considering only the road network merged generative mechanisms of spatial networks, planar networks and proximity graphs.

Modelling RNE in the urban system took place on different urban system layers and with different urban system components. On the transport layer of the urban system, RNE has been modelled in the framework of transport demand forecasting. Within the land use and transport interaction (LUTI) framework, RNE has been modelled as a step in the LUTI feedback relationship. On the land use layer, RNE has been modelled as part of the urban form and land use dynamics. GNM has been used to model the road network in the urban system and emphasised on the network structure and dynamics. The population has been the first urban system component to couple with GNM, modelling the co-evolution of population and urban road network.

The synthesis of modelling RNE knowledge concluded that modelling and simulation using GNM was a suitable tool to advance the understanding of RNE and existing empirical and modelling findings. RNE models could be proposed, considering the evolution of the urban road network structure alone, and the evolution of the urban road network in the urban system, respectively. Gaps identified during this synthesis of existing modelling RNE research included:

- Insufficient generalisation of previous GNMs of urban road network's Link Connection mechanisms, especially regarding the role of proximity relationships;
- Insufficient utilisation of GNMs' potential to model the dynamic RNE process,
- Insufficient integration of GNM and the urban system, including the representation of both the urban road network and the urban system, and the examination of road network spatial structures.

### 5.2.3 Formulate Research Questions

After the literature review, the general research question regarding how urban road networks evolve can be specified based on the synthesised empirical and modelling RNE knowledge as well as gaps identified in existing research. These syntheses led to two proposed models and simulation studies – a generative network model of urban road network evolution and a hybrid model of population and urban road network co-evolution, considering road network alone and in the urban system accordingly. Table 5-2 lists the specified research questions and correspondent research objectives.

**Table 5-2 Specified Research Questions and Objectives**

| | Specified Research Questions | Specified Research Objectives |
|---|---|---|
| **Generative Network Model of Urban Road Network Evolution** | | |
| ***1*** | What is the working mechanism of the Generative Network Model (GNM) in generating the urban road network structure? Can previous models' generative mechanisms be generalised?<br>1. Whether proximity relationships from proximity graphs other than Relative Neighbourhood Graph (RNG*)*, like β-skeletons play a role in modelling RNE? | Propose a generalised GNM of urban road networks.<br>1. Propose a generalised generative mechanism of urban road network structure.<br>2. Explore proximity relationships' role in modelling RNE using simulation. |
| ***2*** | Can the GNM model the dynamic RNE process?<br>1. What is the relationship between the simulated static and dynamic network structure and the generative mechanism?<br>2. Are the simulated networks' dynamic structure comparable to the dynamic RNE process?<br>3. Can modelling and simulation provide insights on empirical RNE findings? | Explore the potential of proposed GNM in modelling the dynamic RNE process.<br>1. Explore the relationship between the simulated static and dynamic network structure and the generative mechanism using simulation.<br>2. Compare the simulated network structure with empirical findings according to the examination framework of elementary network components and explore the generative mechanisms of network characteristics using simulation. |
| **Hybrid Model of Population and Urban Road Network Co-evolution** | | |
| ***3*** | How to integrate GNM of urban road network evolution into the urban system?<br>1. How to represent the urban road network and population?<br>2. What population-urban road network co-evolution mechanism do the correlations between population and urban road network in terms of quantity, spatial structure, and network characteristics, as well as by the mutual influences between road network and the urban system reflect? | Propose a co-evolution model of population and urban road network and representation of both the road network and population.<br>1. Propose representation of both the road network and population.<br>2. Propose a co-evolution mechanism of population and urban road network. |
| ***4*** | What road network spatial structure may arise during the co-evolution of road network and population? How do the simulated road network and population relate?<br>1. How to characterise the spatial structure of urban road networks? | Examine the emerging population and urban road network spatial structure and their relationships.<br>1. Propose a method to characterise the road network spatial structure. |

## 5.3 Proposed Generative Network Models

GNMs modelled the formation and dynamics of complex networks. GNMs hypothesised mechanisms behind network formation and dynamics, designed accordingly generative mechanisms by controlling two processes: Node Addition – adding new nodes, and Link Connection – connecting new nodes to the existing network. The generative mechanisms were implemented through computational simulation to simulate network formation and dynamics, by iterating Node Addition and Link Connection. If simulated networks shared a similar structure with real complex networks, it demonstrated the plausibility of generative mechanisms to explain real-world complex networks' evolution. However, the similarity between simulated and real-world complex networks did not guarantee the proposed generative mechanisms were behind real-world networks' evolution since different processes might generate the same pattern and different generative mechanisms might generate the same network structure. Nevertheless, generation processes that resembled real complex network evolution increased the generative mechanisms' plausibility, hence the necessity to explore the dynamic network evolution process using GNMs and examine the simulated dynamic network structure.

Following GNMs of complex networks, GNMs of urban road networks modelled a network $\mathrm{G} = (\mathrm{V}, \mathrm{E})$; in particular, $\mathrm{V}$ represented a set of nodes which were road network intersections and had spatial locations; and $\mathrm{E}$ represented a set of links which connected nodes in $\mathrm{V}$ planarly, namely links did not cross each other without forming an intersection node. RNE hypotheses were designed into proposed generative mechanisms, directing Node Addition and Link Connection. GNMs of urban road networks assumed planarity and incremental network growth.

### 5.3.1 Link Connection and Propose the Generative Network Model of Urban Road Network Evolution

Link Connection connected newly added nodes to the modelled network; it determined locally whether a link shall connect two nodes. Link Connection was crucial to generate the primal urban road network structure. Two aspects were essential in this process: the proximity relationship used to determine whether two nodes shall be connected and viewing the modelled network as a continuous structure.

#### 5.3.1.1 Proximity Relationships

As reviewed in Chapter 4, Link Connection of spatial networks balanced cost and efficiency. Cost depended on the link length; spatial network nodes' spatial positions were meaningful, which associated costs to Link Connection. Efficiency might refer to the number of links along the path connecting two nodes, or the difference between network distance and Euclidean distance between two nodes. Maximising the former led to a direct connection between two nodes, which created a shortcut in the network and led to small-world and scale-free properties. As the primal urban road network structure was not small-world or scale-free, efficiency from now on referred to the latter. Minimising cost led to Minimal Spanning Tree (MST) which was minimally connected, and maximising efficiency led to Delaunay Triangulation (DT) which was maximally connected under planarity. Link Connection of planar network generation maintained planarity, namely connections of every pair of nodes should obey planarity. Proximity graph model generated spatial and planar networks; in particular, Link Connection examined distance-dependent proximity relationships between all node pairs to determine whether they shall be connected, which led to local connections between neighbouring nodes that satisfied the proximity relationships.

Link Connection of spatial, planar and proximity graph networks was not unrelated. Cost, efficiency and planarity could be seen as proximity relationship criteria, while proximity relationships could be seen as quantifying the preference for cost and efficiency. Therefore, Link Connection to model spatial and planar networks could be thought as a process of examining defined proximity relationships between network nodes, which balanced cost and efficiency, maintained planarity and determined the connectivity of the network. As shown in Figure 5.2, given a set of points, Link Connection of different proximity relationships generated spatial and planar networks of different connectivity.


**Figure 5.2 Link Connection – Proximity Relationship Examination**: The three plots demonstrate performing Link Connection on a same set of nodes, examining proximity relationships between nodes from β-skeleton with β=1.0, 1.5 and 2.0 respectively.

#### 5.3.1.2 Network as a Continuous Structure

The second essential aspect of Link Connection in generating the urban road network structure was the proximity relationship examination happened between new nodes and a continuous network structure, instead of among nodes. In Link Connection, the modelled network was viewed as a continuous structure, which allowed proximity relationship examination to find proximity neighbours of new nodes at any point on the modelled network. As shown in Figure 5.3, the upper panel demonstrated proximity relationship examination between new nodes and a continuous network structure, while the lower panel demonstrated the same examination between new nodes and network nodes. Proximity relationship examination between new nodes and a continuous network structure led to the formation of perpendicular connections, which was crucial to generate urban road networks' connection pattern. On the other hand, proximity relationship examination between new nodes and a discrete network structure led to sharp angles between links at nodes which were unlikely to be seen in urban road networks.

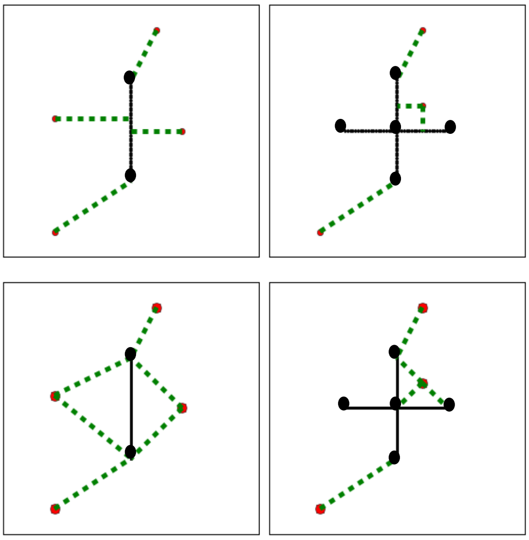


**Figure 5.3 Link Connection – Proximity Relationship Examination between New Nodes and a Continuous Network Structure**: The left and right columns each share a same existing network and new nodes. The upper and the lower panels demonstrate proximity relationship examination between new nodes and a continuous network structure, and between new nodes and network nodes respectively. Black nodes and links represent the existing network, red nodes represent new nodes, green links represent new Link Connections identified by the proximity relationship examination.

#### 5.3.1.3 Link Connection Summary

Link Connection was the second step of the iterative generation process in GNMs. It modelled elementary connection patterns of the urban road network, and its generative mechanism could be generalised by merging that of spatial, planar, proximity graph models and previous GNMs of urban road networks, as a process of proximity relationship examination between new spatial locations and the existing network. More specifically,

- Link Connection examined proximity relationships between new spatial locations and the existing network as a continuous structure, in order to balance Link Connection's cost and efficiency, as well as maintain planarity, which resulted in the formation of elementary urban road network connection patterns.

Following the theorisation in this section, Chapter 6 proposed a GNM of urban road network evolution, which generalised the Link Connection mechanism of urban road network generation. Subsequently, a simulation study was planned to explore the proposed model's capacity in modelling the dynamic RNE process and proximity relationships' role in modelling RNE.

### 5.3.2 Node Addition and Propose the Hybrid Model of Population and Urban Road Network Co-evolution

Node Addition added new road network nodes at specific spatial locations; this process initiated network growth iteratively and influenced the spatial structure of modelled networks. The spatial distribution of network nodes has been used to represent inhomogeneous demand over the space. In modelling spatial networks, the cost of link length was an essential factor, and nodes with shorter Euclidean distance had a higher probability of connecting. Spatial network generation models have designed generative mechanisms of Node Addition to direct spatial distribution of nodes and the network spatial structure.

Previous GNMs of urban road networks, as reviewed in section 4.3.4 and discussed in 4.3.4.4, have used nodes to represent locations of population concentration locations and links to represent roads, thus representing two systems – the population and the urban road network, using one network. This design incorporated the urban system into a GNM and could be reasonable when modelling urban networks, regional transport networks, or the empirical correlation between population density and road network intersection density. However, this representation did not model the urban road network structure studied by this research, as specified in section 2.3.1, which has been used in most empirical RNE research. Thus, previous models' simulation results could not be compared with empirical RNE findings. Further, the modelled population and road network were inherently connected, so that the simulated population and road network structures resulted from both proposed the generative mechanism and the inherent network connectivity, increasing the difficulty to disentangle mutual influences between the two systems of interests.

This study used urban road nodes to represent road network intersections and links represented road segments. A layered urban system and the co-evolving relationship between population and road network were synthesised in Chapter 3, to represent both population and road network. Chapter 8 proposed a hybrid model of population and road network co-evolution, which represented population and road network on two inter-dependent layers. Co-evolution mechanism of population and road network were designed into Node Addition to influence road network spatial structure.

#### 5.3.2.1 Node Spatial Distribution and Network Spatial Structure

Figure 5.4 demonstrated node spatial distribution and its influence on network connectivity and spatial structure. The upper panel from left to right illustrated five potential spatial distributions of 100 nodes - regular grid, dispersed, centralised, clustered, and decentralised, respectively. The lower panel demonstrated Link Connection using the same Link Connection mechanism under the RNG proximity relationship, given the sets of nodes in the upper panel. In terms of regular grid node distribution, Link Connection generated a regular grid. In terms of the four irregular node distributions, connected networks exhibited different spatial structures. This result agreed with the finding reviewed in Chapter 4 section 4.2.2, which have connected US urban road networks using the RNG proximity relationship and found high link correspondence, especially in urban road networks with original grid layouts.

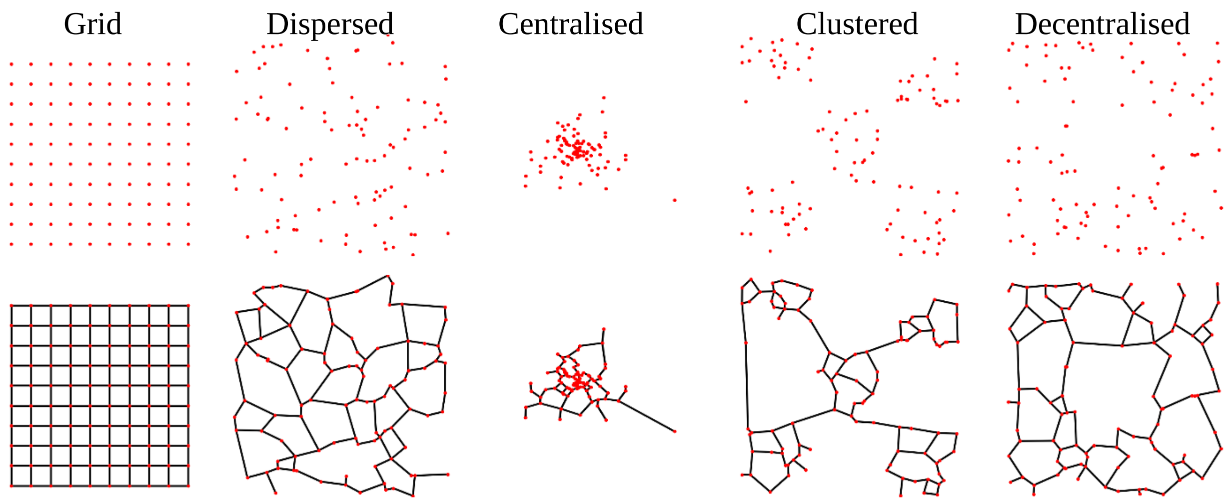



**Figure 5.4 Node Addition – Direct Network Spatial Structure**: The upper panel illustrates five node spatial distributions – regular grid, dispersed, centralised, clustered, and decentralised respectively from left to right of 100 nodes.The lower panel shows the connected networks of the upper panel nodes using a same Link Connection mechanism with the Relative Neighbourhood Graph (RNG) proximity relationship.

#### 5.3.2.2 Node Addition Summary

Node Addition was the first step of the iterative network generation process of GNMs, which

- Initiated network growth,
- Influenced network spatial structure.

Network nodes in the proposed models in this study represented urban road network intersections. In the proposed hybrid model of population and urban road network co-evolution in Chapter 8, road network-population co-evolution mechanism was designed into Node Addition to influence urban road network's spatial structure.

## 5.4 Simulate the Urban Road Network Evolution using GNMs

RNE simulation implemented the proposed RNE models, used computer programs to imitate the formation and dynamics of urban road network structures, and conducted computational experiments.

### 5.4.1 Plan RNE Simulation Studies

Simulation experiments were conducted following the two proposed models, respectively. For the generative network model of urban road network evolution proposed in Chapter 6, simulation experiments in Chapter 7 planned to

- Explore the proposed model's capacity in modelling dynamic RNE process,
- Explore proximity relationships' role in modelling RNE.

The capacity to model the dynamic RNE process showed in the capacity to model both static and dynamic road network structures. Data of the whole network generation process were to be stored instead of only the final generated networks so that both simulated networks' static and dynamic structure could be examined. To explore proximity relationships' role in modelling RNE, simulation experimented with different proximity relationships. Parallels established between microscopic generative mechanism and macroscopic simulated static and dynamic network structures may improve the understanding of network characteristic emergence and proximity relationships' influences in real urban road networks.

For the hybrid model of population and urban road network co-evolution proposed in Chapter 8, simulation experiments in Chapter 9 planned to

- Explore the emerging road network spatial structure,
- Explore the relationship between the simulated population and urban road network.

To explore potential emerging road network spatial structure, simulations experimented with all parameter combinations that controlled population and road network spatial decision preferences enabled by the proposed co-evolution mechanism. The emerged road network spatial structures were characterised by a proposed method which used processes behind the formation of these spatial structures for network spatial structure characterisation. Connections between the proposed co-evolution mechanism and macroscopic simulated structures and their mutual influences were to be established, thus forwarding the understanding of the emergence of urban road network spatial structure and its relationship to the urban system through the co-evolution of population and urban road network.

### 5.4.2 Simulation Settings

This section discussed general settings of conducted simulation experiments and their potential influences on simulation results.

#### 5.4.2.1 Simulation Area

The simulation area was set as a square with sides of unit length. The size and shape of the simulation area were set for observational purposes, rather than represent a specific urban area. As the distance on the simulation area was relative, and the shape was for an observational purpose, the simulation area did not influence the simulated network structure.

#### 5.4.2.2 Initial Condition

The initial road network was assumed to be a small rectangle at the geographical centre of the simulation area. This study did not intend to model human settlements or replicate the historical development of a particular road network. The initial road network did not have social and economic meanings. Still, the topology and geometry of the initial network were expected to influence the simulated network structure. For example, the largest possible initial network that was the same size as the simulation area initiated a process of space division, while a small initial network initiated a process of expansion. The influence of initial condition shall be considered in each simulation study conducted.

#### 5.4.2.3 Growth Rate

The proposed models were incremental. Empirical findings have suggested road network growth rate varied in different historical periods. In terms of iterative growth modelled here, the growth rate did not significantly influence the simulation results. The modelled growth process was historically dependent; different orders of nodes added and connections made consequently resulted in different networks. However, as the growth was modelled iteratively by the same generative mechanism, long term network structure was not affected by the growth rate.

#### 5.4.2.4 Termination Condition

Regarding real-world RNE, it was reasonable to expect the size and density of the road network had limits and could not increase infinitely. Meanwhile, exploring urban boundary and density limits were not research objectives of this study.

The simulated network grew and became denser as simulation advanced. Simulation terminated at user-specified time step when the simulated network reached certain node number so that the research questions could be best investigated. As a result, the simulation termination condition was decided individually for each simulation experiment.

#### 5.4.2.5 Number of Simulation Trials

Each simulation experiment carried out multiple simulation trials with different random seeds to accommodate randomness' influence on simulation results and reach general conclusions. Meanwhile, the number of trials also depended on computational power. Therefore, the number of simulation trials was decided individually for each simulation experiment by balancing computation power and the generality of simulation results.

## 5.5 Examine Simulation Results

Understanding of the urban road network structure depended on the network characteristics examined. Simulation result examination in Chapter 7 of the proposed GNM of urban road network evolution and simulation used the framework of elementary network component characteristics in 5.5.1 to examine both static and dynamic simulated network structures, in order to explore proposed model's capacity in modelling the dynamic RNE process and proximity relationship's role in modelling the urban road network structure. Simulation result examination in Chapter 9 of the proposed hybrid model of population and urban road network co-evolution used the proposed method in 5.5.2, to explore the emerging road network spatial structures and mutual influences between road network and population. Simulation results were compared to empirical findings reviewed in Chapter 2, 3; established relationships between proposed generative mechanisms and simulated structures provided insights into the emergence of inconsistency in empirical findings.

### 5.5.1 Road Network Static and Dynamic Characteristics

Simulation result examination in Chapter 7 aimed to explore proposed models' plausibility in modelling the urban road network structure and the dynamic RNE process. Both static and the dynamic simulated network structures were to be examined using a framework of elementary network component characteristics and dynamics, as proposed in Table 5-3.

The network structure examination framework consisted of the node, link and block, Betweenness Centrality (BC) characteristics and dynamics. These characteristics were selected based on limitations identified in previous research. Empirical RNE research had inconsistency in findings; elementary network characteristics had more reported findings that could be compared horizontally, than more sophisticated network characteristics. Modelling RNE research using GNMs generated static urban road network structures rather than model the dynamic RNE process, thus did not incorporate empirical RNE findings to compare with simulated network dynamics. A network structure examination framework based on elementary network component characteristics and dynamics maximumly utilised existing empirical findings, including both static and dynamic network structures, to characterise general urban road network structure and dynamics.

The proposed network structure examination framework consisted of static and dynamic structure, which differed from previous studies' statistical comparison regarding whether simulated networks reproduced empirical network characteristics. Through examining the dynamic structure, comparisons could be made between the simulated network dynamics and empirical RNE findings. The simulation also enabled observation of elementary network growth of the whole network generation process, which pictured the formation of network structure continuously under the proposed generative mechanism, in comparison to empirical research's inference made from discrete historical moments. This potential further illustrated the plausibility of the proposed generative mechanism in directing network dynamics.

Elementary network component characteristic measures included:

- Node characteristic *degree* $k_i$ referred to the number of links connecting to the node $i$.
- Average node degree $\langle k \rangle = \frac{1}{|V|}\sum_{i=0}^{|V|} k_i$, in which $|V|$ was the number of nodes a network $G$ had and estimated the connections a node had on average.
- Link characteristic *length* $l_{i,j}$ measured the Euclidean distance between node $i$ and $j$.
- Block area $A$ measured the size of blocks in the network.
- Betweenness Centrality *(BC)* measured how frequent a node or link lied on the shortest paths in the network; BC of a node or link $i$ was defined as $BC(i) = \frac{1}{(|V|-1)(|V|-2)}\sum_{s \neq t} \frac{\sigma_{st}(i)}{\sigma_{st}}$, in which $\sigma_{st}$ was the number of shortest path between node pair $s$, $t$, and $\sigma_{st}(i)$ was the number of shortest path between node pair $s$, $t$ on which $i$ lies.

Apart from elementary network component characteristics' dynamics, dynamic network structure included RNE phenomena proposed by empirical RNE research.

- The backbone of urban road networks associated network components' existence time with their BC.
- Densification and Exploration (*DE*) referred to new links' impact on average network BC, in which BC impact $\delta_{BC}(e)$ characterised new links $\delta_{BC}(e) = \frac{[\overline{BC}(G) - \overline{BC}(G\backslash e)]}{\overline{BC}(G)}$, $\overline{BC}(G)$ denoted the average BC of network $G$, and $\overline{BC}(G\backslash e)$ denoted the average BC after removing link $e$ from $G$.

**Table 5-3 Examination Framework of Urban Road Network Static and Dynamic Structure**

| | ***Node degree $k$*** | ***Link length $l$*** | ***Block areas $A$*** | ***Betweenness centrality (BC)*** | ***Backbones of the road network*** | ***Densification and exploration (DE)*** |
|---|---|---|---|---|---|---|
| *Static Characteristics* | $\overline{k_3}$~59.3%, in [44.4%, 59.3%]; $\overline{k_4}$~18.7%, in [5.4%, 42.2%]; $\overline{k_1}$~21.3%, in [7.7%, 41.6%]. (US road networks)<br><br>Planned e.g. US $\langle k \rangle \approx 2.76$ in [2.22, 3.22], Barcelona $\langle k \rangle = 3.42$; Organic e.g. Oxford $\langle k \rangle = 2.32$, Worcester $\langle k \rangle = 2.36$, Edinburgh $\langle k \rangle = 2.43$, Sheffield $\langle k \rangle = 2.42$. | Heavy-tailed distributions: Lognormal, Power-law. | Heavy-tailed distributions: Lognormal, Power-law. | Bimodal distribution: High BC components from a spanning tree and low BC components forming loops. | Correlations between high BC and long existence time of road network components; | Two types of new links in the road network, reflected in different changes of average network BC. |
| *Dynamic Characteristics* | $\langle k \rangle$ may increase, stay constant, or decrease; | Lognormal/ Power-law distribution with concentrating peak; | Power-law/Lognormal distribution with increased slope on the log-log plot; | Depends on network density $\rho_e = \frac{\lvert E \rvert}{E_{DT}}$; Concentrates towards the barycentre as network density increases; | | |
| *Hypotheses* | Planarity resulted in small $k$ range. | Multiplicative processes behind the formation of probability distributions. | $P(A)$ depended on density of the studied area; Multiplicative processes behind the formation of probability distributions. | BC distribution was a planar network property and was decided by network formation process. | Correlations existed among high BC, MST components, geographically central, and the long-existing components. | DE was a planar network property but had temporal and spatial characteristics representing two RNE processes. |
| *Further Research Questions* | How do $k_3$ and $k_4$ emerge? How do different $\langle k \rangle$ dynamics emerge? | How do lognormal $l$ distribution emerge? How do $l$ dynamics emerge? | How do lognormal or power-law $P(A)$ emerge? How do $P(A)$ dynamics emerge? | How do BC distribution emerge? Is the BC distribution controlled by $\rho_e$? | Do hypothetical correlations exist? Does this characterise the backbone of urban road networks? | Do $\delta_{BC}(e)$ distinguish dead-ends and bridging links? Does this characterise DE? |

### 5.5.2 Road Network Spatial Structures

Network science perspective research has shown an insufficient characterisation of urban road networks' spatial structure, namely their spatial distribution and organisation. Some studied network characteristics, such as the block area distribution, exhibited high sensitivity to the density of studied area and road network. Without considering the spatial structure differences behind these network characteristics, empirical research has reported inconsistent findings. Thus, characterisation of road networks' spatial structure may avoid the debate over specific network characteristic probability distributions, by shifting the focus to the various spatial structure and formation processes that led to the variance in network characteristics. At the same time, existing research on road network spatial structures has studied road network patterns such as geometric connection patterns and continuity hierarchy patterns, network density spatial analysis, and quantitative classification. Road network patterns have not connected road network's spatial structure to the urban system; spatial analysis has not captured the network nature of road network's spatial structure; quantitative classification has remained quantitative with limited theorisation.

Empirical findings, as reviewed in Chapter 3 have suggested the spatial structure of urban road networks was likely a spectrum, rather than a few clear-cut types. Also, positive spatial correlations between urban road network and population, as well as between urban road network and economic, physical and functional urban spatial structure in general, have been reported. These empirical findings suggested related processes behind the formation of the road network and urban spatial structures, such as centralisation to decentralisation on the global scale, clustering to dispersion on the local scale, which may be used to characterise the urban road network spatial structure. This characterisation method was consistent with the urban spatial structure. This study proposed

- The spatial structure of urban road networks could be measured with two dimensions - centralisation to decentralisation on the global scale, clustering to dispersion on the local scale, in accordance with the urban spatial structure;
- Network characteristics could characterise the spatial structure of urban road networks.

#### 5.5.2.1 Characterise Road Network Spatial Structures Using Network Characteristics

Figure 5.4 demonstrated different node spatial distributions – regular grid, dispersed, centralised, clustered, decentralised; the connected networks exhibited corresponded spatial structures. The grid network demonstrated the difference between regular and irregular spatial structures. Two network characteristics could characterise these spatial structures:

- Total link length $L_{tot} = \sum_{i,j} l_{i,j}$ was the sum of Euclidean length $l_{i,j}$ of all links in network $G$. $L_{tot}$ measured the total quantity of network length and suggested the spatial coverage and construction cost.
- Maximum shortest path length $\langle l \rangle_{max}$ was the maximum length in network $G$ among all its node pairs' Euclidean shortest path lengths. $\langle l \rangle_{max}$ measured the longest network distance between nodes and suggested the network's diameter and span.

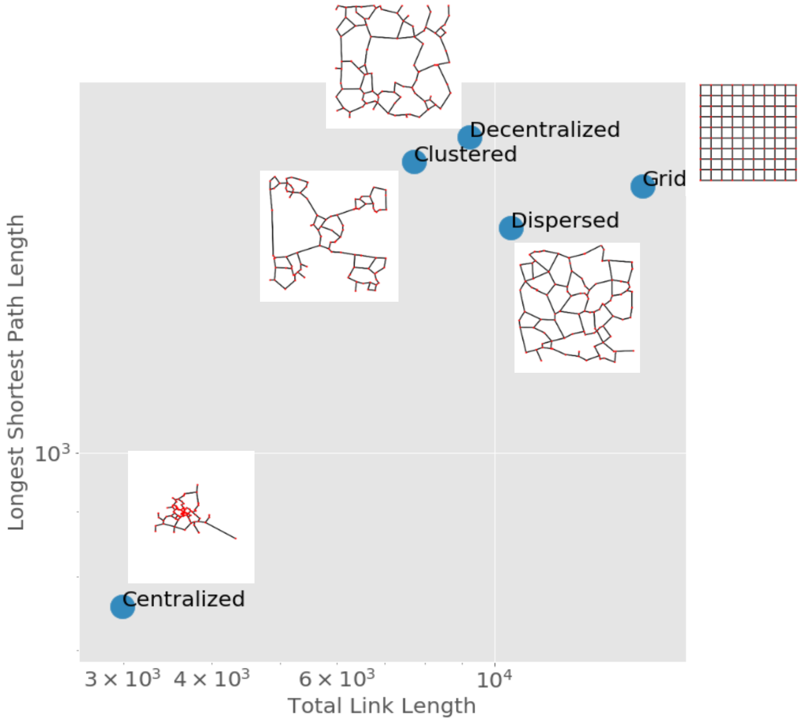



**Figure 5.5 Characterise Road Network Spatial Structure**: Total link length $L_{tot}$ (x axis) and longest shortest path length $\langle l \rangle_{max}$ (y axis) distinguished sample urban road network spatial structures in Figure 5.4. ($L_{tot}$, $\langle l \rangle_{max}$) values of each sample network was plotted with blue points; networks were illustrated next to the ($L_{tot}$, $\langle l \rangle_{max}$) values. A simulation area of 1000*1000 square unit length was assumed and distances in networks were measured accordingly. All networks had 100 nodes. The grid network served as a regular spatial structure in comparison with the sample irregular spatial structures.

Together $L_{tot}$ and $\langle l \rangle_{max}$ may characterise the urban road network spatial structure. As shown by this small example, a centralised spatial structure network was likely to have small $L_{tot}$ and $\langle l \rangle_{max}$, depicting a compact layout with a close distance between nodes over a small area. A decentralised spatial structure road network was likely to have large $\langle l \rangle_{max}$. $\langle l \rangle_{max}$ approximated the diameter of the whole area, and there were nodes very far away from each other, since network nodes located near the fringe of an urban area. A dispersed road network was likely to have large $L_{tot}$. Nodes distributed evenly and loosely, suggesting high connectivity, large cost to connect, and similarity to a grid. A clustered road network was likely to have relatively small $L_{tot}$ and relatively large $\langle l \rangle_{max}$, as distances were large among multiple clusters. Figure 5.5 demonstrated $L_{tot}$ and $\langle l \rangle_{max}$ characterised the road network spatial structure according to the centralised to decentralised and clustered to dispersed dimensions, with network examples in Figure 5.4.

## 5.6 Chapter Conclusion

This chapter proposed a modelling and simulation methodology to approach the urban road network evolution (RNE). This methodology provided a feasible scope 5.2.1 of network characteristics and dynamics to study the urban road network evolution, from a network science perspective. This methodology proposed to address the evolution of urban road networks through the two iterative RNE process Node Addition 5.3.2 and Link Connection 5.3.1, respectively. The proposed methodology consisted of formulating research questions 5.2 within the research scope and from syntheses of existing empirical and modelling RNE knowledge 5.2.2, proposing generative network models (GNMs) 5.3, designing simulation experiments 5.4, and examining simulation results 5.5.

Existing network science perspective RNE research has accumulated a considerable amount of topological and geometrical network characteristics findings but showed insufficient horizontal comparison, inconsistent findings, lack of integration with the urban system. The proposed RNE modelling and simulation framework using GNM aimed to address these limitations by two RNE modelling and simulation studies, targeting respectively the emergence of elementary road network characteristics considering the urban road network alone and the emergence of road network spatial structure in the urban system. Chapter 6-9 propose the generative network model of urban road network evolution and the hybrid model of population and road network co-evolution and conducted simulation experiments, exploring emerging road network characteristics, dynamics, spatial structures, and relationships to the urban system.

Overall, the proposed RNE modelling and simulation framework brought together the long-standing research interest in urban road network evolution, a bottom-up complex network modelling and simulation approach using GNM and increasing empirical RNE findings. This methodology distinguished from alternative approaches to RNE by modelling explicitly the structure and dynamics of urban road networks, instead of modelling the whole transport or land use layers, but had the flexibility to integrate with long-established urban and transport theories as well.

# Chapter 6 Generative Network Model of the Urban Road Network Evolution

## 6.1 Chapter Introduction

Transport network and its dynamics have been modelled explicitly or implicitly with approaches including transport demand forecasting, land use and transport Interaction (LUTI), urban modelling, and network science; the various modelling approach has differed in the urban factors and layers of interest, as reviewed in Chapter 4. Compared to alternative modelling approaches, generative network models (GNM) model explicitly the urban road network structure and dynamics, as illustrated in Figure 6.1.

Existing empirical network science perspective RNE research, as reviewed in Chapter 2, has accumulated considerable urban road network structure and dynamics findings, which required further understanding because of the present inconsistency in the findings and the lack of consideration regarding mechanisms behind the emergence of observed empirical RNE characteristics. Existing GNMs of urban road networks, as reviewed in Chapter 4, have not compared network generative mechanisms horizontally, which may be generalised using proximity relationships. Existing GNMs have not modelled primal urban road networks but used nodes to represent urban centres of population concentration and links as the road network. This modelling choice has differed from most empirical RNE research that has used the primal representation, causing issues regarding whether the simulated networks could be compared to empirical primal urban road network findings. Further, current modelling RNE research has not explored the potential of GNM in modelling the dynamic RNE process. Parallels may be established between the simulated network dynamics and the dynamic RNE process, e.g. by investigating the network generation process, comparing the simulated network structure dynamics with empirical RNE findings.

This chapter aims to answer the first research question of this thesis, as proposed in Chapter 1 and specified in Table 5-2:

1. What is the working mechanism of previous GNMs in generating urban road network structure? Can previous models' generative mechanisms be generalised?

   a) Whether proximity relationships from Proximity graphs other than RNG, like β-skeletons play a role in modelling RNE?

This chapter proposes a generative network model of urban road network evolution 6.3 with a generalised Link Connection mechanism 6.2. This model considers the road network structure alone without the urban system, as illustrated in Figure 6.1. 6.4 summarises the proposed model with an algorithm. 6.5 plans the simulation experiments to explore emerging urban road network structures and proximity relationships' role in modelling RNE. Next chapter conducts simulation experiments and examined simulation results, regarding emerging network structure and dynamics under the generalised Link Connection mechanism.

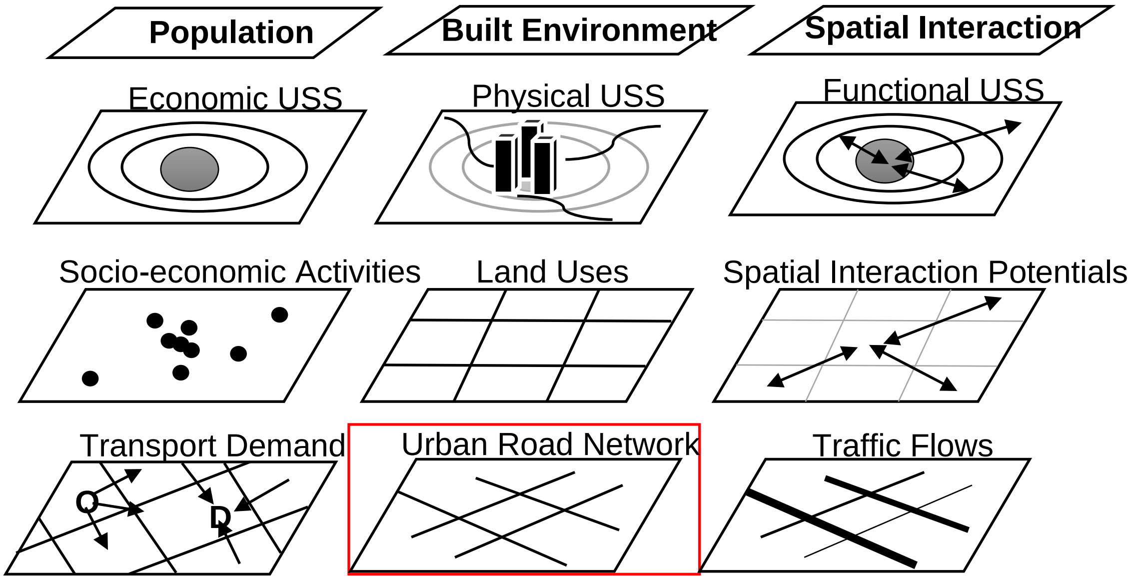



**Figure 6.1 Generative Network Model of Urban Road Network Evolution**

## 6.2 Generalise the Generative Mechanism of Urban Road Network Evolution

Empirical research, as reviewed in Chapter 2 has suggested associations between the microscopic growth of network components and the macroscopic road network characteristics and dynamics in urban road networks' evolution. Urban road networks evolved with addition and connection of elementary network components, which led to the emergence of different macroscopic network characteristics and dynamics. Urban road networks were likely first to form a skeleton of major paths, then developed locally by the growth of minor network components. Urban road networks' connectivity, represented by node degree, was stable under the planar constraint. There were abundant short links, many medium-length links and very few very short or very long links, exhibiting a lognormal link length distribution. Block areas related to the urban density; for example, from the dense urban centre outwards to the sparse urban periphery, block areas were likely to exhibit power-law or lognormal decay, namely heavy-tailed distributions with abundant small blocks and a few very large blocks. This network structure had an inherent hierarchy. For example, shortest paths between node pairs repeatedly passed through network components on an underlying spanning tree of high Betweenness Centrality (BC) components; while alternative circuitous paths had low BC, leading to a separation between high and low BC components. The high BC network components further corresponded with long-existing components and tended to concentrate around the geographical centre of the network. New links, depending on whether they bridged two existing links or formed new dead-ends, had different influences on the average network BC. Empirical findings have suggested the evolution of urban road networks emerged bottom-up from changes of basic network components.

Regarding incremental growth, this bottom-up urban road network evolution could be viewed as two iterative processes: Node Addition - adding new nodes and Link Connection - connecting new nodes by new links. Node Addition directed spatial distribution and organisation of the network, while Link Connection formed elementary connection patterns. Node Addition in modelling spatial networks differed from modelling general complex networks, as spatial positions of nodes were meaningful. Link Connection in modelling planar networks differed from modelling general spatial networks, which maintained planarity and formed planar connection patterns. Meanwhile, modelling spatiality and planarity did not guarantee the generation of the urban road network structure. Among spatial and planar networks, proximity graphs showed structural similarity with urban road networks, indicating proximity relationships may play a role in the formation and dynamics of urban road networks.

Thinking of the urban road network evolution in terms of the two iterative processes, Node Addition reflected transport infrastructure supply and interaction with the urban system, which was likely to respond to inhomogeneous transport demand over the space. Thus, the Node Addition mechanism needed to be considered in the context of the urban system. When considering the road network alone, the mechanism of Node Addition could be thought of as externally given.

Link Connection connected new nodes to the existing urban road network, which equalled to finding locations on the existing network for new nodes to connect. Previous GNMs of urban road networks have not compared their Link Connection mechanism horizontally. The urban street pattern model and the centre competition model, as reviewed in 4.2.3.2 and 4.2.3.4 accordingly, have described Link

Connection as new nodes first connected with minimal link length to the existing road network according to a local optimal mechanism, then created loops by connecting to points on the existing network that satisfied the relative neighbourhood graph (RNG) proximity relationship. The city graph model, as reviewed in 4.2.3.3, has described Link Connection as connecting new nodes to points on the existing network in an intersection of point sets. This set of points intersected the point set whose connections to new nodes maintained planarity of the network, the set of points that were orthogonal projections of new nodes on the existing network, and the set of points that satisfied RNG proximity relationships of the new nodes.

As a spatial network, costs were associated with link formation; considering cost, Link Connection tended to form local connections between new nodes and the existing network with short link length, e.g. connecting a new node to the nearest location on the existing network which led to a tree structure. At the same time, Link Connection considered efficiency; loop structure created short-cuts between nodes that led to increased efficiency compared to a tree structure. Balancing cost and efficiency locally in Link Connection, the macroscopic urban road network structure that lay between a tree and a complete circuitous structure emerged. Besides the process of balancing cost and efficiency, planarity was maintained. This whole process could be generalised as locally examining proximity relationships between new nodes and an existing network. Thus, this study proposed that Link Connection was a process which examined the proximity relationship between a new spatial location and the existing urban road network. The proximity relationship examination found connection locations for new nodes on the existing network, balancing cost and efficiency while maintaining planarity at the same time.

## 6.3 Generative Network Model of the Urban Road Network Evolution

Following the generalised generative mechanism, this section proposed the generalised generative network model of urban road network evolution. An urban road network $\mathrm{G(t)} = [\mathrm{V(t)}, \mathrm{E(t)}]$, in which $\mathrm{V}$ represented a set of nodes $\mathrm{v}$ – road intersections with spatial locations $\mathrm{c}$ in $\mathrm{C(t)}$ and $\mathrm{E}$ represented a set of links $\mathrm{e}$ – road segments connecting nodes in $\mathrm{V}$, evolved with time $\mathrm{t}$ by iterating the following two processes.

### 6.3.1 Node Addition

At time $\mathrm{t}'$, Node Addition added new node $\mathrm{v}'$ at location $\mathrm{c}'$ to existing network $\mathrm{G(t)}$ so that $\mathrm{V(t')} = \{\mathrm{V(t)} + v'\}$. The spatial location of the new node $\mathrm{c}'$ was given externally.

### 6.3.2 Link Connection

Link Connection examined the proximity relationship $\mathrm{P}(\beta)$ between new node $\mathrm{v}'$ and the existing network $\mathrm{G}(\mathrm{t})$, found a set of points $\{p\}$ on $\mathrm{G}(\mathrm{t})$ which satisfied $\mathrm{P}(\beta)$; connected $\mathrm{v}'$ and $\{p\}$ with links $\{e'\}$ so that $\mathrm{V}(\mathrm{t}') = \{V(t) + v' + p\}$, $\mathrm{E}(\mathrm{t}') = \{E(t) + e'\}$ and $\mathrm{G}(\mathrm{t}') = [V(t'), E(t')]$.

The proximity relationship $\mathrm{P}(\beta)$ was the proximity relationship used to define the family of proximity graphs β-skeletons and was controlled by a single parameter β. New node $\mathrm{v}'$ and a point $p$ were proximity neighbours and connected if the lune between two discs with radius $\beta d_{\mathrm{v}'p}/2$ centred at $\left(\left(1-\frac{\beta}{2}\right)\mathrm{c}', \frac{\beta}{2}p'\right)$ and $\left(\frac{\beta}{2}\mathrm{c}', \left(1-\frac{\beta}{2}\right)p'\right)$ had no third node, $\beta \in [1.0,2.0]$. $\mathrm{c}'$ and $p'$ were the coordinates of $\mathrm{v}'$ and $p$. $\beta < 1.0$ led to non-planar networks, and $\beta \geq 2.0$ led to disconnected networks; $\beta = 1.0$ equalled the Gabriel Graph (GG) proximity relationship, and $\beta = 2.0$ equalled to the RNG proximity relationship.

## 6.4 Computer Model and Algorithm

### 6.4.1 Computer Model

The proposed RNE model was implemented with the Python programming language and package NetworkX, which offered the network data structure. The modelled urban road network was implemented as a NetworkX Graph with additional node attribute – coordinates and link attribute – Euclidean length. Node Addition and Link Connection were implemented as adding new nodes and links to the NetworkX Graph. In Link Connection, the existing network was approximated by a set of a large number of points, so that the proximity relationships between new nodes and the existing network could be examined. In more details, each link of the existing network was divided into small segments by a fixed length; all the dividing points on the links as well as the nodes of the existing network made up the point set to approximate the existing network. Examination of the proximity relationship between a new node and the existing network was approximated by examining the proximity relationship between the new node and the set of points - point approximation of the network. This approximation simplified the implementation of the proposed proximity relationship examination. Its limitation lied in that connection points on existing network found for new nodes were approximations of the analytical ones. The accuracy of approximation was controlled by the fixed length used to divide each link and was set to be the highest within the computation power.

### 6.4.2 Algorithm

1. Initialisation:
    a. Initialise the initial urban road network $G(0)$;
    b. Create approximation points set $Q(0)$ of $G(0)$;
    c. Set iteration number $t = 1$;
2. While iteration number $t \leq N$ Total iteration number:
    a. Node Addition:
        i. Add a new node with node attributes to $G(t)$; (Node ID, Spatial coordinates, Age);
        ii. Append the new node to Q(t);
    b. Link Connection:
        i. Find proximity neighbours of the new node using proximity relationship P(β):
            1. Construct Delaunay triangulation on Q;
            2. Calculate pairwise distance between points in Q;
            3. Test among the Delaunay neighbours of new node and find proximity neighbours of the new node;
            4. If two approximated orthogonal projection of the new node on a link are both found as proximity neighbours, choose one;
        ii. Connect the new node to its proximity neighbours:
            1. If the proximity neighbour is not a node in $G(t)$:
                a. Separate the original link where the proximity neighbour lies on into two links on each side of the proximity neighbour;
                b. Add the proximity neighbour into $G(t)$;
                c. Connect the new node to the proximity neighbour;
            2. Else:
                a. Connect the new node to the proximity neighbour;
    c. $t = t + 1$;

## 6.5 Simulation Experiments

### 6.5.1 Simulation Experiment Objectives

The following Chapter 7 implemented the proposed model in this chapter, performed simulation experiments, and examined the simulated networks to explore the proposed research questions. This section designed simulation experiments.

First, the simulation experiment explored the potential of the proposed model in modelling the dynamic RNE process. This objective was approached by examining both simulated networks' static and dynamic structure and establishing relationships between the simulated network structure and the proposed generative mechanism, in order to examine the capacity of the proposed model in simulating plausible network structure and directing plausible network dynamics. Previous GNMs, as reviewed in Chapter 4, have generated network structures sharing statistical similarity with empirical urban road networks but have not investigated the network generation process and simulated networks' dynamic structures. Empirical research reviewed in Chapter 2 has suggested potential parallels between the network generation process and the dynamic RNE process. Thus, the association between the two may be established by investigating the whole network generation process and looking into simulated network characteristic dynamics through a series of network snapshots, examining the static network structure of each snapshot and the changes of dynamic network structure between snapshots. Studying the dynamic network structure would quantify how the simulated network structure changed and relate the microscopic changes of network components with the emergence of macroscopic network characteristics, thus demonstrating the plausibility of proposed the generative mechanism.

Further, both simulated network static and dynamic structure were compared with empirical findings according to the examination framework of elementary network components proposed in Chapter 5 section 5.5. Aiming at generating and reproducing statistical network characteristics, previous modelling and simulation studies have compared their results only with empirical findings of static urban road networks but not with empirical RNE findings which have quantified how urban road networks changed. Empirical RNE research has documented direct empirical evidence, thus were critical in understanding the dynamic RNE process. Meanwhile, as empirical research has studied individual urban road networks and employed different methods, their results have exhibited inconsistency. By looking into the processes behind the emergence of inconsistency in empirical findings, simulation experiments may advance the understanding of empirical findings.

Nevertheless, modelling the dynamic RNE process did not mean picture step by step the evolution process any particular urban road network but referred to the formation and dynamics of a generic urban network structure.

Second, simulation experiments attempted to proximity relationships' role in modelling RNE using simulation. The proposed model in this chapter generalised generative mechanism of urban road network evolution, using proximity relationships from proximity graphs β-skeletons. Plausibility of this generalisation was to be examined through simulated networks' static and dynamic structure as discussed above. If the proposed model could generate urban road network structure similar to existing models' simulated network structure, as well as broader plausible network structures, it demonstrated the proposed model effectively generalised the generative mechanism of urban road networks.

To explore the role of proximity relationship in modelling urban road network structure, simulation experiments were to be conducted with proximity relationship $\mathrm{P}(\beta)$ parameter $\beta = 1.0, 1.5, 2.0$, respectively. Chapter 7 section 7.6 examined the simulated networks accordingly. $\beta = 2.0$ equalled to proximity relationship of RNG, which has been used in previous models. Generation of plausible urban road network structure at $\beta = 1.0, 1.5$ would evaluate the generalised mechanism and reveal the role of proximity relationship in generating the urban road network structures. Simulated networks under proximity relationships with $\beta = 1.0, 1.5, 2.0$ would be compared.

### 6.5.2 Simulation Trials

Each simulation trial was carried out on a unit square simulation area. The initial urban road network was a rectangle in the geographical centre of the simulation area. Parameters $\beta$ which controlled the proximity relationship $\mathrm{P}(\beta)$, and $N$ was the total iteration number. At each time step, the simulation performed Node Addition and Link Connection. Node Addition added one new node to a random location on the simulation area. Link Connection examined the proximity relationship $\mathrm{P}(\beta)$ between the new node and the existing network and connected the new node to points on the existing network that satisfy $\mathrm{P}(\beta)$. The simulation trial terminated when reaching $N$.

Each simulation experiment conducted a user-specified number of simulation trials with changing random seeds to acquire general results of the model behaviour of interest. The number of trials was specified by observing the variations of simulation results between simulation trials, which decided an appropriate number of trials required to achieve general model results.

### 6.5.3 Sensitivity Analysis

Parameters that might influence simulation results using the proposed model included the initial condition, the spatial distribution of new nodes, the number of new nodes added at each iteration, the point approximation accuracy of the network, allowed connections of each new node to found points on the existing network that satisfied the proximity relationship, simulation termination condition, and the number of trials performed for each experiment.

The initial condition assumed an initial small rectangular urban road network at the geographical centre of the simulation area. This setting did not intend to specify a particular urban road network with historical or socio-economic meanings but was a choice of model implementation. The initial condition was expected to influence the simulation results; for example, a small initial network led to network dynamics as a process of growth and expansion, while a large initial network led to network dynamics as a process of space division. The influence of initial condition was to be examined in the next chapter along with the simulation results.

The spatial distribution of new nodes was assumed to be random in the simulation experiment. Previous models have tested the assumption of exponential node spatial distribution and found the resulted network reproduced power distribution of empirical block areas. The spatial distribution of new nodes was regarded as influenced by the urban system and was to be explored in Chapter8, 9. The random distribution of new nodes here did not imply spatial locations of real urban road network's intersections were random. It was a model implementation choice made to avoid arbitrary assumptions of new road network spatial decision. Also, randomness enabled the observation of variations in simulation results, so that the modelled behaviour of interest could be better examined.

The point approximation accuracy of the network influenced the precision of connecting points on the existing network for new nodes found in Link Connection. It was set to the highest within computational power. Allowed connections of each new node among found points on the existing network that satisfied the proximity relationship influenced elementary connection pattern of the network. Fewer connections allowed reduced the connectivity of the network; for example, if a new node was allowed to connect to only one point among the found points on the existing network that satisfied the proximity relationship, the simulated network developed into a tree structure. This simulation allowed the connection of new nodes to all the found points so that the role of proximity relationship could be explored. Simulation termination condition and the number of trials performed for each experiment were decided for each computer experiment according to the level of generality in simulation results.

## 6.6 Chapter Conclusion

This chapter addressed the first research question of this thesis and generalised Link Connection in the generative mechanism of urban road networks, as in section 6.2. This chapter proposed a generative network model (GNM) of urban road network evolution with the generalised Link Connection as in 6.3, 6.4. 6.5 planned next chapter's simulation experiments to examine the role of β-skeletons proximity relationships in urban road network generation, as well as the proposed model's potential in modelling the dynamic RNE process.

The proposed model addressed three limitations in previous GNMs, which were identified in 4.2.3.5. First, this model used the primal representation in which nodes represented road intersections, and links represented road segments, differing from previous GNMs' modelled network structures using nodes to represent urban centres of population concentration and links to represent road network. The usage of primal representation enabled comparison of simulated network structures with primal empirical RNE findings, which constituted most empirical RNE research. Second, the proposed model generalised the Link Connection mechanism of urban road network generation, as a process of proximity relationship examination between a new node and the existing road network. Previous GNMs have not compared generative mechanisms horizontally. Link Connection has been described as a process of new nodes first connecting to the nearest point, then to the RNG neighbours on the existing network. Link Connection has also been described as a process of new nodes connecting to an intersection point set of points that maintain planarity, orthogonal projections of the new node on the existing network, and RNG neighbours. In doing so, previous models' Link Connection has modelled the network structures under the generalised Link Connection mechanism with $\beta = 2.0$. Third, this study proposed to model the dynamic RNE process, beyond previous studies' network generation, and addressed previous studies' limitation in not including empirical RNE findings into the simulation result examination.

This study proposed that GNMs of urban road networks combined generative mechanisms of spatial networks, planar networks and proximity graphs, merging link length cost, efficiency, planarity and proximity relationship. The generative mechanism of the urban road network structure iterated two processes - Node Addition and Link Connection. Node Addition directed the spatial structure, and Link Connection directed elementary connection patterns of urban road networks. In particular, Link Connection examined the proximity relationship between a new spatial location and the existing road network, with proximity relationship from proximity graph β-skeletons $\beta \in [1.0, 2.0]$.

Chapter 7 examines both simulated static and dynamic network structure, in comparison to existing empirical and modelling RNE findings, and explores simulated network structures under different β values. As discussed in 7.6, the generalised generative mechanism not only gave rise to plausible network structure and dynamics but also modelled a broader spectrum of plausible urban network structure than previous models, by changing the value of $\beta$. Network connectivity increased as $\beta$ decreased; network structures modelled with $\beta = 1.0$ exhibited the closest average node degree to empirical findings. $\beta < 1.0$ led to non-planar network structures while $\beta > 2.0$ led to unconnected network structures, hence the range $\beta \in [1.0, 2.0]$.

# Chapter 7 Generative Network Model of the Urban Road Network Evolution – Simulation Results

## 7.1 Chapter Introduction

This chapter examines the simulated network structure and dynamics, using the proposed generative network model of urban road network evolution in chapter 6. This chapter aims to answer the second research question of this thesis, as proposed in Chapter 1 and specified in Table 5-2:

2. Can GNM model the dynamic RNE process?

a) What is the relationship between the simulated static and dynamic network structure and the generative mechanism?

b) Are the simulated networks' dynamic structure comparable to the dynamic RNE process? Can modelling and simulation provide insights on empirical RNE findings?

First, to explore the proposed model's capacity in modelling the dynamic RNE process, 7.2 - 7.5 examine simulated networks' node, link, block, betweenness centrality characteristics and dynamics, which establish the relationship between simulated static and dynamic network structures and the proposed generative mechanism, in comparison to empirical RNE findings. Simulated network characteristics and dynamics are concluded from the results of 30 simulation trials.

Second, section 7.6 explores the role of proximity relationship from proximity graphs β-skeletons in modelling the urban road network structure, in order to examine the proposed model's generalisation of urban road network generative mechanism. Each β value's influence on the simulated network structure is concluded from the results of 30 simulation trials. 7.7 concludes the findings of simulation experiments and summarises simulated network structure and dynamics with Table 7-1.

## 7.2 Node Characteristics

### 7.2.1 Static Node Degree Distribution

The simulated networks had on average $54.1\%$ $\mathrm{k}_3$ nodes in the range of $[51.6\%, 56.4\%]$, $21.8\%$ $\mathrm{k}_1$ nodes in the range of $[18.2\%, 24.5\%]$, and $0.7\%$ $\mathrm{k}_4$ nodes in the range of $[0.3\%, 1.2\%]$, as shown in Figure 7.1. All 30 simulated networks had a majority of $\mathrm{k}_3$ nodes, which agreed with empirical findings reviewed in 2.3.2.1, e.g. US urban road networks have been found to have a majority of $\mathrm{k}_3$ nodes (on average $59.3\%$, in the range of $[44.4\%, 77.8\%]$). Meanwhile, simulated networks had low $\mathrm{k}_4$ nodes compared to empirical findings, e.g. US urban road networks have been found to have on average $18.7\%$ $\mathrm{k}_4$ nodes, in the range of $[5.4\%, 42.2\%]$. Previous generative network models (GNMs) of urban road networks have generated urban road network structures with organic ratio $\mathrm{r_N} \approx 1.0$, as reviewed in 4.2.3 and summarised in Table 4-1. $\mathrm{r_N}$ measures the ratio of $\mathrm{k}_1$ and $\mathrm{k}_3$ nodes among all nodes; $\mathrm{r_N} \approx 1.0$ meant almost all nodes of the generated networks were $\mathrm{k}_1$ and $\mathrm{k}_3$, as the simulation results here.

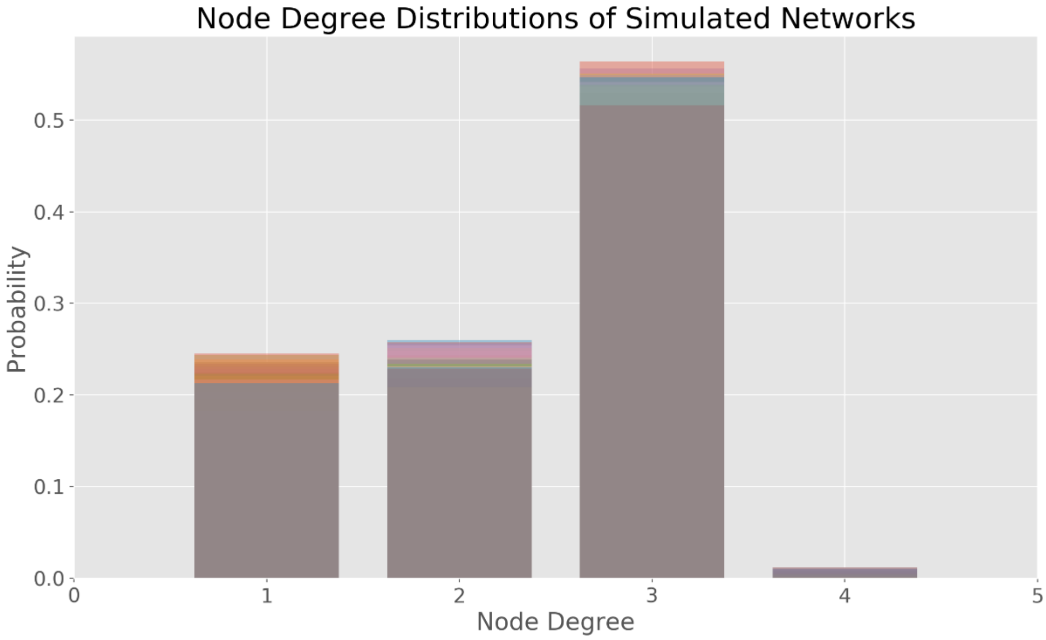



**Figure 7.1 Node Degree Distribution of Simulated Networks**: This plot shows node degree distributions of 30 simulated networks. The x-axis represents node degrees presented in the simulated networks, $\mathrm{k} = 1,\ 2,\ 3,\ 4$; the y-axis represents proportions of nodes of each node degree. Each colour represents one simulation trial's simulated network node degree distribution, and there were 30 in total. The simulated networks had on average $54.1\%$ $\mathrm{k}_3$ nodes in the range of $[51.6\%, 56.4\%]$, $21.8\%$ $\mathrm{k}_1$ nodes in the range of $[18.2\%, 24.5\%]$, and $0.7\%$ $\mathrm{k}_4$ nodes in the range of $[0.3\%, 1.2\%]$.

### 7.2.2 Static Average Node Degree

Figure 7.3 shows the dynamics of ratios between link and node number of simulated networks, namely the dynamics of average node degree $\langle k \rangle = 2\frac{|E|}{|V|}$. 30 $\langle k \rangle$ dynamics trajectories lay within a small range; all were close to linear and can be fitted well by linear regression with a slope of 1.18, yielding $\langle k \rangle = 2.36$ of all simulated networks. In comparison to empirical findings reviewed in 2.3.2, simulated networks' $\langle k \rangle$ had similar value to urban road networks that have been recognised as organic, such as Oxford with $\langle k \rangle = 2.32$, Worcester with $\langle k \rangle = 2.36$, Edinburgh with $\langle k \rangle = 2.43$, Sheffield with $\langle k \rangle = 2.42$. However, simulated networks' $\langle k \rangle$ was low compared to urban road networks that have been recognised as planned, such as $\langle k \rangle = 2.76$ of US urban road networks in the range of $[2.22, 3.22]$, Barcelona with$\langle k \rangle = 3.42$. $\langle k \rangle$ of previous models have reported $\langle k \rangle \approx 2.6$, which showed similar characteristics with the simulated networks here. Both node degree distribution and $\langle k \rangle$ suggested the proposed model simulated reasonable $\mathrm{k}_3$ proportion but low $\mathrm{k}_4$ proportion compared to planned urban road networks.

The Link Connection mechanism directed elementary connection patterns of simulated networks. $\mathrm{k}_3$ nodes were T-junctions with one road segment intersecting another road segment perpendicularly. Under the proposed model, Node Addition added one new node at a random location and Link Connection connected the new node by examining the proximity relationship between the new node and the existing network, namely finding new node's connection points on the existing network. The proximity relationship used for these simulation trials was β-skeleton proximity relationship with $\beta = 2.0$, which equalled to that of the Relative Neighbourhood Graph (RNG). The resulted primary $\mathrm{k}_3$ connections in the simulated networks showed the proposed Link Connection mechanism modelled the emergence of $\mathrm{k}_3$ connection pattern. Thus, this mechanism of examining new spatial locations' local proximity to the existing road network, behind $\mathrm{k}_3$ connection pattern, may relate to real-world $\mathrm{k}_3$ nodes' construction. The same $\mathrm{k}_3$ node majority in both simulated network structures and empirical urban road networks indicates parallels between real-world $\mathrm{k}_3$ formation and the proposed Link Connection mechanism.

On the other hand, simulated networks had almost no $\mathrm{k}_4$ nodes, showing that grid patterns would not emerge under the proposed generative mechanism. $\mathrm{k}_4$ nodes suggested grid urban layouts. 5.3.2.1 demonstrated the emergence of $\mathrm{k}_4$ nodes under the proposed Link Connection mechanism. When a grid layout of new nodes in Node Addition was given, the proposed Link Connection mechanism could form grid connection patterns and $\mathrm{k}_4$ nodes. Since this simulation experiment intended to explore the emergence of elementary road network characteristics, rather than node spatial distribution and organisation, the proposed model set Node Addition to generate new node at random locations, avoiding arbitrary spatial decision preferences. The simulation showed $\mathrm{k}_3$ nodes could emerge under random new node locations while $\mathrm{k}_4$ required predetermined grid layout design. The majority of $\mathrm{k}_3$ nodes and the difference of $\mathrm{k}_4$ node proportions between simulated networks, organic, and planned urban road networks suggests that urban road networks lie between planned grid layouts and not-centrally-planned organic growth patterns.

### 7.2.3 Dynamic Node Degree Distribution

Node degree distribution stayed stable after initial drastic changes. Figure 7.2 shows node degree distribution dynamics of 30 simulated networks, in which node degree distribution dynamics displayed the same trend across simulations. During simulated networks' growth to about 700 nodes, their node degree distributions only experienced drastic changes when the number of nodes was less than around 100, and then stayed stable. In other words, node degree distributions of simulated networks formed after initial network changes and remained stable, with a majority of $k_3$ nodes, many $k_1$ nodes, and few $k_4$ nodes. This result indicates real urban road networks may experience the same growth process - drastic changes in the initial stage of network formation and long persistence of the network structure afterwards. This result also indicates the influences of individual network components decrease as the scale of the network increases, maintaining a stable and consistent network structure.

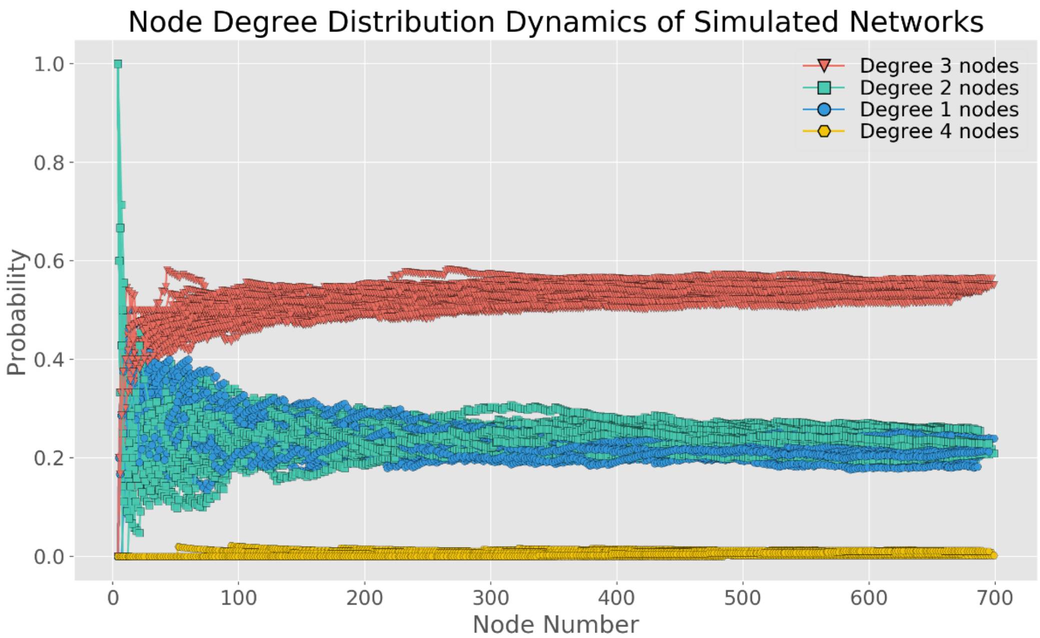



**Figure 7.2 Node Degree Distribution Dynamics of Simulated Networks**: This plot shows the dynamics of 30 simulated networks' node degree distributions. The x-axis represents the increase of node number as simulated networks grew and the y-axis represents the proportions of nodes at each node degree $k_1$, $k_2$, $k_3$, $k_4$. Each simulation trial had four trajectories of $k_1$, $k_2$, $k_3$, $k_4$ node proportions dynamics: red triangles represent $k_3$ nodes, blue circles represent $k_2$ nodes, and yellow hexagons represent $k_4$ nodes. 30 simulated networks' trajectories were plotted together and showed the same trend of dynamics with a majority of $k_3$ nodes, many $k_1$ nodes, and few $k_4$ nodes, which formed after initial drastic changes and then persisted.

### 7.2.4 Dynamic Average Node Degree

Empirical findings, reviewed in 2.3.2.2, reported increased, decreased, and constant $\langle k \rangle$ in different real urban road networks. The increase of $\langle k \rangle$ is likely to reflect the transformation of road network connection patterns from tree to circuitous and grid ; the decrease of $\langle k \rangle$ is likely to reflect the opposite transformation from circuitous and grid to tree; and the constant $\langle k \rangle$ is likely to reflect the organic growth of urban road networks characterised by the addition of $k_3$ and $k_1$ connections. These transformations have been further interpreted and associated with different empirical urban road network developments. For example, the transformation of road network connection patterns from tree to circuitous and grid has been associated with the grid development (Barrington-Leigh and Millard-Ball, 2015). The transformation from circuitous and grid to tree has been associated with sprawl development which has been regarded to have a high proportion of $k_1$ dead ends (Barrington-Leigh and Millard-Ball, 2015); this transformation has also been associated with organic growth characterised by mainly $k_3$ and $k_1$ connections (Masucci et al., 2013; Strano et al., 2012).

As shown by Figure 7.3, simulated networks exhibited almost constant $\langle k \rangle$, portraying stable growth by consistent $k_3$ connection patterns. As the trajectories of ratios between link and node number were linear, their slopes and $\langle k \rangle$ remained nearly constant during the growth of simulated networks. This result may be interpreted as sharing the same trend of a nearly constant $\langle k \rangle$ with empirical organic urban road networks, which grow by consistent $k_3$ and $k_1$ connection patterns. With the consistent $k_3$ and $k_1$ growth, the simulated networks did not show changing proportions of $k_1$ and $k_4$ nodes, which might cause $\langle k \rangle$ to increase or decrease.

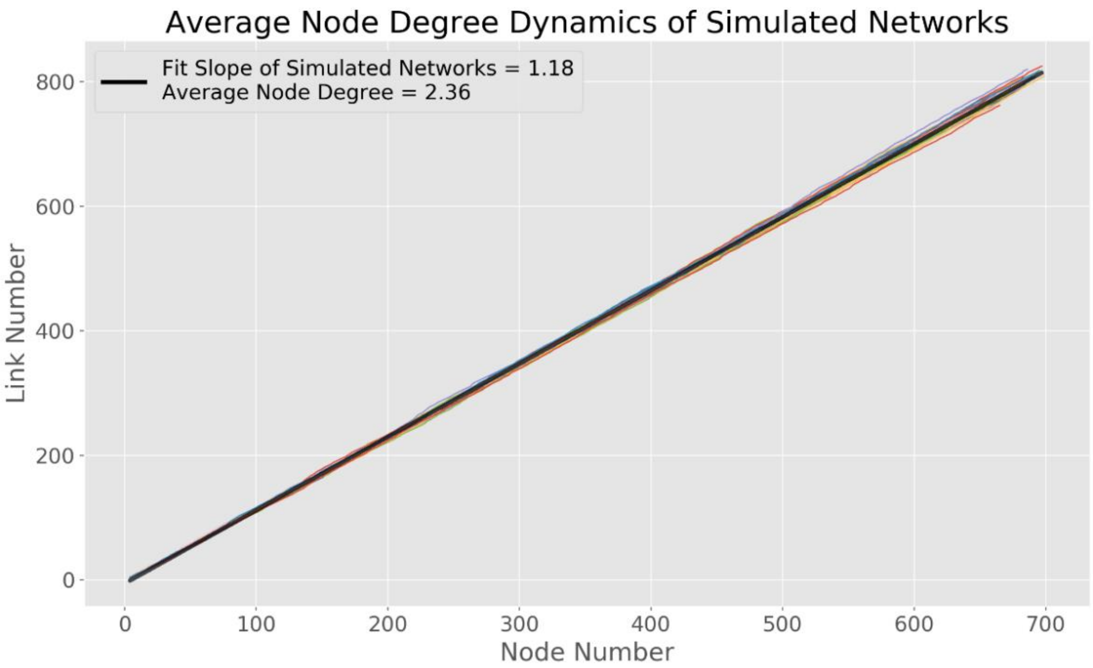



**Figure 7.3 Average Node Degree Dynamics of Simulated Networks**: This plot shows dynamics of the ratio between node and link number of 30 simulated networks. The x-axis represents the increase of node number with the growth of simulated network; the y-axis represents the increase of link number. The link/node ratio dynamics of each simulated network was plotted by a line of different colour; 30 ratio dynamics were plotted together. The data of all 30 simulated networks were fitted by a line, which had slope of 1.18; thus, the average node degree $\langle k \rangle$ of all simulated networks was 2.36.

### 7.2.5 Node Characteristics Summary

2.3.2.3 specified the following research questions based on gaps identified in the empirical RNE research:

- How do $k_3$ and $k_4$ emerge? What RNE mechanism does this reflect? Do $k_3$ and $k_4$ relate to unplanned and planned growth? How do different $\langle k \rangle$ dynamics emerge, namely why does $\langle k \rangle$ increase, decrease, or remain constant with time? What RNE mechanism does this reflect?The simulated network grew by consistent $k_3$ and $k_1$ connection patterns, which led to node degree distribution with a majority of $k_3$ nodes, many $k_1$ nodes and few $k_4$ nodes. In this growth process, $\langle k \rangle$ remained almost constant.

$k_3$ and $k_4$ nodes could both emerge under the proposed Link Connection mechanism, which examined the local proximity relationship between new spatial locations and the existing road network. Meanwhile, $\mathrm{k}_3$ nodes emerged under random new node locations while $\mathrm{k}_4$ required predetermined grid node distribution. Without predetermined grid distribution, $k_4$ node proportion that agreed with empirical planned urban road networks would not emerge under the proposed Link Connection mechanism. Therefore, it was reasonable to associate $k_4$ nodes with the central planning of grid layout and $k_3$ nodes with self-organised urban growth.

Simulated network structures' majority of $k_3$ nodes as in empirical findings but lower $k_4$ proportion than the planned networks suggest real-world urban road networks lie between planned grid layouts and not-centrally-planned self-organised growth patterns. Central planning and self-organisation coexist in the evolution of urban road networks. Simulated networks' node degree proportion agreed with previous GNMs, suggesting GNM's generative mechanism may model elementary connection patterns of self-organised urban road networks.

$\langle k \rangle$ dynamics are likely to depend on elementary connection patterns by which the network grows. When the network grows by consistent connection patterns, e.g. $k_3$ nodes in the simulation, $\langle k \rangle$ is likely to remain constant. When network grows by increased planned grid connection patterns, $\langle k \rangle$ is likely to increase with increased $k_4$ nodes. When network grows by increased $k_1$ connection patterns, such as in urban sprawl, $\langle k \rangle$ is likely to decrease. Empirical findings of increase, constant, and decrease $\langle k \rangle$ are likely to relate to the proportion of different elementary network connection patterns.

## 7.3 Link Characteristics

### 7.3.1 Static Link Length Distribution

Link length $\mathrm{l}$ of the simulated networks exhibited right-skewed distributions with a majority peak of short to medium length links and a heavy tail of long links. Figure 7.4 plots 30 simulated networks' $\mathrm{l}$ distribution histograms side by side; simulated networks' $\mathrm{l}$ distributions displayed the same overall shape, showing the consistent generic structure of simulated networks.

Empirical research reviewed in 2.3.3.1 has reported inconsistent findings regarding real urban road networks' $\mathrm{l}$ distribution among a few heavy-tailed distributions, e.g. lognormal, power-law, and exponential. As pointed out in 2.3.3.2, empirical research has focused on the debate of different probability distributions, with limited consideration of the mechanism behind the generation of each observed probability distribution. Addressing this identified limitation, Figure 7.4 fits simulated networks' link length data with three different probability density functions, which were normal, lognormal and power-law distributions.

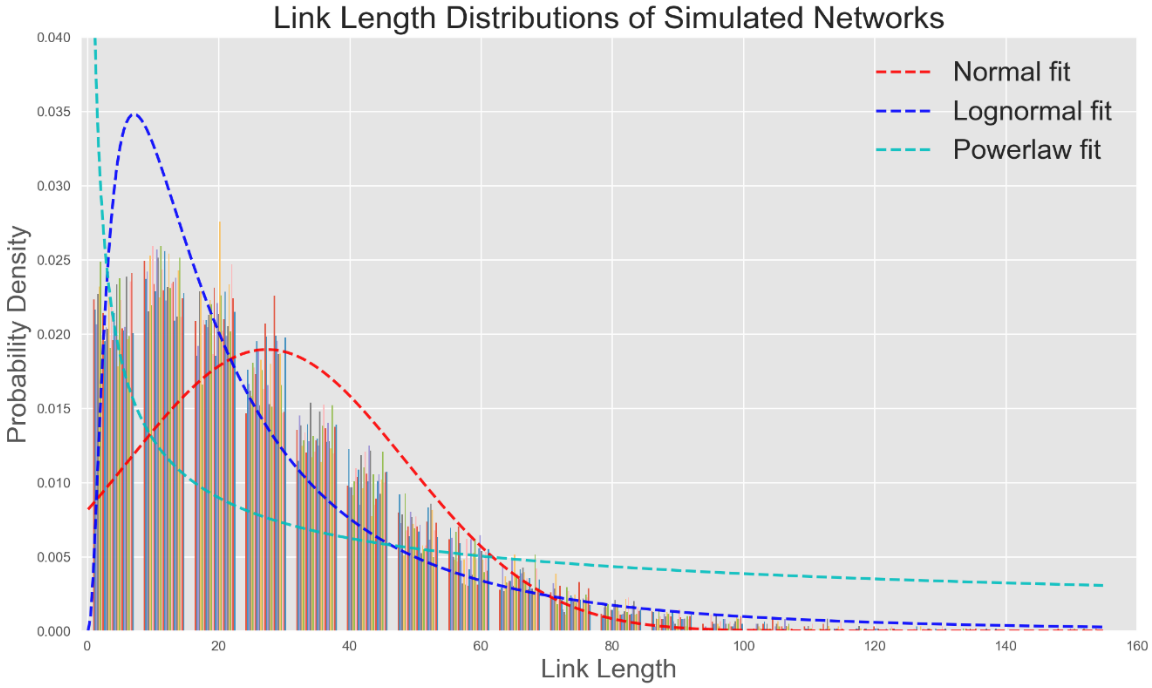



**Figure 7.4 Link Length $l$ Distributions of Simulated Networks**: This plot shows 30 simulated networks link length $l$ distributions. The x-axis represents link length; the y-axis represents probability density. The histogram shows 30 simulated network's $l$ distribution histograms side by side; each bin consists of 30 coloured lines; each line represents one simulated network' values falling in this bin's range. Three probability density function fit curves are used to fit simulated networks' $l$ distribution, which are normal, lognormal and power-law respectively.

Compared to the empirical lognormal and power-law findings, simulated networks' l distributions lay between normal and lognormal. The head of l distributions, namely the majority of link length which were short to medium, was less than that of a lognormal distribution, as shown by the space between the lognormal fit curve and the histograms. At the same time, it was more than that of a normal distribution, as shown by the excess of small link length values above the normal fit curve. The tail of simulation networks' l distributions fit better the lognormal distribution, which described the existence of a small number of very long links. The power-law distribution, as reported in some empirical research, did not fit simulated networks' l distribution. As seen in Figure 7.4, the head of the power-law fit curve overfit the very short link length instead of capturing the majority of medium to short link length peak, and the tail overfit the small number of long links.

Simulated networks' l distribution resulted from simulated network dynamics. As reviewed in 2.3.3.2.1, lognormal and normal distributions have been distinguished by their generation processes: the former results from a multiplicative process while the latter results from an additive process. A random variable following the lognormal distribution is a product of multiplicative changes in which change of the random variable to a later state are proportionate to the random variable at the previous state, while a random variable following the normal distribution results from additive changes. In the context of simulated networks, some network links resulted from a multiplicative process - the iterative division of earlier longer links. In the early stage of simulated network dynamics, long links were formed as the simulation area was empty. As simulated networks grew and simulation area's density increased, new links intersected these long links, resulting in the split of these long links into shorter links. In this process, the change of link length was proportionate to the original long links' length. Thus, network links resulted from such splitting process could be seen as the product of a multiplicative link splitting process.

Meanwhile, this multiplicative process was not the only process that generated simulated network links. New links also connected to the simulated network at network nodes without intersecting existing network links. This additive process alone would lead to a normal distribution. Together, normal and lognormal distributions corresponding to multiplicative and additive link generation processes constituted simulated networks' $l$ distribution.

This association of simulated networks' link length distribution with its generation process may explain the inconsistency in empirical link length distributions. Differences of the observed real-world link length distributions may reflect the difference in their formation processes, such as the multiplicative splitting process of early long links into later shorter links and the additive process of random length links. Thus, the different reported $l$ distributions may have characterised different network dynamics processes.

Compared to the simulated networks, empirical $l$ distribution has not reported normal distribution characteristics. This result may be explained by the proposed model's Node Addition design, which positioned new nodes at random locations on the simulation area. New links of random length were sometimes added when adding nodes at random locations, these new links of random length were generated by the additive process that led to the normal distribution. This result may further relate to the planned versus self-organised network structures, as discussed in 7.2. Real urban road networks under central planning are unlikely to add road segments of random length. New road segments that intersect two parallel existing roads perpendicularly are likely to have the same length; very short links that presented in the simulated networks are unlikely to be constructed. This formation process enabled real urban road network $l$ distributions to be better modelled by the multiplicative process, as new links' length are likely to be proportionate to existing links, which may have enhanced the empirical lognormal $l$ distribution fit.

### 7.3.2 Dynamic Link Length Distribution

Figure 7.5 shows one simulated network's l distribution dynamics with network growth, demonstrating in changes of the simulated network's l distribution among six time steps.

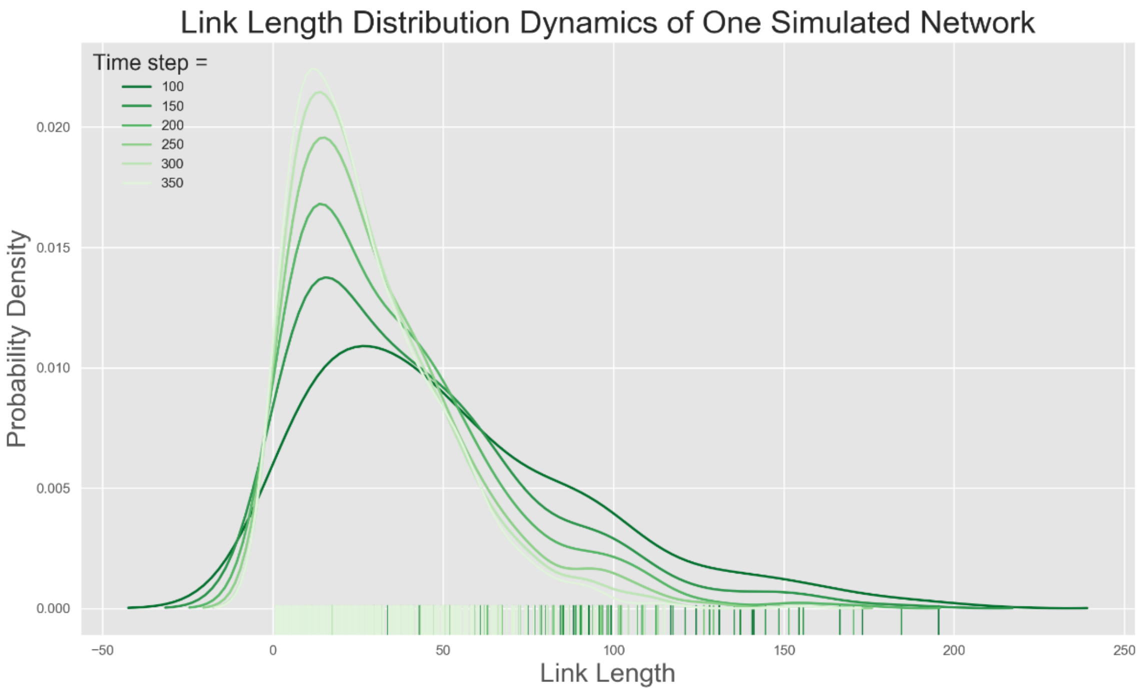



**Figure 7.5 Link Length $l$ Distribution Dynamics of One Simulated Network**: This plot shows the link length $l$ distribution dynamics of one simulated network. The x-axis represents link length; the y-axis represents probability density. Simulated network's estimated $l$ distributions at six time steps $t = 100, 150, 200, 250, 300, 350$ are drawn to indicate the trend of $l$ distribution dynamics. Raw link length data are drawn as vertical strokes along the x-axis.

As the simulated network grew, the shape of l distribution persisted; the peak of the distribution concentrated and shifted slightly to the left; in other words, new links added as the networks grew were mostly short around the peak value, increasing the peak of l distribution. At the same time, the range of l decreased; long links formed in earlier stages of network dynamics were divided into shorter segments when intersected by new links. The empirical findings reviewed 2.3.4.4 reported a concentrating peak as well, but without the peak shifting to smaller values and the decreasing range of link length. This result suggests the multiplicative process that led to the empirical lognormal l distribution may differ from the multiplicative splitting process in simulated networks' dynamics. The long roads may be treated as the same entity when intersected by new links and divided into segments; new short links with length proportionate to the existing links may be added; new long roads may also be added, such as highways and belt roads despite the increasing spatial density, maintaining the lognormal distribution.

### 7.3.3 Link Characteristics Summary

2.3.3.2 specified the following research questions based on gaps identified in empirical RNE research regarding urban road networks' link characteristics.

- How does the lognormal $l$ distribution emerge? Does it result from the link composition of few extremely short and long links, many medium links and abundant short links? What RNE mechanism does this reflect?
- Does $l$ persist in following the lognormal distribution, and how does this distribution change as the network grows? How do new links influence $l$'s distribution, and what RNE mechanism does it reflect?

Simulated networks had a majority of small to medium length links and a small number of very long links, which exhibited combined lognormal and normal link length l distribution. As the network grew, the $l$ distribution maintained the overall shape with its peak concentrating, with the increase of short length links around the peak value. Simulated networks' $l$ distribution and dynamics shared empirical urban road networks' characteristics. Simulation suggests l distribution is likely to reflect urban road networks' formation process and characterise the network dynamics, which may explain the inconsistency in empirical findings over the heavy-tailed distributions. Lognormal distribution is likely to be associated with a multiplicative splitting process. In the simulated network dynamics, long links formed at the early stage of network dynamics; as the network grew, long links split into shorter links, and the changes were proportionate to the original long link length; this multiplicative process led to the lognormal characteristic of simulated networks' l distribution. New links of random length were also added and gave rise to the normal characteristic of simulated networks' l distribution.

Simulated link length characteristic and dynamics suggest a general RNE process, in which long links form at the early stage of network dynamics and persist; most new links added afterwards are short links and have a proportionate length to existing links. The proposed model is shown to be capable of giving rise to link length characteristics observed in real-world urban road networks. Rather than debating over different link length distributions, the simulation provided access to explore the formation processes of these distributions, establishing the relationship between the proposed generative mechanism and the simulated network structures. The enabled observation of continuous network dynamics process pictured the elementary network growth process and how the proposed generative mechanism directed elementary network dynamics. In comparison, empirical research only inferred the RNE process from discrete observations of individual urban road networks.

Modelling and simulation improved the understanding of empirical findings and their inconsistency.

## 7.4 Block Characteristics

### 7.4.1 Static Block Area Distribution

Figure 7.6 plots 30 simulated networks block area distribution histograms side by side and fitted normal, lognormal and power-law probability density functions. The block area distribution $\mathrm{P(A)}$ of simulated networks exhibited heavy-tailed right skewness, with probability decreasing the block area increased. The 30 simulated networks exhibited the same overall shape of $\mathrm{P(A)}$, showing the consistent generic structure of simulated networks.

The overall shape of simulated networks' $\mathrm{P(A)}$ fit better the lognormal and power-law distributions. Lognormal and power-law distributions captured better the heavy tail of $\mathrm{P(A)}$, namely the small number of large area blocks. As shown in the inset plot of Figure 7.6, normal distribution did not describe the presence of the small number of large block areas. Between lognormal and power-law distributions, lognormal distribution described most of the large values but not all, while power-law distribution described almost all large values but had an overfitting tendency. The heavy tail of $\mathrm{P(A)}$ showed lognormal or power-law distributions and could not be captured by the normal distribution. The head of $\mathrm{P(A)}$ deviated from that of a lognormal or power-law distribution, as both these distributions over-described the number of smallest blocks. Between the two, lognormal distribution fit better than power-law distribution. The distribution of small area blocks indicated the presence of a normal distribution regime which fit the small to medium area blocks.

Empirical research reviewed in 2.3.4.1 has reported inconsistent $\mathrm{P(A)}$ findings between lognormal and power-law distributions. Simulation results may improve the understanding regarding the emergence of this inconsistency in empirical findings. Like with the link length distribution, differences of generation processes and mechanisms may explain the different block area distributions. Both lognormal and power-law distributions have been explained as resulting from multiplicative processes, as reviewed in 2.3.3.2.1. In the context of urban road networks, large area blocks formed in the early stage of network dynamics are likely to be divided into small area blocks continuously, and the change of block areas was proportionate to the area of the initial block. Such a multiplicative division process may lead to the heavy tail of $\mathrm{P(A)}$. On the other hand, because of the random new node positioning in Node Addition, blocks of random size were added as well, hence the additive change which formed the normal distribution characteristic in the head of $P(A)$.

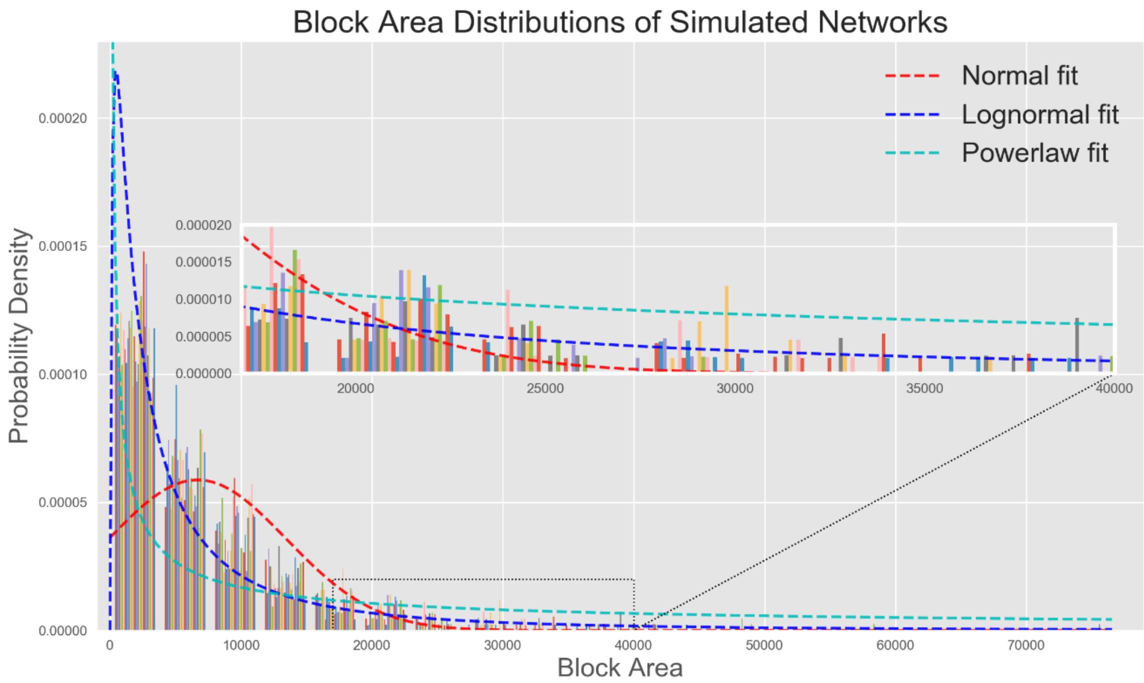



**Figure 7.6 Block Area $A$ Distributions of Simulated Networks**: This plot shows 30 simulated networks block area $P(A)$ distributions. The x-axis represents block area; the y-axis represents probability density. The histogram shows 30 simulated network's $P(A)$ histograms side by side; each bin consists of 30 coloured lines; each line represents one simulated network' values falling in this bin's range. Three probability density function fit curves are drawn over the histograms, which are normal, lognormal and power-law fit of all the link length data respectively.

In summary, block area distribution $P(A)$ of the simulated networks exhibited normal, lognormal and power-law characteristics, which resulted from both multiplicative and additive changing processes. The heavy tail of $P(A)$ suggests an iterative spatial division process as an urban road network develops.

### 7.4.2 Dynamic Block Area Distribution

Figure 7.7 shows simulated networks' block area distribution $P(A)$ dynamics, demonstrating by changes of one simulated network's $P(A)$ with six time steps. Simulated networks' $P(A)$ dynamics supported the inferrence made from static $P(A)$ distribution that the simulated network dynamics could be charactetised as a multiplicative process because of the iterative space division. As simulated networks grew, the peak of $P(A)$ concentrated and shifted to the left. These changes showed that as the simulated networks grew, larger blocks formed at an earlier stage of network dynamics were divided into smaller ones, which increased the number of small blocks that formed the peak and decreased the number of medium to large blocks towards the tail.

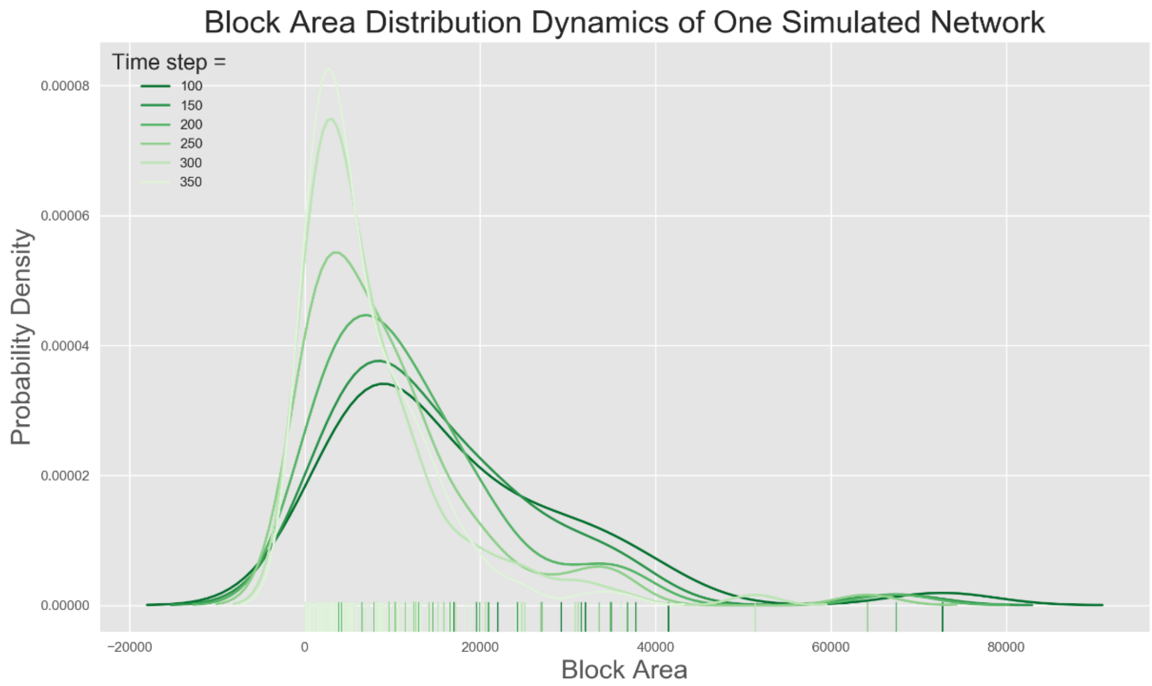



**Figure 7.7 Block Area $A$ Distribution Dynamics of One Simulated Network**: This plot shows the block area distribution $\mathrm{P(A)}$ dynamics of one simulated network. The x-axis represents block area $\mathrm{A}$; the y-axis represents probability density. This simulated network's estimated $\mathrm{P(A)}$ at six time steps $t = 100, 150, 200, 250, 300, 350$ are drawn to indicate the trend of $\mathrm{P(A)}$ dynamics. Raw block area data are drawn as vertical strokes along the x-axis.

Empirical findings reviewed in 2.3.4.2 reported different $\mathrm{P(A)}$ dynamics. $\mathrm{P(A)}$ of the London road network, which has been reported to follow a lognormal distribution, exhibited a decreasing and right shifted peak, in contrast to simulated networks. This empirical finding meant that the area of most blocks in the London road network increased rather than decreased, which may result from the network expansion. As the London road network expanded, new blocks formed on the newly urbanised area were larger than most of the existing blocks. The changing process of blocks may still be viewed as multiplicative, with the newly added blocks having size proportionate to the existing blocks; thus, $\mathrm{P(A)}$ of London kept following the lognormal distribution. On the other hand, the Groane road network, which has been reported to follow a power-law distribution, showed an increasing power-law exponent as the network developed. This empirical finding suggests the Groane network did not expand as the London road network and experienced space division which divided medium to large blocks into smaller ones and caused the power-law exponent to increase.

Comparing empirical and simulated networks' $P(A)$ dynamics suggested diverse potential changing processes in real-world urban road network dynamics, other than the space division. For example, whether the studied road network expands during the studied period may lead to different results. Still, block area dynamics may be perceived as multiplicative processes, with changes of block area proportionate to existing blocks.

### 7.4.3 Block Characteristics Summary

2.3.4.3 specified the following research questions based on gaps identified in empirical RNE research regarding urban road networks' block characteristics.

- What leads to the emergence of lognormal or power-law $P(A)$ distributions in the road network? Is one of them more suitable to describe $P(A)$ and what RNE mechanism does this reflect?
- How does $P(A)$ change as the road network grows; does it persist in following a lognormal or power-law distribution, and how do the characteristics of the distributions change? What RNE mechanism does this reflect?

The simulated networks' block area distribution $P(A)$ was right-skewed with a heavy tail and probability decreasing as the block area increased. The heavy tail may suggest lognormal or power-law distributions, which are likely to result from multiplicative processes such as continuous spatial division of larger blocks into smaller ones. Because of the random design in Node Addition, simulated networks' $P(A)$ also exhibited normal distribution characteristics in small to medium size blocks, which resulted from an additive changing process like the addition of random size blocks. Lognormal and power-law distributions may both capture the heavy tail of $P(A)$, with lognormal distribution fit better the simulated networks' overall block area distribution. Compared to the simulated networks, real-world urban road networks are likely to experience various multiplicative process other than the spatial division; the areas of added new blocks are likely proportional to existing blocks, enforcing the lognormal or power-law distribution. Whether road network expands during studied period is likely to influence the conclusion of $P(A)$ dynamics; expanding road networks may add blocks larger than most of the existing ones while non-expanding road networks may change by increasing level of spatial division.

## 7.5 Betweenness Centrality Characteristics

### 7.5.1 Static Betweenness Centrality Characteristics

2.4.1 reviewed that centrality has been a key topic in urban road network studies, aiming at understanding the spatial locations more important than others. Among many centrality measures, Betweenness Centrality (BC) has found the most meaningful application in revealing the urban road network structure. Empirical research on urban road network BC have found the concentration of BC on a small number of network components and interpreted this finding as the hierarchy of urban road network. Meanwhile, there have been disagreements regarding the BC distribution over several heavy-tailed distributions, such as exponential, power-law. Recent empirical research on a large number of global urban road networks has reported urban road networks' BC followed a bimodal distribution, which separated around the BC value equalled to the number of network nodes, into high BC components from an underlying tree structure and low BC components forming alternative loop paths. This bimodal BC distribution has been regarded as a planar network property; it was not influenced topologically by local rewiring or geometrically by edge weight changes and was only influenced by network density – the ratio of network edge number against completely connected networks. With the network density increasing from minimally connected to maximally connected, the bimodal BC distribution emerged as alternative loop paths formed beyond a tree structure; and the spatial correlation of high BC components increased, leading to the concentration of BC near the barycentre of the network.

Figure 7.8 shows the simulated networks' link BC distribution and spatial distribution. The left and right subplots draw the same BC distribution. The left subplot draws simulated networks' BC distribution using histogram with logarithmic binning; the bin sizes increase exponentially. The right subplot first applies a logarithmic transformation to the link BC values, then plots the distributions using the histogram on the linear scale with fitted probability density curves. The 30 simulated networks displayed the same overall probability distribution, demonstrating the consistent generic structure of simulated networks.

Simulated networks' BC distribution was right-skewed with a heavy tail; most of the network links had low BC values, and a small number of links had very large BC. The simulated networks' BC distribution displayed characteristics of a bimodal distribution, with two modes separated by the peak, as shown in the left subplot. The two modes separated at BC value around the number of nodes, into high and low BC components, in agreement with the empirical finding.

The right subplot captures two well-defined peaks after the log-transformation of link BC values; the left peak corresponded with the separation of low and high BC values around the number of nodes, the right peak captured the logarithmic mode of high BC values in simulated networks centring around $10^4$. The high BC links made up on average 59.5% of the total link BC while the small BC links made up on average

2.3% in the simulated networks. The inset plot visualises the two identified peaks: links with BC values smaller than the left peak value - the number of nodes $\mathrm{BC} < |\mathrm{V}|$ were coloured in red while links with $\mathrm{BC} > 10^4$ – the right peak value was coloured in black. Empirical research has associated the high BC components with an underlying spanning tree structure and low BC components with loops in the real-world urban road network. The two peaks identified in simulated networks did not conform to tree and loop structure exactly; however, the high BC links with $\mathrm{BC} > 10^4$ captured the major routes in the network around the geographical centre while the low BC links corresponded to links of minor significance such as the dead-ends.

The agreement of simulated networks' bimodal BC distribution characteristics with the empirical findings suggests the possibility of BC distribution as a planar network property, consisting of high and low BC components which may be identified quantitatively. Besides the quantitative separation of high and low BC around the number of network nodes that agreed with the empirical findings, simulation results further identified two modes of simulated networks' BC distribution after logarithmic transformation of BC values, revealing characteristics of high and low BC distributions respectively.

At the same time, there were differences between the simulated networks' BC characteristics and empirical findings. The number of small BC components in the simulated networks was less than that of the real urban road networks, as shown in the head of BC distribution; and the number of very large BC components was less than that of the real urban road networks as well, as shown in the trail of BC distribution. This result suggests the difference between low and high BC values is smaller in the simulated networks than in the real urban road networks, indicating a lower level of hierarchy difference. Also, the high BC components did not precisely correspond to an underlying tree structure, and neither did low BC components to loops. These disagreements are likely to result from the Node Addition design, which added new nodes to random locations of the simulation area. In the studied empirical urban road networks, new network nodes and links are likely to correlate spatially, such as in high density central urban areas, resulting in increased concentration of BC and the deepened hierarchy. Nevertheless, this model design did not interfere with the emergence of the bimodal BC distribution, supporting the hypothesis of BC distribution as a property shared by planar networks.

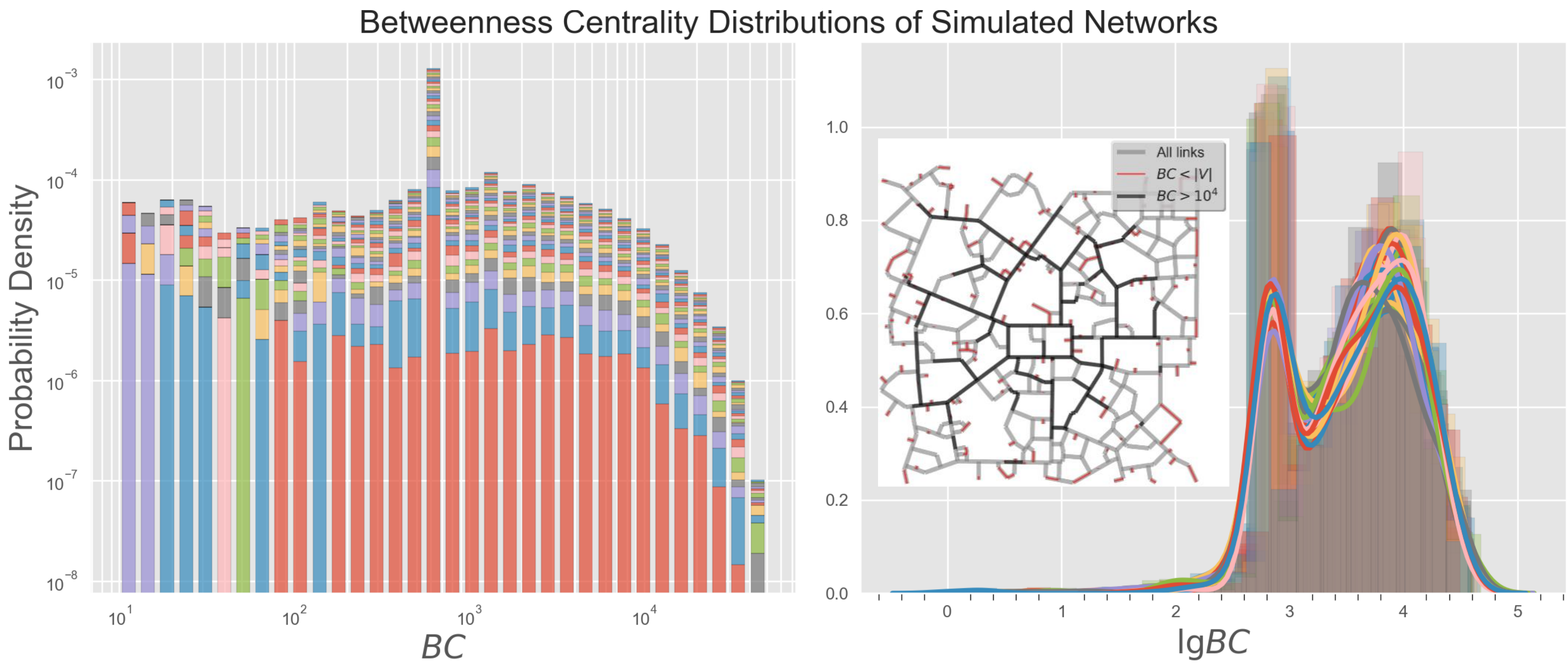



**Figure 7.8 Betweenness Centrality Distributions of Simulated Networks**: The left and right subplots draw the same link BC distribution of 30 simulated networks. The left subplot draws the distribution using histogram with logarithmic binning; the x-axis represents BC values, the y-axis represents probability density, both axes are on the logarithmic scale; thus, the bins are not of an equal size but increase exponentially at the base of 10. The right subplot first applies logarithmic transformation to the BC values, then draws the BC distribution using histogram; the x-axis represents logarithms of BC values at the base of 10, the y-axis represents probability density, both axes are on the linear scale. The inset plot of the right subplot visualises the two identified peaks in one simulated network; network links with BC values smaller than the left peak are coloured in red, while links with BC larger than $10^4$ are coloured in black. The peak in the left subplot correspond to the left peak of the right subplot, both centring around the BC value that equals to the number of network nodes.

### 7.5.2 Dynamic Betweenness Centrality Characteristics

Looking into the BC distribution dynamics, Figure 7.9 normalises simulated networks' BC values by $\frac{1}{(|V|-1)(|V|-2)}$, $|V|$ was the number of nodes. The main and inset plots draw the same BC distribution dynamics of one simulated network; the main plot draws BC distribution histograms and probability density estimations at six time steps on linear scales; the inset plot first applies a logarithmic transformation on BC values, then draws probability density estimations on the linear scales.

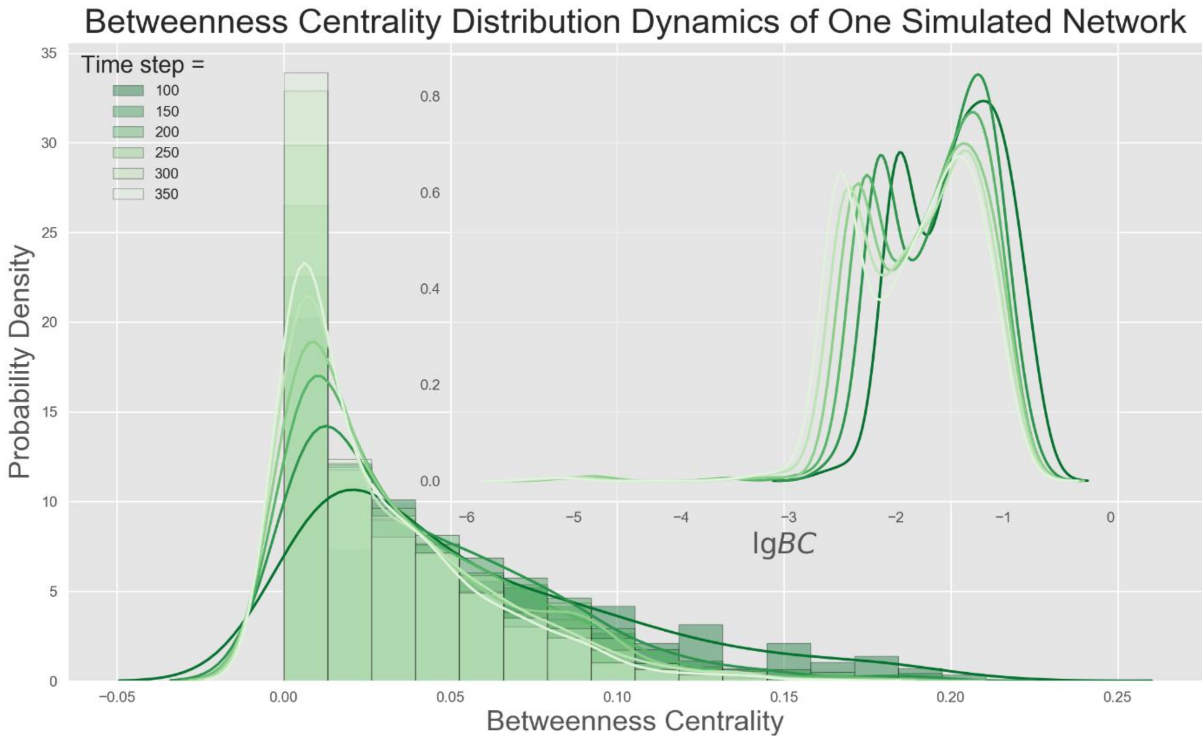



**Figure 7.9 Betweenness Centrality Dynamics of One Simulated Network**: The main and inset plots draw the same BC distribution dynamics of one simulated network at six time steps $t = 100, 150, 200, 250, 300, 350$. The main plot draws BC distribution histograms and probability density estimations on linear scales; the x-axis represents BC values; the y-axis represents probability density. The inset plot first applies logarithmic transformation on BC values, then draws probability density estimations on the linear scales; the x-axis represents $\log BC$, the y-axis represents probability density.

Empirical findings, as reviewed in 2.4.2, have reported stable BC distribution in real urban road networks. The BC distribution has been regarded as determined by network density $\rho_e = \frac{|E|}{E_{DT}}$ – the ratio between the number of links in a network and that of the Delaunay triangulation realised on the network nodes; $\rho_e$ of real urban road networks has shown a small value range between $[0.4{,}0.6]$ and have not exhibited significant variations with time because of planar constraint and stable connectivity. In the example of the Paris road network, as $\rho_e$ has been reported to remain stable in the last two hundred years, without changes of the BC distribution.

BC distribution maintained an overall shape as simulated network grow: on the linear scale as in the main plot, the BC distribution remained right-skewed with most of the network links having small BC and a small number of links having very large BC; in the inset plot, the logarithmic BC distribution displayed the bimodal characteristics throughout the network dynamics. As discussed in 7.1 about node characteristics, simulated networks' degree distribution and average degree remained stable along with the network growth because of stable new node connection patterns, $\rho_e$ of the simulated networks remained around $0.4$ along with the network dynamics. In disagreement with the empirical findings, the BC distribution of simulated networks did not remain precisely the same but decreased as a whole as the network grew. This result was shown in the increasing peak of small BC values and the decreasing BC range in the main plot, as well as the left shift of BC distributions in the inset. This disagreement may result from different scaling methods applied in empirical research. Nevertheless, simulated networks showed persistent bimodal characteristics throughout the network dynamics, suggesting a stable network BC structure with the high and low BC component separation.

### 7.5.3 The Backbone of Urban Road Networks

The Backbone of urban road networks has been used to refer to an empirical RNE phenomenon that the most critical roads in an urban road network persisted through time, which associated roads' age with their BC, as reviewed in 2.4.3.

Figure 7.10 and Figure 7.11 demonstrate the relationship between simulated networks' link age and BC. In the left plot of each upper panel, links were divided into five equal age groups since the beginning to the end of the simulation. Links were coloured according to their age group: the red links were oldest in the network and then yellow, green, light blue and dark blue. In the right plot of each upper panel, link BC was ranked and divided into five groups according to 20$^{th}$, 40$^{th}$, …, 100$^{th}$ BC percentiles. Links were coloured accordingly: the red links had the highest BC values, then yellow, green, light blue and dark blue. To explore initial network spatial location's influence on simulation results, simulation experiment starting from a square network - the border of the simulation area as shown in Figure 7.11 was implemented besides the default initial condition that started from a rectangle network in the geographic centre as in Figure 7.10. The lower panels of Figure 7.10 and Figure 7.11 show Link BC's cumulative probability distributions by each link age group and for 30 simulated networks starting from the two initial conditions respectively.

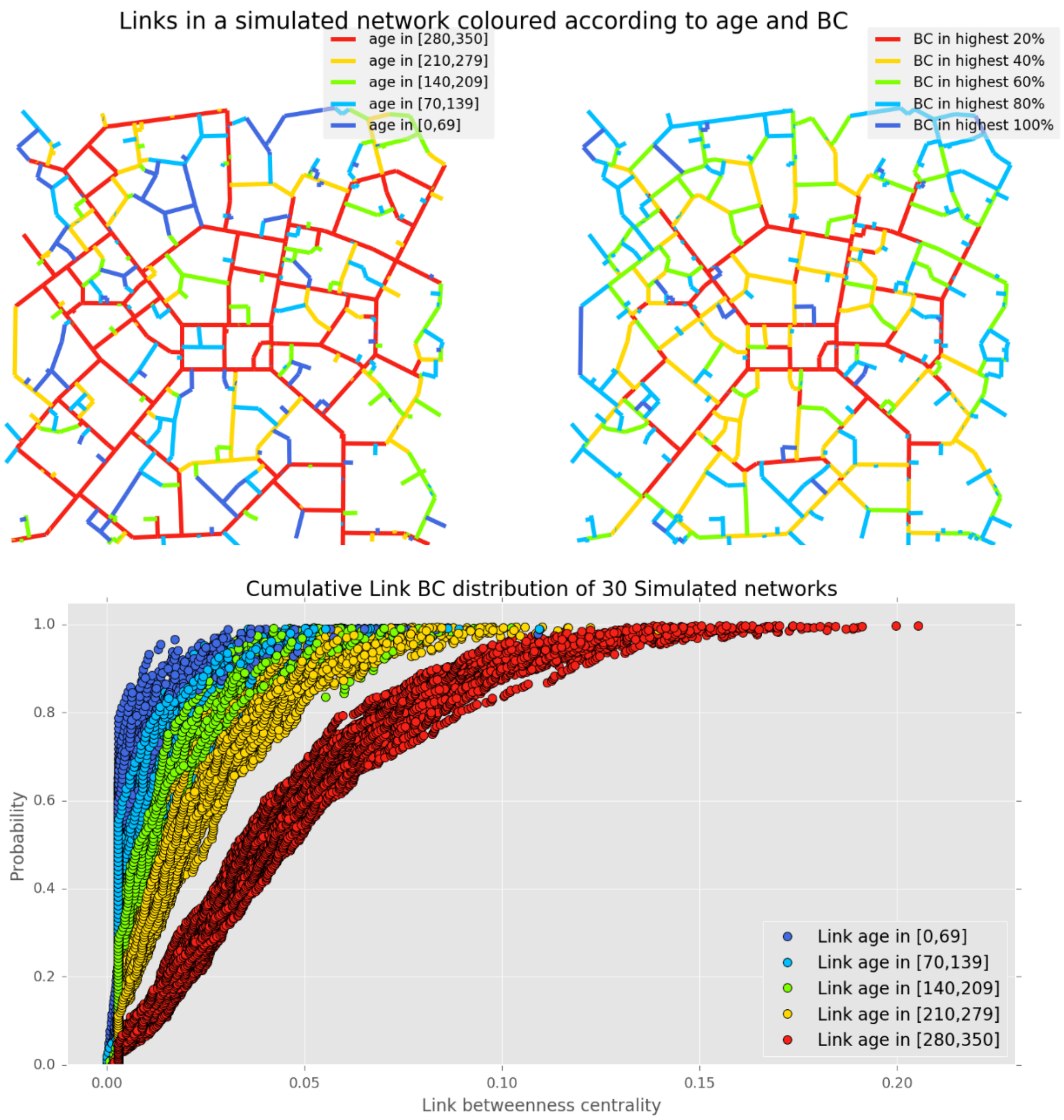



**Figure 7.10 The Backbone of Simulated Networks**: This plot demonstrates the relationship between simulated networks' link existence time and BC, for simulation experiments with initial condition - a small rectangle network at the geographical centre of the simulation area. The upper panel colours one simulated network according to link existence time and BC respectively. The left network is coloured according to links added in five equal periods since the beginning to the end of simulation: the red links are oldest in the network, and then yellow, green, light blue and dark blue. The right network is coloured according to five link BC ranks at 20th, 40th, …, 100th BC percentiles: the red links have highest BC values, then yellow, green, light blue and dark blue. The lower panel plots link BC's cumulative probability distributions by each link age group and for 30 simulated networks: the red dots are the oldest links' BC probability distribution, then yellow, green, light blue and dark blue.

The correlation between link existence time and BC were observable in both Figure 7.10 and Figure 7.11. In both simulation experiments, existence time and BC both captured important routes in the simulated networks; existence time and BC had correlations, shown in the red long-existing and high BC major paths and blue short-existing and low BC minor links. The visual association was confirmed by the BC cumulative probability distributions as shown in the lower panels: red points representing oldest links in the network had overall highest BC; BC, in general, decreased with link existence time.

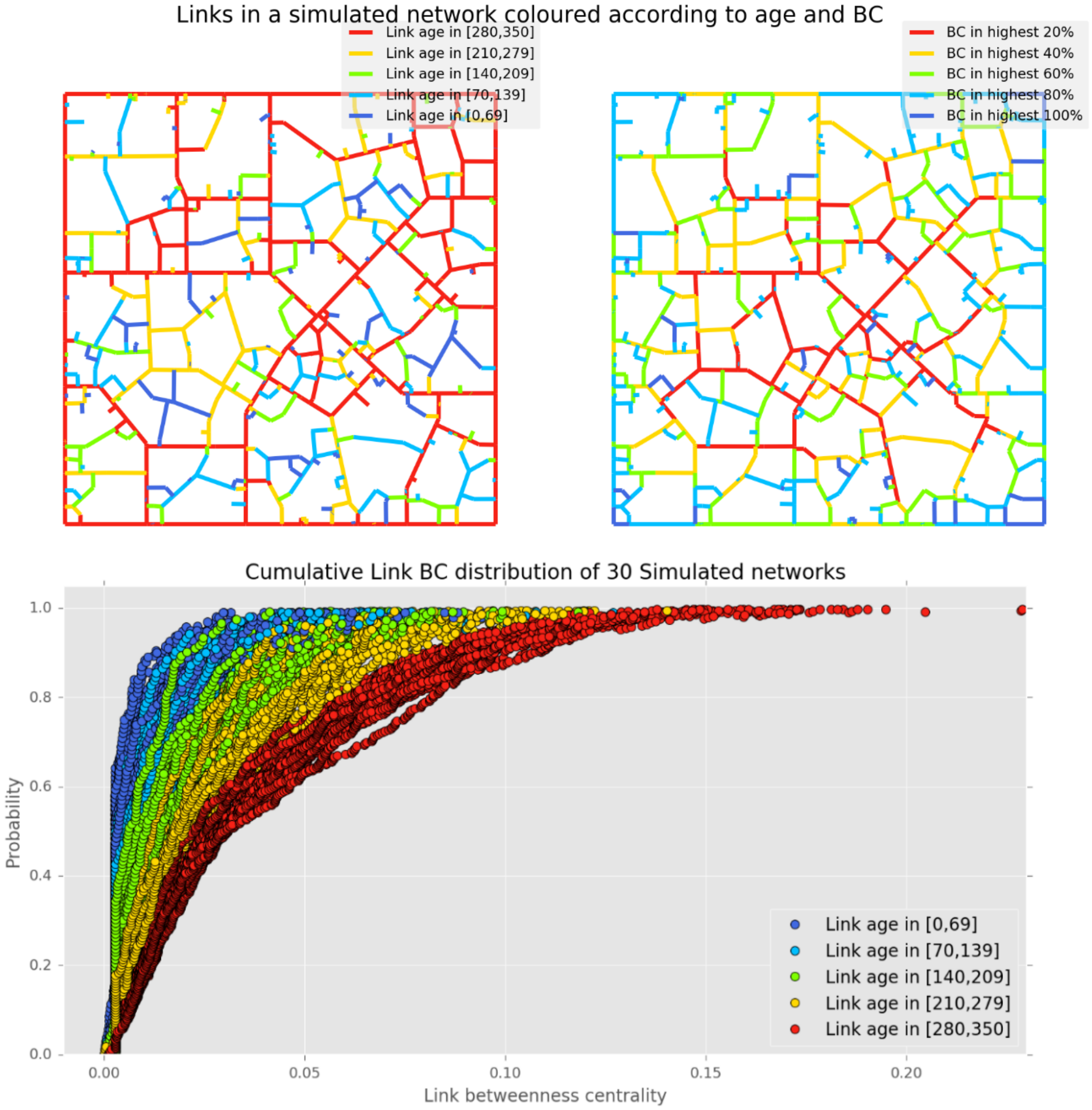



**Figure 7.11 The Backbone of Simulated Networks – Initial Network's Influence**: This plot demonstrates the relationship between simulated networks' link existence time and BC, for simulation experiments with initial condition - a large square network at the border of the simulation area. The upper panel colours one simulated network according to link existence time and BC respectively. The left network is coloured according to links added in five equal periods since the beginning to the end of simulation: the red links are oldest in the network, and then yellow, green, light blue and dark blue. The right network is coloured according to five link BC ranks at 20th, 40th, …, 100th BC percentiles: the red links have highest BC values, then yellow, green, light blue and dark blue. The lower panel plots link BC's cumulative probability distributions by each link age group and for 30 simulated networks: the red dots are the oldest links' BC probability distribution, then yellow, green, light blue and dark blue.

Initial geographical location influenced the simulation results; though both simulation experiments reached the same conclusion, the link existence time – BC correlation was stronger when network dynamics started from the small rectangle network at the geographical centre compared to the border of the simulation area. This result was shown in the visual correspondence in the upper panels of Figure 7.10 and Figure 7.11, as well as in the BC cumulative probability distributions by age groups in the lower panels. The influence of the spatial location of the initial network suggested road importance measured by BC captured road segments around the geographical centre of the urban road network. The correspondence between long-existing and high BC road segments may be explained as long-existing road segments which occurred in the early stage of road network dynamics are likely to span across the urban area given low urban density and occupy central locations as the urban area develops at the same time outwards. The empirical finding of link existence time and importance correlation is likely to identify geographically central roads which may occur in the early stage of road network formation and have high BC in the current network.

In comparison to the empirical backbone phenomenon, one difference was the smallest values of each link age group's BC. In the Groane road network, smallest BC values of the oldest link group were still larger than the rest of the links. However, in the simulated networks, though older links, in general, had larger BC, all age groups shared similar smallest BC values.

### 7.5.4 Densification and Exploration

Densification and exploration (DE) have been used to refer to two types of new links identified through examining Link BC impact $\delta_{bet}$ of new links on average network BC, as reviewed in 2.4.4. The DE phenomenon has been regarded as different new links urbanisation functions: the former bridged existing roads which densified the urban area and the other extended the existing network. The two types of new links have been reported to occur at different stages of the road network and urban development in different proportions.

Figure 7.12 shows $\delta_{bet}$ distributions of new links during 30 simulated network dynamics, divided into five equal periods. In agreement with the empirical findings, $\delta_{bet}$ distributions of the simulated networks all exhibited two peaks; these two peaks persisted throughout the simulated network dynamics. The left peak had negative values and corresponded mostly with bridging new links - densification; the right peak had positive values and corresponded mostly with dead-end new links - exploration. Along with the simulated network dynamics, two $\delta_{bet}$ peaks both moved towards $0$ and became more concentrated. This result showed that a single new link's impact on the average network *BC* decreased as network size increased. The ratio between the two groups did not show meaningful changes as in empirical findings. For instance, the right peak in Groane road network evolution eventually disappeared, indicating the exploration new links would decrease as urban road network developed into a mature stage. This disagreement suggested more sophisticated urban factors which may include urbanisation, population dynamics, design and planning paradigm shift. accounted for the ratio changes of DE in real-world urban road network dynamics, beyond topological and geometrical development of Node Addition and Link Connection. To account for such urban factors and model the following changes of urban road networks, a specific design of generative mechanism aiming at particular urban factors was required. The temporal structure of DE is further discussed in 9.2.2.

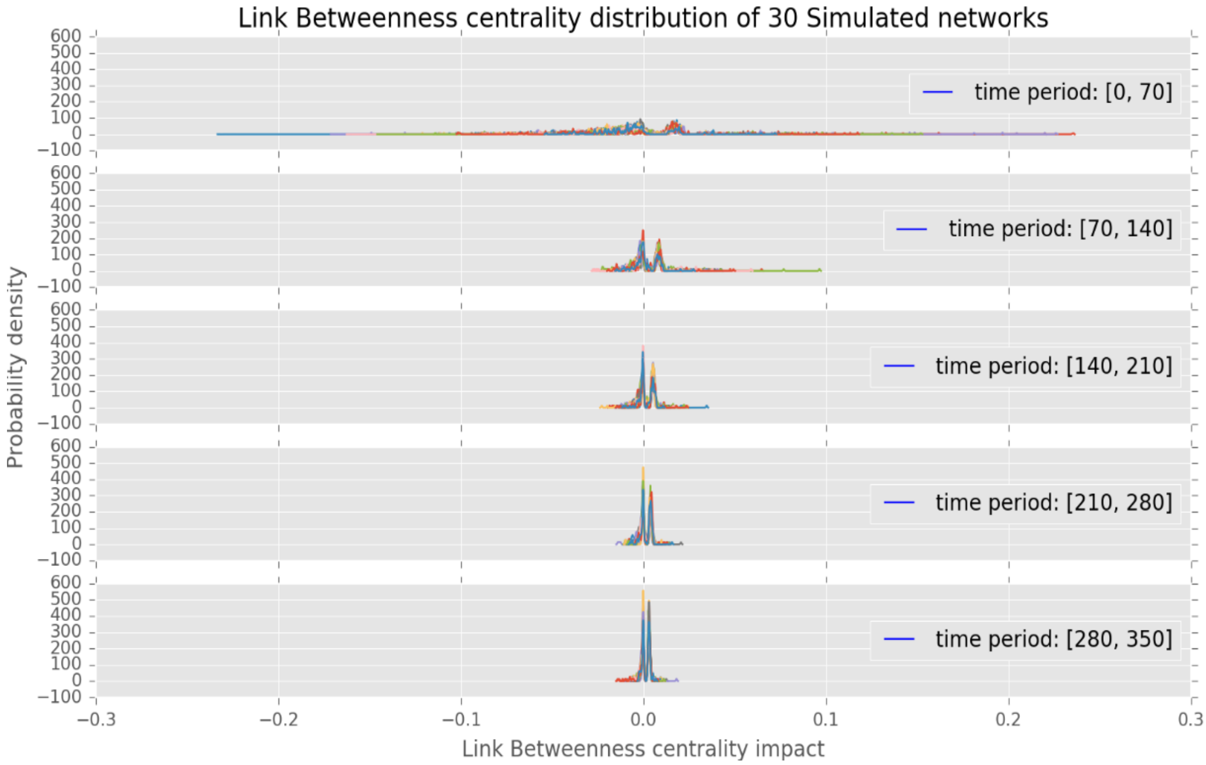



**Figure 7.12 Link Betweenness Centrality (BC) Impact $\delta_{bet}$ Dynamics of Simulated Networks**: The five panels show $\delta_{bet}$ distributions of new links during 30 simulated network dynamics, divided into five equal periods. The x-axis represents BC impacts $\delta_{bet}$; the y-axis represents probability density.

One aspect that has not been investigated in empirical RNE research was the spatial locations of DE links. Figure 7.13 demonstrated the spatial distribution of identified DE new links in one simulated network along with the simulated network dynamics: the left peak – densification links were coloured in green and the right peak – exploration links in red. Figure 7.13 clearly showed the green densification links correspond in general to new links bridging two existing links while the red exploration links correspond to dead-ends or the links next to dead-ends. The two groups did not exhibit particular spatial distribution patterns. For instance, exploration may be more frequent at the urban frontier, while densification may happen at both sparse and dense urban areas. Nevertheless, DE links' behaviours to divide and explore space were observable: the green densification links further divided larger blocks into smaller ones while the red exploration links extended the network into unoccupied space. The spatial structure of DE is further discussed in 9.2.2.

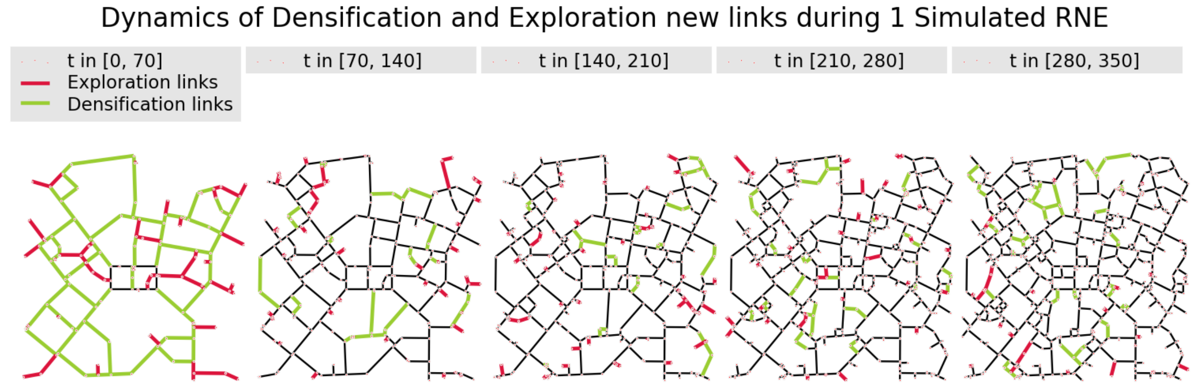



**Figure 7.13 Spatial Locations of Densification and Exploration in Simulated Networks**: The five subplots demonstrate spatial distribution of identified DE new links in one simulated network along with the simulated network dynamics, from left to right. Densification links – the left peak are coloured in green; exploration links - the right peak are coloured in red.

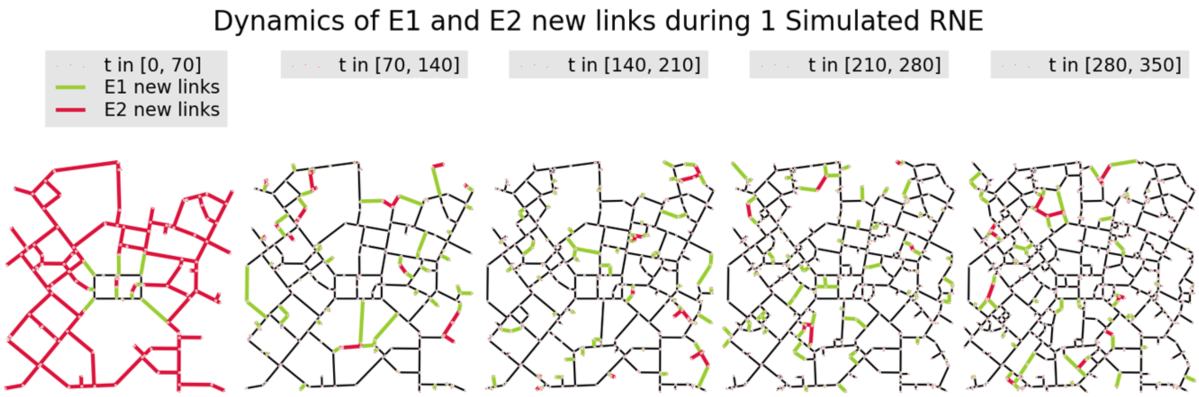



**Figure 7.14 New Link End Nodes Composition $E_i$ Dynamics of Simulated Networks**: The five subplots demonstrate spatial distribution of new links of different end nodes composition $E_i$ in one simulated network along with the simulated network dynamics, from left to right. $E_1$ meant a new link $e$ occurred in a studied period had one end node attached to new network infrastructure occurred as well in this period and the other end node to existing network infrastructure before this period. $E_1$ links are coloured in green while $E_2$ links are coloured in red.

To further explore the types of new links in the simulated networks, Figure 7.14 shows the dynamics of new link end nodes composition $E_i$ during the simulated dynamics of one simulated network. $E_i$ separated new links by the number of end nodes attached to new network infrastructure during a period. For example, $E_0$ meant a new link $e$ occurred in a studied period had no end nodes attached to new network infrastructure, i.e. both its end nodes attached to existing network infrastructure before the studied period. $E_1$ meant a new link $e$ occurred in a studied period had one end node attached to new network infrastructure occurred as well in the same period and the other end node to existing network infrastructure before this period. Two types of new links were identified in the simulated networks by $E_i$, demonstrated in Figure 7.14: $E_1$ links were coloured in green while $E_2$ links were coloured in red.

Network dynamics depicted by $E_i$ showed the network dynamics of simulated networks could be divided into two phases, beyond the DE processes. An early stage of network dynamics during which the simulated network went through large scale global changes, as shown in the majority of red $E_2$ links in the leftmost subplot and later stages of minor local changes, as shown in the majority of green $E_1$ links in the following subplots. This result showed potential spatial processes other than DE to characterise urban road network dynamics and reflected $E_i$'s capacity in detecting both global and local urbanisation. $E_i$ also identified one limitation of the proposed model, shown in the absence of $E_0$ links. New link creation of the proposed model was always initiated by the addition of new nodes in Node Addition, namely links only formed in Link Connection after the addition of a new node. When two existing roads were to be connected by a new link, real-world road networks used an $E_0$ link with two end nodes attached to two existing roads. Whereas in terms of the simulated networks, a new node had to be generated first between two existing roads, followed by two new links extending from this new node to connect the two existing roads on each side of the new node; namely, an $E_0$ link was approximated by two $E_1$ links. This design that Link Connection only followed Node Addition led to the absence of $E_0$ new links and one limitation of the simulated networks. Despite this limitation, BC impacts $\delta_{bet}$ was still capable of capturing the bridge links, each approximated by two $E_1$ links, suggesting the robustness of the DE property which is likely a topological property of planar networks.

### 7.5.5 Betweenness Centrality Characteristics Summary

2.4.5 specified the following research questions based on gaps identified in empirical RNE research regarding urban road networks' BC characteristics.

- Does BC follow bimodal distributions, consisting of high BC components from an underlying tree structure and low BC components forming alternative loop paths in the road networks? Does network density control the BC distribution? How do BC distribution emerge, and what RNE mechanism does this reflect?
- How do BC distribution change with time, and what RNE mechanism does this reflect?
- Do high BC components and the components from the underlying high BC tree structure, near the barycentre, and long existing in the road network correlate?

Do these correlations characterise the proposed RNE phenomenon - backbones of the road network? What RNE mechanism does this reflect?

- Do $\delta_{BC}(e)$ distinguishes dead-ends and bridging links? Do dead-ends and bridging links perform different functions in the road network and have different spatial and temporal characteristics? Do dead-ends and bridging links and their functions characterise the observed RNE phenomenon DE? What RNE mechanism does this reflect?

The simulated networks shared BC characteristics and dynamics with real-world urban road networks, including the bimodal BC distribution, the correlation between component existence time and BC, and the bimodal distribution of new links' impact on average network BC. These results demonstrated the plausibility of simulated network structure in modelling urban road networks and dynamics. On the other hand, this showed BC characteristics may be planar network properties, and planar networks at the network density similar to urban road networks are likely to share these BC characteristics, which explains the broad observations of these BC characteristics.

Simulated networks' BC distribution confirmed the bimodal distribution found in empirical research and the separation of high and low BC at the value equalled to the number of network nodes. This result suggested the existence of a high and low structural hierarchy of the urban road network centrality. The simulated network had not confirmed that high BC components come from an underlying tree structure in the network, and the low BC components formed the alternative loop paths. In the case of the simulated network, high BC components captured the major routes near the geographical centre of the network while low BC components were minor links such as dead-ends. Also, the simulated network had not confirmed that the BC distribution remained stable with the stable network density. Instead, BC of the whole network decreased as the network grew in size, which may be caused by a different scaling method used to calculate BC in empirical studies.

The simulated network confirmed the correlation between network components' existence time and BC; long-existing network components had high BC. In term of the simulated network, this correlation related to broader correlations between network components of high BC, near the geographical centre, and long-existing, as well as the correlations between network components of low BC, being minor links like dead-ends. This result suggested that the simulated network dynamics consisted of initial global changes and later local changes. In the initial stage of network dynamics, network spanned the simulation area and occupied the geographical centre; these network components were long-existing, near the geographical centre and had high BC. The later stages of simulated network dynamics were local changes which further divided and extended the existing network into the large blocks formed in initial network dynamics; size and location of components added at that time were restricted by spatiality and planarity and had small BC. This result also showed the planar constraint, under which new links formed after initial global changes were constrained as minor road segments.

The limitation of the simulated networks first showed in the lower level of BC hierarchy and the lack of meaningful spatial and temporal dynamics, which suggested such spatial and temporal inhomogeneous are likely to come from urban factors that were not considered by the proposed model's generative mechanism. Second, the design of iterative network generation by Node Addition followed by Link Connection lacked the consideration for the addition of new links which was not initiated by the purpose to connect new nodes. Despite the limitations, the simulated networks shared key characteristics of BC distribution and dynamics with empirical findings of real urban road networks.

## 7.6 The Effect of Proximity Relationships

As reviewed in 4.2.3 and further discussed in 5.3.1, the previous GNMs of urban road networks have not compared the Link Connection mechanism horizontally. Link Connection has been described as a process of new nodes first connecting to the nearest point, then to the RNG neighbours on the existing network. Link Connection has also been described as a process of new nodes connecting to an intersection point set of points that maintain planarity, orthogonal projections of the new node on the existing network, and RNG neighbours.

Recognising this limitation, the proposed model generalised Link Connection as examining the proximity relationship between a new spatial location and the existing road network, in which the proximity relationship was not fixed but might vary in a quantitative range. The range of proximity relationship implemented come from the family of proximity graphs - β-skeletons. To explore proximity relationship's role in forming simulated network structure and dynamics, this section examined simulated networks generated under β-skeleton proximity relationship $\beta = 1.0$, $\beta = 1.5$, and compared to simulated networks generated under $\beta = 2$ which were used in previous sections. $1.0 \leq \beta \leq 2.0$ because $\beta \leq 1.0$ led to non-planar networks and $\beta \geq 2$ led to disconnected networks. $\beta = 1.0$ equalled the proximity relationship that generated Gabriel Graph (GG); $\beta = 2.0$ equalled to the proximity relationship that generated Relative Neighbourhood Graph (RNG) and was used in previous models.

Figure 7.15 shows simulated networks and dynamics under β-skeleton proximity relationships $\beta = 1.0, 1.5, 2.0$ at time step $t = 0, 100, 200, 300$, starting from the same initial network and using the same random seed. The overall structure and dynamics of simulated networks under $\beta = 1.0, 1.5$ were similar to that of $\beta = 2.0$, which were measured by the framework of elementary network component characteristics as in previous sections. The simulated network under $\beta = 1.0$ had average node degree $\langle k \rangle = 2.78$, which was closer to empirical findings of planned urban road networks, e.g. US urban road networks $\langle k \rangle = 2.76$, than the simulated networks under $\beta = 2.0$ in previous sections.

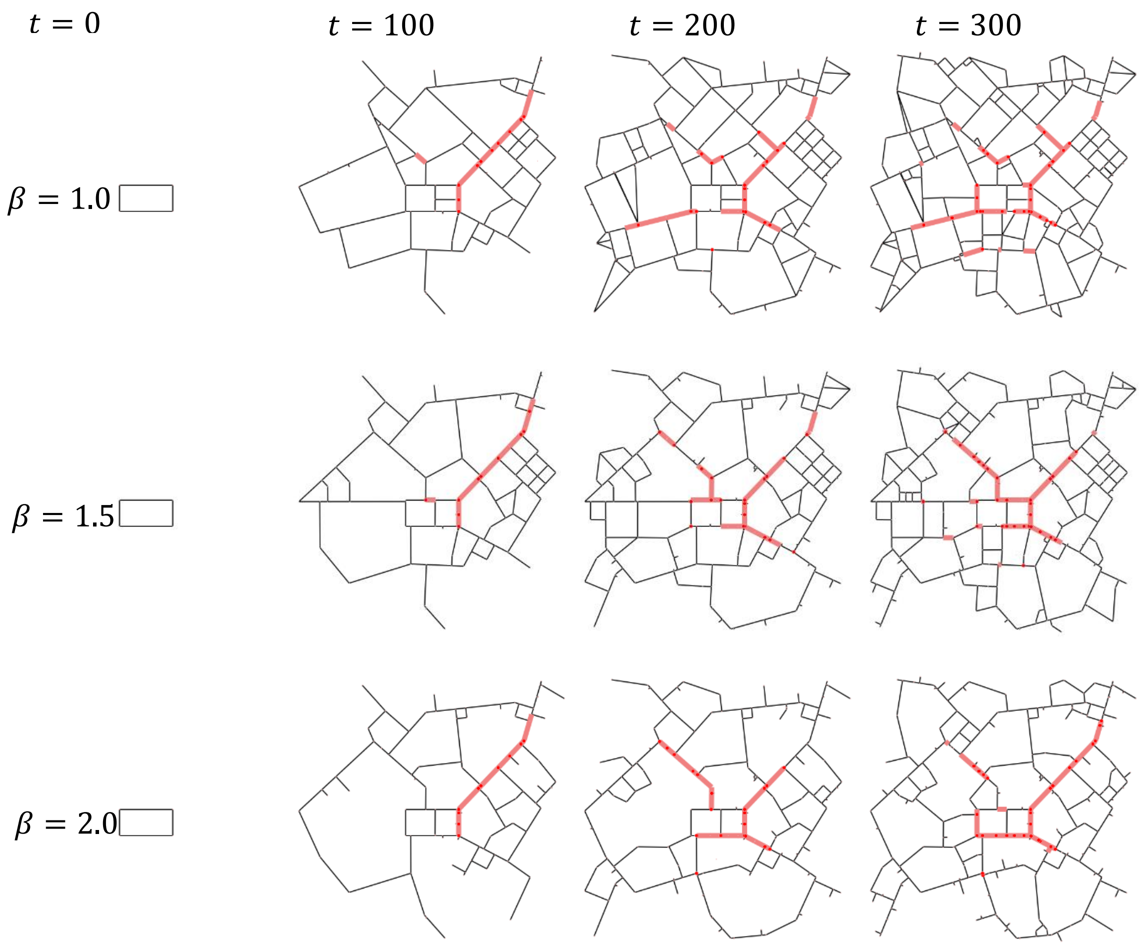



**Figure 7.15 The Effect of Proximity Relationship**: The three panels demonstrate simulated networks and dynamics under proximity relationship $\beta = 1.0,\ 1.5, 2.0$, respectively, starting from the same initial network and using the same random seed. Network dynamics are demonstrated by snapshots at time step $t = 0,\ 100, 200, 300$. Network components with the highest BC are coloured in red.

As can be observed in the simulated networks, $\beta = 1.0$ led to a higher occurrence of $k_4$ nodes and grid patterns, though still fewer than planned grid road networks. Also, new links under $\beta = 1.0$ had a larger proportion of densification links than exploration links compared to the $\beta = 2.0$ examined in 7.5.4, which was similar to real-world urban road networks; namely, the proportions of new links being dead-ends and bridge links were closer to real-world road networks (reviewed in 2.4.4). From the top to the bottom panel in Figure 7.15, with the increase of $\beta$, the network connectivity modelled by Link Connection decreased. Meanwhile, $\beta = 1.0, 1.5$ led to the occurrence of sharp angles in the simulated networks, which were limitations of these proximity relationships. These findings agreed with the finding reviewed in 4.2.2, which have compared network structures constructed by connecting the Tokyo road network nodes with β-skeleton proximity relationships and the real-world network. Constructed network structures with β-skeleton proximity relationships $\beta \in [1.0,1.5]$ had the highest link correspondence with the Tokyo road network. Simulation results in this section showed network connectivity modelled by the Link Connection mechanism with $\beta \in [1.0,1.5]$ was closer to empirical planned urban road networks.

### 7.6.1 The Effect of Proximity Relationship Summary

Chapter 4 identified the limitation of previous GNMs of urban road networks in insufficient horizontal comparison of the Link Connection mechanism. The proposed GNM in Chapter 6 generalised Link Connection as a process to examine the proximity relationship between a new spatial location and the existing network, using β-skeletons proximity relationship with $\beta \in [1.0,2.0]$. This section answered the following research question specified in Chapter 4:

- Whether proximity relationships from proximity graphs other than RNG, like β-skeletons play a role in modelling RNE?

Simulation networks structure and dynamics under β-skeleton proximity relationships $\beta = 1.0,1.5, 2.0$ in this section showed the generalised Link Connection mechanism is capable of modelling urban road network structure and dynamics and may model a broader range of plausible network structures than previous GNMs of urban road networks, by changing the value of $\beta$. The simulated network structure and dynamics with different $\beta$ values suggested proximity relationships from β-skeleton proximity graphs in the range $\beta \in [1.0, 2.0]$ was essential to the generation of the urban road network structure. Link Connection could be controlled quantitatively by parameter $\beta$. The examination of proximity relationships achieved three things: it balanced link length and cost while maintained planarity; the former modelled spatiality and the latter modelled planarity; beyond spatiality and planarity, β-skeleton proximity relationships with $\beta \in [1.0, 2.0]$ formed elementary connection patterns of urban road networks, as reflected by the plausible simulated network characteristics and dynamics.

**Table 7-1 Findings and Conclusions – Generative Network Model of Urban Road Network Evolution**

| Network Characteristics | Previous Empirical Findings | Previous Models' Findings | This Study's Findings and Conclusions |
|---|---|---|---|
| **Node** | Static:<br>• Majority node degree $k_3$, e.g. on average $59.3\%$ in the range of $[44.4\%, 77.8\%]$ in US;<br>• Planned US $\langle k \rangle \approx 2.76$ in $[2.22, 3.22]$, Barcelona $\langle k \rangle = 3.42$; Organic Oxford $\langle k \rangle = 2.32$, Worcester $\langle k \rangle = 2.36$, Edinburgh $\langle k \rangle = 2.43$, Sheffield $\langle k \rangle = 2.42$.<br>Dynamic:<br>• Reported $\langle k \rangle$ dynamics' findings inconsistent: increased, decreased, stayed constant. | Static:<br>• Organic ratio $r_N = \frac{k_3+k_1}{\sum_i k_i} \approx 1.0$;<br>• $e \approx 1.3$, $\langle k \rangle \approx 2.6$. | Static:<br>• Simulated networks under $\beta = 2.0$ had a majority of $54.1\%$ $k_3$ nodes, in the range of $[51.6\%, 56.4\%]$;<br>• Simulated networks under $\beta = 2.0$ had low $k_4$ node proportion $0.7\%$, in the range of $[0.3\%, 1.2\%]$;<br>• $\beta = 2.0$, $\langle k \rangle \approx 2.36$; $\beta = 1.0$, $\langle k \rangle \approx 2.78$.<br>Dynamic:<br>• Node degree $k_i$ distribution stayed stable after initial drastic changes.<br>• $\langle k \rangle$ was nearly constant.<br>Conclusions:<br>• Simulated networks' majority of $k_3$ agreed with empirical findings; high $k_3$ and $k_1$ proportion agreed with previous models.<br>• Simulated networks' $\langle k \rangle$ was close to empirical findings of organic urban road networks.<br>• $k_3$ was the main connection pattern under the proposed Link Connection mechanism using proximity relationship from β-skeletons with $\beta$ in $[1.0, 2.0]$. $k_4$ required a predetermined grid node distribution Node Addition mechanism design. The simulation suggested urban road networks lie between planned grids and organic $k_3$ growth patterns.<br>• $\langle k \rangle$ dynamics resulted from changes of node degree $k_i$ proportions: increase of $k_4$ increased $\langle k \rangle$; increase of $k_1$ decreased $\langle k \rangle$; stable connection patterns led to constant $\langle k \rangle$.<br>• Network connectivity increased with $\beta$. |
| **Link** | Static:<br>• Link length $\mathrm{l}$ findings inconsistent among heavy-tailed distributions: power-law, lognormal, exponential; | Static:<br>• $\mathrm{l}$ distribution not examined by all previous studies; exponential lognormal $\mathrm{l}$ | Static:<br>• Simulated networks' $\mathrm{l}$ distribution exhibited both lognormal and normal distributions' characteristics;<br>Dynamic:<br>• $\mathrm{l}$ distribution maintained the overall shape, with concentrating peak and decreasing range of values. |

| | | | |
|---|---|---|---|
| | Dynamic:<br>• $l$ dynamics findings inconsistent: power-law, lognormal distribution with concentrating peak. | distribution reported. | Conclusions:<br>• Simulated networks' $l$ distribution and dynamics shared empirical urban road networks' characteristics: the distribution was right skewed with a majority of short to medium links and a small number of long links; as the network grew, the $l$ distribution maintained the overall shape with its peak concentrating.<br>• Simulated networks $l$ distribution exhibited both lognormal and normal distribution characteristics. The former resulted from multiplicative generation processes, such as longer roads from an earlier stage of road network evolution dividing proportionately into shorter segments; the latter resulted from additive processes, such as adding new links of random lengths. |
| **Block** | Static:<br>• Block area $A$ findings inconsistent among heavy-tailed distributions: power-law, lognormal; sensitive to density of the studied area;<br>Dynamic:<br>• $P(A)$ dynamics findings inconsistent: power-law with increasing exponent, lognormal with decreasing peak. | Static:<br>• $P(A)$ followed power-law distribution given exponential node spatial distribution. | Static:<br>• Simulated networks' $P(A)$ was righted skewed with heavy tail and exhibited normal, lognormal, and power-law distributions' characteristics;<br>Dynamic:<br>• $P(A)$ maintained the overall shape, with concentrating peak and decreasing range of values.<br>Conclusion:<br>• Simulated networks' $P(A)$ and dynamics shared empirical urban road networks' characteristics: righted skewed with heavy tail and probability decreased as the block area increased.<br>• $P(A)$ exhibited normal, lognormal, and power-law characteristics: the latter two resulted from multiplicative processes, such as the iterative spatial division of larger blocks into smaller ones; the former resulted from additive process, such as the addition of random size blocks.<br>• Besides density, $P(A)$ dynamics was also influenced by whether road network expanded during studied period; expanding road networks may add blocks larger than most of the existing ones while non-expanding road networks change by increasing level of spatial division. |
| **BC** | Static:<br>• BC distribution findings inconsistent: bimodal distribution separated around BC value equals to the number of nodes, power-law, exponential;<br>Dynamic: | Static:<br>• Concentration of BC on a small number of network component; exponential BC | Static:<br>• Simulated networks' BC followed a bimodal distribution, separating around the BC value that equalled to the number of nodes;<br>Dynamic:<br>• BC maintained the overall shape, with concentrating peak and decreasing range of values. |

| | | | |
|---|---|---|---|
| | • Bimodal BC distribution reported to be determined by network density $\rho_e$ and stay stable because of the small $\rho_e$ range of real-world urban road networks.<br>• Backbone of urban road networks: correlation found between long-existing and high BC roads;<br>• Densification and exploration: two types of new links that increased or decreased average network BC, respectively. | distribution reported. | • Backbone of urban road networks: correlation found between long-existing and high BC links;<br>• Densification and exploration: two types of new links found that increased or decreased average network BC, respectively.<br>Conclusions:<br>• Simulated networks exhibited a bimodal BC distribution, correlations between high BC and existence time, and two types of new links increased or decreased average network BC respectively, in agreement with empirical findings.<br>• The simulation suggested connections between BC related empirical findings, which may all result from the network formation process: the BC distribution and dynamics, the backbone of urban road networks, densification and exploration.<br>• BC related characteristics and dynamics may result from a network formation process of initial global changes and later local changes. In the initial stage of network dynamics, network spanned the simulation area and occupied the geographical centre; these network components were long-existing, near geographical centre and had high BC. The later stages of simulated network dynamics were local changes which further divided and extended the existing network into the large blocks formed in initial network dynamics; size and location of components added then were restricted by spatiality and planarity and had small BC.<br>• Simulated networks suggested BC-based characteristics were properties shared by planar networks. DE were two only possible connection patterns for new links. This explained frequent observations of such characteristics. However, urban road networks' BC may differ from other planar networks by spatial and temporal characteristics, which were likely to be influenced by urban factors. |

## 7.7 Chapter Conclusions

This chapter addressed the second research question of this thesis and explored the capacity of the proposed GNM of urban road network evolution in chapter 6 to model the dynamic RNE process. This chapter examined both the static and dynamic simulated network structure in 7.2 - 7.5. Original simulation findings of a general urban road network structure and dynamics were yielded, as summarised in sections 7.2.5, 7.3.3, 7.4.3, 7.5.5 on the node, link, block, betweenness centrality characteristics and dynamics, respectively. Table 7-1 outlined this chapter's simulation findings, in comparison with empirical findings and previous simulation results.

This chapter addressed three limitations in previous studies. First, existing modelling RNE research has stopped at network generation and has not explored the capacity of GNM in modelling the dynamic RNE process. Second, existing modelling RNE research has not integrated empirical RNE findings into simulation result examination, because of the network generation objective. Third, empirical RNE research has had insufficient horizontal comparison and shown inconsistency in findings. This study stored and investigated the whole simulated dynamics, rather than only the final generated networks. This study integrated with the empirical RNE findings in simulation result examination and established the relationship between the generative mechanism, the simulated network structure and dynamics, and the empirical RNE characteristics. Exploration of the continuous simulated network dynamics showed the potential processes that led to the emergence of the inconsistency in empirical RNE findings.

This chapter demonstrated that the proposed GNM could model plausible static and dynamic urban road network structures and portrayed the evolution of a general urban road network structure, as outlined in Table 7-1. Elementary road network connection patterns may emerge from the Link Connection process, which examines the proximity relationship between a new spatial location and the existing network. Network connectivity changes with specific proximity relationships. The urban road network evolution may be characterised by stable connections, multiplicative and additive growth corresponding with continuous large component division and random size component addition, the initial formation of a major path skeleton and later local changes of minor components.

# Chapter 8 Hybrid Model of the Population and Urban Road Network Co-evolution

## 8.1 Chapter Introduction

Road network and the urban system co-evolve: the spatial structure of road network and the urban system have been found to correlate and exhibit global centralisation and decentralisation as well as local clustering and dispersion as reviewed in Chapter 3, suggesting a co-evolution mechanism of push and pull forces on different urban layers behind urban system formation and dynamics. Research fields such as Transport demand forecasting, Land use and Transport Interaction, Urban modelling, and Network science have all involved explicitly or implicitly modelling of the transport network and its dynamics while differ in the urban factors and layers of interest, as reviewed in Chapter 4. Most approaches have not considered the urban road network structure and dynamics explicitly but focused on other urban components, as illustrated in Figure 8.1. Meanwhile, different approaches have shared an understanding of the urban system: population and their socio-economic activities are fundamental to existence and operation of the urban system and have fundamental demand for social interactions which require to overcome space; transport networks enable such spatial interactions of population. The population have been regarded as generating and representing the urban spatial structure. Generative Network Model (GNM) could model explicitly urban road networks' structure and dynamics, as demonstrated in Chapter 6, 7 by the proposed GNM of urban road network evolution. Together, modelling the co-evolution of population and urban road network may be a starting point to understand RNE in the urban system.

Existing GNMs have modelled the co-evolution of urban road network and population, as reviewed in 4.3.4, but have represented population and road network using one network, with nodes representing population concentrated locations and links representing roads. Under this model design, population and road network were related inherently, being one network's nodes and links; and the modelled population and road network structure, as well as their relationship, were not only influenced by the proposed co-evolution mechanisms, but also by the built-in network connectivity between nodes and links. This modelling choice has increased the difficulty to disentangle and understand mutual relationships and interactions between population and road network. Also, previous models have assumed fixed population and road network mutual influences in proposed co-evolution mechanisms, e.g. using the land-use and transport interaction, rather than experiencing all potential population and road network spatial decision possibilities. This modelling choice may limit the diversity of simulated spatial structures. Further, previous models have limited consideration of the spatial structure of urban road networks, in terms of characterisation and the relationship between road network spatial structure and the urban spatial structure.

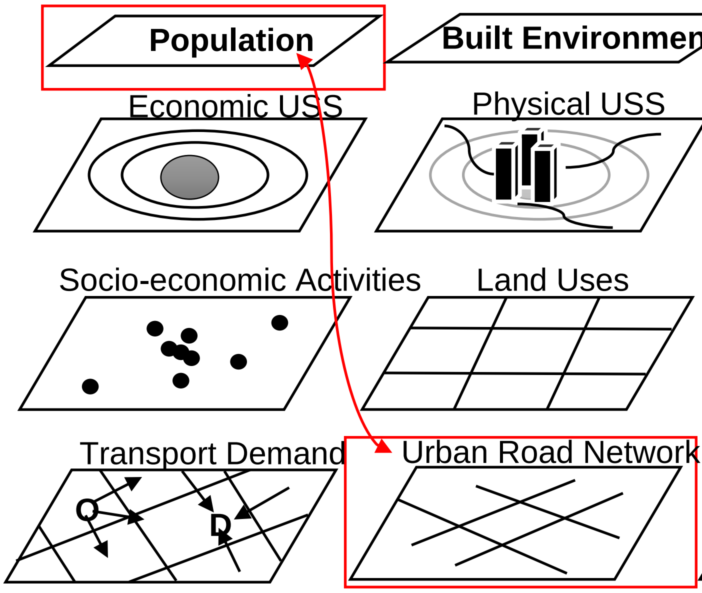



**Figure 8.1 Hybrid Model of Population and Urban road network Co-evolution**

This chapter aims to answer the third research question of this thesis, as proposed in Chapter 1 and specified in Table 5-2:

3. How to integrate GNM of urban road network evolution into the urban system?

   a) How to represent both the urban road network and population?
   b) What population-urban road network co-evolution mechanism do the correlations between population and urban road network in terms of quantity, spatial structure, and network characteristics, as well as by the mutual influences between road network and the urban system reflect?

This chapter proposes a hybrid model of population and urban road network evolution 8.2, which integrates GNM into the urban system. This model proposes a representation of the population and urban road network that addresses previous GNMs' limitation in representation, a population and urban road network co-evolution mechanism 8.2.1, and a framework to examine the modelled structure. 8.2.2 explains the implementation of the proposed co-evolution mechanism. 8.2.3 describes the hybrid GNM and the proposed representation of urban road network and population; 8.2.4 summarises the proposed model with an algorithm. The next chapter explores the emerging population and urban road network spatial structures and relationships under this chapter's proposed model in simulation experiments.

## 8.2 Hybrid Generative Network Model: Co-evolution of the Population and the Urban Road Network

### 8.2.1 The Population and Urban Road Network Co-Evolution Mechanism

The urban system could be expected to change with two processes, dynamics of population and dynamics of the road network, considering only population and road network. The process of Population Dynamics was referred to as Population dynamics, and the process of Road Network Dynamics was referred to as Road Network Dynamics. On a microscopic level, population and Road Network Dynamics happened individually and locally with individual population and road network component's behaviours and interactions; individual population and road network components behaved and interacted considering components of their kind and concerning components of the other kind. Table 8-1 listed the processes in Population Dynamics and Road Network Dynamics, respectively, which were explained in the following sections.

**Table 8-1 Population and Road Network Co-Evolution Mechanism - Population Dynamics and Road Network Dynamics**

| **Population Dynamics** | **Road Network Dynamics** |
|---|---|
| ***k* Criteria $C_k$**<br>• $C_1$: Impact of Distance to Road network $\mathbf{d_{pop}}$<br>• $C_2$: Impact of Population density $\boldsymbol{\rho}$ | ***k'* Criteria $C_{k'}$**<br>• $C_3$: Impact of Distance to Population $\mathbf{d_{RN}}$<br>• $C_4$: Impact of Flow within Radius $\sum \mathbf{flow}$ |
| **Generate** *j* candidate population locations | **Generate** *j'* candidate road node locations |
| **Calculate** *j* candidates' $C_k$ Measure Values: $v_{k,j}$<br>• $C_1$: $v_{1,1}$, …, $v_{1,j}$<br>• $C_2$: $v_{2,1}$, …, $v_{2,j}$ | **Calculate** *j'* candidates' $C_{k'}$ Measure Values: $v_{k',j'}$<br>• $C_3$: $v_{4,1}$, …, $v_{4,j'}$<br>• $C_4$: $v_{4,1}$, …, $v_{4,j'}$ |
| **Evaluate** j candidates' $C_k$ Measure Values $v_{k,j}$ with:<br>• Measure value preference parameter $\beta_k$: $\beta_1$, $\beta_2$<br>• Criteria weights $\alpha_k$: $\alpha_1$, $\alpha_2$ | **Evaluate** j' candidates' $C_k$ Measure Values $v_{k'j'}$ with:<br>• Measure value preference parameter$\beta_k$: $\beta_3$, $\beta_4$<br>• Criteria weights $\alpha_k$: $\alpha_3$, $\alpha_4$ |
| **Score** *j* candidates: $U = U_1, \ldots, U_j$<br>• Select new population locations based on U | **Score** *j'* candidates: $U = U_1, \ldots, U_{j'}$<br>• Select new road node locations based on U |

#### 8.2.1.1 Population Dynamics

Population Dynamics made the spatial decision of new population location. At every time step, Population Dynamics chose from $j$ candidates $j^*$ locations to add new population. Two criteria $C_1$ and $C_2$ were evaluated to make this spatial decision. $C_1$ was the impact of candidate population location's distance to road network $d_{pop}$, on the spatial decision. $C_2$ was to the impact of existing population density $\rho$ around the candidate location. The criteria could have positive or negative impacts, denoted by $\beta_k \in \{-1,1\}$. The Population Dynamics mechanism did not assume fixed one-way influences from the two factors $d_{pop}$ and $\rho$ on the spatial decision of new population locations but allowed the model to explore both positive and negative possibilities, as illustrated in Figure 8.2.

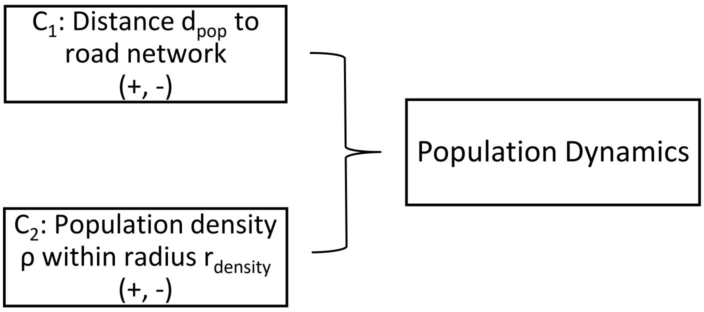



**Figure 8.2 Population Dynamics**

**Table 8-2 Population Dynamics Mechanism**

| Impact Indicator $(\beta_1, \beta_2)$ | Criteria $C_1$ / Criteria $C_2$ | Criteria Impact | Criteria Value Preference | New Population Location Preference |
|---|---|---|---|---|
| $(d_{pop}^{+}, \rho^{+})$ | $d_{pop}$ | Positive | Large value | Remote to existing road network |
| | $\rho$ | Positive | Large value | Dense existing population |
| $(d_{pop}^{+}, \rho^{-})$ | $d_{pop}$ | Positive | Large value | Remote to existing road network |
| | $\rho$ | Negative | Small value | Sparse existing population |
| $(d_{pop}^{-}, \rho^{+})$ | $d_{pop}$ | Negative | Small value | Close to existing road network |
| | $\rho$ | Positive | Large value | Dense existing population |
| $(d_{pop}^{-}, \rho^{-})$ | $d_{pop}$ | Negative | Small value | Close to existing road network |
| | $\rho$ | Negative | Small value | Sparse existing population |

For example, new population location might prefer high accessibility and be close to the road network; in this case, $\beta_1 = -1$ for $C_1$, a large distance between candidate locations and existing road network $d_{pop}$ had a negative impact on the spatial decision, namely, population preferred small $d_{pop}^{-}$. New population location might as well prefer being remote to the road network, potentially to seek space or avoid pollution and noise; in that case, $\beta_1 = 1$, large $d_{pop}^{+}$ had a positive impact on the spatial decision. Regarding existing population density, new population location might prefer dense area for high accessibility of social interactions and socio-economic activities; in this case, $\beta_2 = 1$ for $C_2$, large population density $\rho$ within certain radius $r_{density}$ to the candidate locations $\rho$ had a positive impact on the spatial decision, namely population preferred large density $\rho^{+}$. New population location might as well prefer sparse area for low land price and more space; in that case, $\beta_2 = -1$, large $\rho$ had a negative impact on the spatial decision and population preferred small $\rho^{-}$ and sparse area.

Table 8-2 listed the combinations of impact indicator $\beta_k$ in population dynamics. Criteria $C_k = (C_1, C_2)$, impact indicator $\beta_k = (\beta_1, \beta_2)$ were weighed with impact weights $\alpha_k = (\alpha_1, \alpha_2)$ to evaluate $j$ candidate population locations for spatial decision score $U_j$.

#### 8.2.1.2 Road Network Dynamics

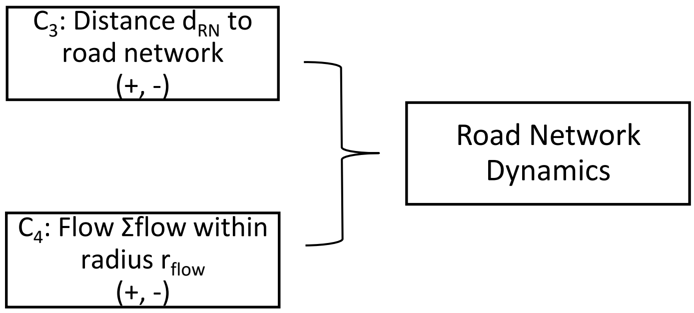



**Figure 8.3 Road Network Dynamics**

Road dynamics made spatial decisions to add new road network nodes and links. At every time step, road dynamics chose among candidate locations $j'$ candidates $j^{*\prime}$ locations to add new road network nodes, then performed Node Addition and Link Connection as the GNM for urban road network evolution proposed in Chapter 6, at the chosen new node locations. Two criteria $C_3$ and $C_4$ were evaluated to make this spatial decision. $C_3$ was the impact of road node location's distance to population $d_{RN}$, on the spatial decision. $C_4$ was the impact of network flow $\sum flow$ within certain distance $r_{flow}$ to a road node. The next section 8.2.1.2.1 explained $\sum flow$ calculation. The Road dynamics mechanism did not assume fixed one-way influences either, from the two factors $d_{RN}$ and $\sum flow$ on the spatial decision of new road network locations, as illustrated in Figure 8.3.

Table 8-3 listed the combinations of impact indicator $\beta_k$ in Road Network Dynamics. Criteria $C_k = (C_3, C_4)$, impact indicators $\beta_k = (\beta_3, \beta_4)$ were weighted with impact weights $\alpha_k = (\alpha_3, \alpha_4)$ to evaluate $j'$ candidate population locations for spatial decision score $U_j$, to choose $j'^{*}$ new node locations. After making spatial decisions of new network node locations, Node Addition and Link Connection were performed, which added new road network nodes and connected them to the existing network, completing Road Network Dynamics of the time step.

**Table 8-3 Road Network Dynamics Mechanism**

| Impact Indicator $(\beta_3, \beta_4)$ | Criteria $C_3$ / Criteria $C_4$ | Criteria Impact | Criteria Value Preference | New Road Network Locations Preference |
|---|---|---|---|---|
| $\left(d_{RN}^{+}, \sum flow^{+}\right)$ | $d_{RN}$ | Positive | Large value | Remote to existing population |
| | $\sum flow$ | Positive | Large value | High existing flows |
| $\left(d_{RN}^{+}, \sum flow^{-}\right)$ | $d_{RN}$ | Positive | Large value | Remote to existing population |
| | $\sum flow$ | Negative | Small value | Low existing flows |
| $\left(d_{RN}^{-}, \sum flow^{+}\right)$ | $d_{RN}$ | Negative | Small value | Close to existing population |
| | $\sum flow$ | Positive | Large value | High existing flows |
| $\left(d_{RN}^{-}, \sum flow^{-}\right)$ | $d_{RN}$ | Negative | Small value | Close to existing population |
| | $\sum flow$ | Negative | Small value | Low existing flows |

#### 8.2.1.2.1 $\boldsymbol{flow_{(i,j)}}$

The quantity $flow_{(i,j)}$ was defined to measure the population's potential usage of the road network. Given a certain population with spatial distribution, and a road network, $flow_{(i,j)}$ attempted to capture the potential population interaction flows realised by the road network on a link $(i,j)$. $flow_{(i,j)}$ was calculated as follows.

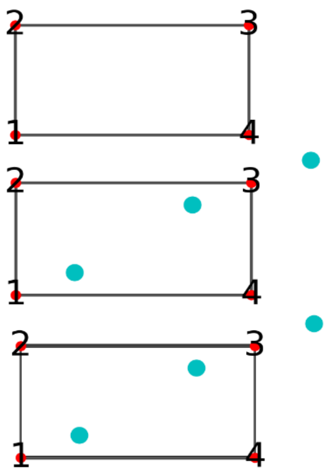
First, the population at different locations were loaded to the nearest road network nodes: a road network node $i$ was assigned the sum population $P_i$ to which it was the nearest node. Road network nodes with population loaded were then paired as origins and destinations (ODs), for the population's interactions through the road network. For each pair of OD nodes $(s,t)$, quantity $(P_s + P_t)$, the sum of their loaded population, was split equally among all the shortest paths between this pair. Each time a link lied on such a shortest path, its $flow_{(i,j)}$ incremented by $\frac{(P_s + P_t)}{\delta_{s,t}} \cdot d_{(i,j)}$. $\delta_{s,t}$ denoted the number of shortest paths between an OD pair $s,t$, and $d_{(i,j)}$ denoted Euclidean length of link $i,j$. Flow calculation was summarised as:

$$flow_{(i,j)} = \sum_{s,t}(P_s + P_t) \cdot d_{(i,j)} \frac{\delta_{s,t}(i,j)}{\delta_{s,t}};$$

$s \neq t$; $i \neq j$; $s,t,i,j \in V$; where $\delta_{s,t}i,j$ denoted the number of shortest paths passing link $i,j$.

The concept and calculation of $flow_{(i,j)}$ was inspired by Betweenness Centrality (BC), which calculated the centrality of a network component by its frequency on shortest paths between all node pairs. BC used all node pairs in a network as homogeneous OD pairs. To integrate population, $flow_{(i,j)}$ adjusted BC to use only nodes with the loaded population as ODs, the loaded population as node weights. To differentiate two links of different length passed by a same number of population, $flow_{(i,j)}$ was designed as the product of population $\frac{(P_s+P_t)}{\delta_{s,t}}$ and link length $d_{(i,j)}$, instead of only population $\frac{(P_s+P_t)}{\delta_{s,t}}$. The quantity $\sum_{s,t}(P_s + P_t)\cdot\frac{\delta_{s,t}(i,j)}{\delta_{s,t}}$ was referred to as $flow'_{(i,j)}$ and compared with $flow_{(i,j)}$ as in Figure 8.4. $flow_{(i,j)}$ may as well relate to traffic flow measure $vehicle \cdot km$, which was the product of vehicle number and distance travelled.

Figure 8.4 compared BC, $flow'_{(i,j)}$ to $flow_{(i,j)}$. Figure 8.4 (a) demonstrated that BC used all node pairs as ODs; all links had the same BC in this example. (b) showed $flow'_{(i,j)}$ included population by using only node pairs with the loaded population as ODs but did not differentiate link of different lengths. (c) demonstrated $flow_{(i,j)}$ used in the proposed model, which considered both population and link length when calculating link flow.




(a) $\boldsymbol{BC}_{(i,j)} = \sum_{s,t}\frac{\delta_{s,t}(i,j)}{\delta_{s,t}}$;

$BC_{(1,2)} = \frac{\delta_{1,2}(1,2)}{\delta_{1,2}} + \frac{\delta_{1,3}(1,2)}{\delta_{1,3}} = 1.5$;

Similarly, $BC_{(2,3)} = BC_{(1,4)} = BC_{(3,4)} = 1.5$.

(b) $\boldsymbol{flow'}_{(i,j)} = \sum_{s,t}(P_s + P_t)\cdot\frac{\delta_{s,t}(i,j)}{\delta_{s,t}}$;

$flow'_{(1,2)} = flow'_{(2,3)} = flow'_{(1,4)} = flow'_{(3,4)} = (P_1 + P_3)\cdot\frac{1}{2} = 1.5.$

(c) $\boldsymbol{flow}_{(i,j)} = \sum_{s,t}(P_s + P_t)\cdot d_{(i,j)}\frac{\delta_{s,t}(i,j)}{\delta_{s,t}}$;

$flow_{(1,2)} = flow_{(3,4)} = 150$;

$flow_{(2,3)} = flow_{(1,4)} = 300$.

**Figure 8.4 Betweenness Centrality, Flow', Flow Comparison**: On a small rectangular network, link length $d_{1,2} = d_{3,4} = 100$; $d_{2,3} = d_{1,4} = 200$. Blue points represent population locations; each had population $\mathrm{P} = 1$. (a) demonstrates link *BC* calculation; (b) demonstrates a quantity $flow'_{(i,j)}$; (c) demonstrates $flow_{(i,j)}$ used in the proposed model.

The spatial distribution of population influenced $flow_{(i,j)}$. Both Figure 8.5 and Figure 8.6 showed $flow_{(i,j)}$ captured potential population spatial interactions realised through the road network. $flow_{(i,j)}$ was influenced by the size of the population, the structure of the road network, as well as the spatial distribution of population regarding the road network.

Figure 8.5 demonstrated $flow_{(i,j)}$ on a small example network with four nodes and four links and given three units population with different spatial distributions; $flow_{(i,j)}$ were visualised with link width. In the left plot, all three units of the population were loaded to the same road network node 3; because population interactions on the same node were not considered, all four links had $flow_{(i,j)} = 0$. In the middle plot, two units of the population were loaded to node 3 and one unit to node 1, forming one OD pair 1,3. Two shortest paths existed between the OD pair 1,3; thus the $P_1 + P_3 = 3$ were split between the two shortest paths. As $d_{(1,2)} = d_{(3,4)} = 100$, link 1,2 and 3,4 had $flow = 150$; as $d_{(2,3)} = d_{(1,4)} = 200$,link 2,3 and 1,4 had $flow = 300$. In the right plot, three units of the population were loaded to node 1, 3, 4, respectively. The calculated link flows changed again.

$$P_1 = 1, P_3 = 2; \{(s,t), \dots\} = \{(1,3)\};$$

$$f_{(1,2)} = (P_1 + P_3) \cdot d_{(1,2)} \cdot \frac{\delta_{1,3}(1,2)}{\delta_{1,3}} = 3 \cdot 100 \cdot \frac{1}{2} = 150;$$

$$f_{(2,3)} = (P_1 + P_3) \cdot d_{(2,3)} \cdot \frac{\delta_{1,3}(2,3)}{\delta_{1,3}} = 3 \cdot 200 \cdot \frac{1}{2} = 300;$$

$$f_{(1,4)} = (P_1 + P_3) \cdot d_{(1,4)} \cdot \frac{\delta_{1,3}(1,4)}{\delta_{1,3}} = 3 \cdot 200 \cdot \frac{1}{2} = 300;$$

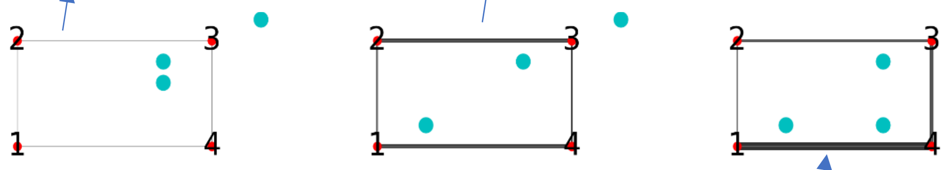
$$f_{(3,4)} = (P_1 + P_3) \cdot d_{(3,4)} \cdot \frac{\delta_{1,3}(3,4)}{\delta_{1,3}} = 3 \cdot 100 \cdot \frac{1}{2} = 150.$$



$$P_1 = 0,\ P_2 = 0, P_3 = 3, P_4 = 0;$$

$$\{(s,t), \dots\} = \{\ \};$$

$$f_{(1,2)} = f_{(2,3)} = f_{(1,4)} = f_{(3,4)} = 0.$$




$$P_1 = 1, P_3 = 1, P_4 = 1; \{(s,t), \dots\} = \{(1,3), (1,4), (3,4)\};$$

$$f_{(1,2)} = (P_1 + P_3) \cdot d_{(1,2)} \cdot \frac{\delta_{1,3}(1,2)}{\delta_{1,3}} + (P_1 + P_4) \cdot d_{(1,2)} \cdot \frac{\delta_{1,4}(1,2)}{\delta_{1,4}} + (P_3 + P_4) \cdot d_{(1,2)} \cdot \frac{\delta_{3,4}(1,2)}{\delta_{3,4}} = 100;$$

$$f_{(2,3)} = (P_1 + P_3) \cdot d_{(2,3)} \cdot \frac{\delta_{1,3}(2,3)}{\delta_{1,3}} + (P_1 + P_4) \cdot d_{(2,3)} \cdot \frac{\delta_{1,4}(2,3)}{\delta_{1,4}} + (P_3 + P_4) \cdot d_{(2,3)} \cdot \frac{\delta_{3,4}(2,3)}{\delta_{3,4}} = 200;$$

$$f_{(1,4)} = (P_1 + P_3) \cdot d_{(1,4)} \cdot \frac{\delta_{1,3}(1,4)}{\delta_{1,3}} + (P_1 + P_4) \cdot d_{(1,4)} \cdot \frac{\delta_{1,4}(1,4)}{\delta_{1,4}} + (P_3 + P_4) \cdot d_{(1,4)} \cdot \frac{\delta_{3,4}(1,4)}{\delta_{3,4}} = 600;$$

$$f_{(3,4)} = (P_1 + P_3) \cdot d_{(3,4)} \cdot \frac{\delta_{1,3}(3,4)}{\delta_{1,3}} + (P_1 + P_4) \cdot d_{(3,4)} \cdot \frac{\delta_{1,4}(3,4)}{\delta_{1,4}} + (P_3 + P_4) \cdot d_{(3,4)} \cdot \frac{\delta_{3,4}(3,4)}{\delta_{3,4}} = 300.$$

**Figure 8.5 $flow_{(i,j)}$ Demonstration – Influence of Population Spatial Location on Network Flows**: The three plots demonstrate the calculation of $flow_{(i,j)}$ with changing population locations. The left plot's population located near the same node, $flow_{(i,j)} = 0$, indicating no spatial interactions realised by the road network. The middle and the right plots demonstrate another two potential population layout and the consequantial $flow_{(i,j)}$.

Figure 8.6 demonstrated population spatial distribution's influence on a larger example network with population $\sum_i P_i = 500$ of different spatial distributions. Population in the left and middle plots followed negative exponential distributions $f(x) = \lambda e^{-\lambda x}\ x \geq 0$, with $\lambda = 0.012$ and $\lambda = 0.005$ respectively. Population in the right plot followed a uniformly random distribution. This figure showed flows spread and increased as the population dispersed over the network.

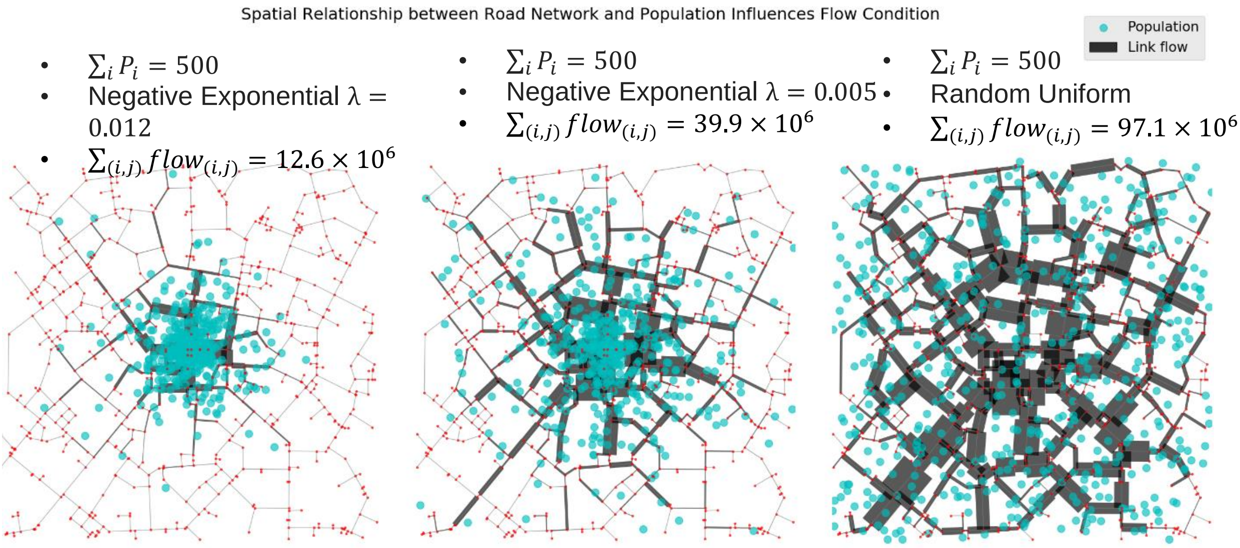



**Figure 8.6 $flow_{(i,j)}$ Demonstration – Influence of Population Spatial Location on Network Flows**: The three plots demonstrate $flow_{(i,j)}$ on a same network with the same number of population $\sum_i P_i = 500$. Different population spatial distributions – exponential with parameter $\lambda = 0.012$, $\lambda = 0.005$ and random uniform, led to different $flow_{(i,j)}$. Red points represent network nodes, black links represent network links. Blue points represent population location. $flow_{(i,j)}$ were visualised with link width.

### 8.2.2 Criteria Evaluation

The last section introduced the proposed population and urban road network co-evolution mechanism: Population Dynamics and Road Network Dynamics. Population Dynamics used two criteria $C_1$ distance to road network $d_{pop}$ and $C_2$ population density $\rho$ around the candidate location, to make the spatial decision of new population location. Road Network Dynamics used two criteria $C_3$ distance to road network $d_{RN}$ and $C_4$ total flow $\sum flow$ within radius $r_{flow}$ to the candidate location, to make the spatial decision of new road network node location and performed Node Addition and Link Connection. This section explained how criteria $C_k = (C_1, C_2, C_3, C_4)$ were evaluated to choose among candidate locations the new population and road network node at each time step.

The criteria $C_k$ of the two processes Population Dynamics and Road Network Dynamics were controlled by two sets of parameters $\alpha_k$ and $\beta_k$. $\beta_k \in \{-1,1\}$ and controlled the preference for large or small values of criteria $C_k$. $\beta_k = -1$ preferred small values and $\beta_k = 1$ preferred large values. $\alpha_k \in [0,1]$ and controlled the strength of criteria $C_k$. For example, $\alpha_1 = \alpha_2 = 1$ meant $C_1$ and $C_2$ were set with the same strength in Population Dynamics. For $j$ candidate locations, each candidate was evaluated by $k$ criteria $C_k$, yielding criteria values $v_{j,k}$; bringing together individual criteria values, the candidate received an overall score $U_j$ according to the following evaluation equation:

**Equation 1 Criteria Evaluation**

$$U_j = \sum_k \frac{1}{\sum_{k=1}^{k} \alpha_k} \alpha_k \cdot \frac{v_{max,k} - v_{j,k}}{v_{max,k} - v_{min,k}}.$$

Right half of the equation $\frac{v_{max,k} - v_{j,k}}{v_{max,k} - v_{min,k}}$, referred to as $v_{j,k}'$, normalised candidates $j$'s $k^{\text{th}}$ criteria values using maximum and minimum $v_{max,k}$ and $v_{min,k}$ among all candidates' $k^{\text{th}}$ criteria values. Normalised $v_{j,k}'$ were then weighted with $\alpha_k$ to compute the overall score $U_j$ combining all criteria.

#### 8.2.2.1 Criteria Evaluation Numerical Demonstration

This section demonstrated criteria evaluation with a small example. Assuming there were two candidates $j_1$, $j_2$ that needed to be evaluated by the two criteria $C_1$ and $C_2$, when $\beta_1 = \beta_2 = 1$, $\alpha_1 = \alpha_2 = 1$, the following procedures were performed to calculate $j_1$'s evaluation score $U_1$ (with pseudo values):

1. Measure $j_1, j_2$ and acquire $C_1$ measure's values $v_{j,1}$: $[v_{1,1}, v_{2,1}] = [50{,}100]$ (sample $v_{j,1}$ given, i.e. the $d_{pop}$ measurement);
2. Measure $j_1, j_2$ and acquire $C_2$ measure's values $v_{j,2}$: $[v_{1,2}, v_{2,2}] = [7{,}6]$ (sample $v_{j,2}$ given, i.e. the $\rho$ measurement);
3. Normalise $v_{1,1}$:
   a. $v_{1,1} = 50$;
   b. $v_{max,1} = 100$; $v_{min,1} = 50$;
   c. Normalise $v_{1,1}$: $v_{1,1}' = \frac{v_{max,1} - v_{1,1}}{v_{max,1} - v_{min,1}} = \frac{100-50}{100-50} = 1$;
4. Normalise $v_{1,2}$:
   a. $v_{1,2} = 7$;
   b. $v_{max,2} = 7$; $v_{min,2} = 6$;
   c. Normalise $v_{1,2}$: $v_{1,2}' = \frac{v_{max,2} - v_{1,2}}{v_{max,2} - v_{min,2}} = \frac{7-7}{7-6} = 0$;
5. Calculate $U_1 = \alpha_1 \cdot v_{1,1}' + \alpha_2 \cdot v_{1,2}' = \frac{1}{2} \cdot 1 + \frac{1}{2} \cdot 0 = \frac{1}{2}$.

The above example showed larger $v_{j,k}$ approach $v_{j,k}' \to 0$ after normalisation, and smaller $v_{j,k}$ approach $v_{j,k}' \to 1$ . As $v_{1,2}$ was maximum among $v_{j,2}$, $v_{1,2}' = 0$; as $v_{1,1}$ was minimum among $v_{j,1}$, $v_{1,1}' = 1$.

Similarly, $j_2$'s score $U_2$ was:

1. Normalise $v_{2,1}$:
   a. $v_{2,1} = 100$;
   b. $v_{max,1} = 100$; $v_{min,1} = 50$;
   c. Normalise $v_{2,1}$: $v_{2,1}' = \frac{v_{max,1} - v_{2,1}}{v_{max,1} - v_{min,1}} = \frac{100-100}{100-50} = 0$;
2. Normalise $v_{2,2}$:
   a. $v_{2,2} = 6$;
   b. $v_{max,2} = 7$; $v_{min,2} = 6$;

c. Normalise $v_{2,2}$: $v'_{2,2} = \frac{v_{max,2}-v_{2,2}}{v_{max,2}-v_{min,2}} = \frac{7-6}{7-6} = 1$;

3. Calculate $U_2 = \alpha_1 \cdot v'_{2,1} + \alpha_2 \cdot v'_{2,2} = \frac{1}{2} \cdot 0 + \frac{1}{2} \cdot 1 = \frac{1}{2}$.

Because $\beta_1 = \beta_2 = 1$, $C_1$ preferred large $v_{j,1}$ whose $v_{j,1}' \rightarrow 0$, and $C_2$ also preferred large $v_{j,2}$ whose $v_{j,2}' \rightarrow 0$. Because $C_1$ and $C_2$, as both $C_k$ preferred large $v_{j,k}$ whose $v_{j,k}' \rightarrow 0$, small overall $U_j \rightarrow 0$ were desirable. In this example, $U_1 = U_2 = \frac{1}{2}$, candidates $j_1$, $j_2$ received same level of preference.

On the other hand, if both $\beta_1 = \beta_2 = -1$, $C_1$ preferred small $v_{j,1}$ whose $v_{j,1}' \rightarrow 1$, and $C_2$ also preferred small $v_{j,2}$ whose $v_{j,2}' \rightarrow 1$. Then large overall $U_j \rightarrow 2$ were desirable. The next section discussed the situations when $\beta_k$ did not have same sign values, namely, when criteria had opposite preferences for large or small values.

#### 8.2.2.2 Opposite $\boldsymbol{\beta_k}$

For $j$ candidates, when criteria $C_k$ all preferred large values, e.g. all $\beta_k = 1$, evaluation chose the candidate with $j^*$ lowest $U$ score; and when $C_k$ all preferred small values, e.g. all $\beta_k = -1$, evaluation chose $j^*$ candidates with highest $U$. When $\beta_k$ did not all prefer large or small values, and individual criteria had opposite preferences over large or small values, the overall preference for $U$ could not be determined. In this situation, measurement values *of $C_k$ whose $\beta_k = 1$* were reversed and their opposite values were normalised. Equivalently, the measurement values of criteria whose $\beta_k = -1$ could be reversed, serving the same purpose to translate criteria with opposite value preferences before normalisation so that an overall preference of $U$ could be made.

Following the example in the last section 8.2.2.1, if the sign of $\beta_2$ flipped, namely $\beta_1 = 1$ and $\beta_2 = -1$, $U_1$ changed to:

1. Normalise $v_{1,1}$:
    a. Reverse $v_{j,1}$: $v_{j,1} = [-50, -100]$;
    b. $v_{1,1} = -50$;
    c. $v_{max,1} = -50$; $v_{min,1} = -100$;
    d. Normalise $v_{1,1}$: $v'_{1,1} = \frac{v_{max,1}-v_{1,1}}{v_{max,1}-v_{min,1}} = \frac{(-50)-(-50)}{(-50)-(-100)} = 0$;
2. Normalise $v_{1,2}$:
    a. $v_{1,2} = 7$;
    b. $v_{max,2} = 7$; $v_{min,2} = 6$;
    c. Normalise $v_{1,2}$: $v'_{1,2} = \frac{v_{max,2}-v_{1,2}}{v_{max,2}-v_{min,2}} = \frac{7-7}{7-6} = 0$;
3. Calculate $U_1 = \alpha_1 \cdot v'_{1,1} + \alpha_2 \cdot v'_{1,2} = \frac{1}{2} \cdot 0 + \frac{1}{2} \cdot 0 = 0$.

Similarly, $U_2$ changed to:

1. Normalise $v_{2,1}$:

a. Reverse $v_{j,1}$: $v_{j,1} = [-50, -100]$;
b. $v_{2,1} = -100$;
c. $v_{max,1} = -50$; $v_{min,1} = -100$;
d. Normalise $v_{2,1}$: $v'_{2,1} = \frac{v_{max,1} - v_{2,1}}{v_{max,1} - v_{min,1}} = \frac{(-50)-(-100)}{(-50)-(-100)} = 1$;

2. Normalise $v_{2,2}$:
   a. Reverse $v_{1,2}$: $v_{1,2} = [7,6]$;
   b. $v_{max,2} = 7$; $v_{min,2} = 6$;
   c. Normalise $v_{2,2}$: $v'_{2,2} = \frac{v_{max,2} - v_{2,2}}{v_{max,2} - v_{min,2}} = \frac{7-6}{7-6} = 1$;
3. Calculate $U_2 = \alpha_1 \cdot v'_{2,1} + \alpha_2 \cdot v'_{2,1} = \frac{1}{2} \cdot 1 + \frac{1}{2} \cdot 1 = 1$.

In this example, $C_2$ preference disagreed with $C_1$: $\beta_1 = 1$, $C_1$ preferred large $v_{j,1}$ which normalised to ${v_{j,1}}' \to 0$; $\beta_2 = -1$, $C_2$ preferred small $v_{j,2}$ which normalised to ${v_{j,2}}' \to 1$. $\beta_1 = 1$, namely $C_1$ preferred large measurement values $v_{j,1}$, equalled preferring small reversed $v_{j,1}$; thus, measurement values $v_{j,1}$ of $C_1$ were reversed; the reversed $v_{j,1}$ normalised to ${v_{j,1}}' \to 1$. This design translated $C_1$ from preferring large values into preferring small reversed values to coordinate with $C_2$'s preference for small values so that Criteria evaluation could reach an overall score $U \to 2$, regardless of the opposite preferences of large or small among criteria. Followingly, candidate $j_2$ which had larger $C_1$ measure values, smaller $C_2$ measure values and an overall larger $U_2 = 1$ was chosen.

#### 8.2.2.3 Demonstrate Choosing New Road Node Location in One Time Step

This section performed the spatial decision making of Road Network Dynamics proposed in 8.2.1.2 and the Criteria evaluation process proposed in 8.2.2, with a small example and for one time step. Figure 8.7 showed a road network with four nodes (red points) and four links (black lines), three population points (blue points), and three candidate new road node locations (green points). Given this road network and population distribution, this section demonstrated spatial decision to choose among the three candidate new node locations 1, 2, 3.

Figure 8.8 listed the Criteria evaluation process of the three candidate new road network node locations with Road Network Dynamics criteria $C_3$, $C_4$ - the impact of $d_{RN}$ which measured road network distance to existing population and the impact of $\sum flow$ which measured potential population interactions realised through road network, under all $(\beta_3, \beta_4)$ combinations, at $r_{flow} = 50{,}150{,}250{,}350$, when $(\alpha_3, \alpha_4) = (1,1)$. The header line listed the four possible $(\beta_3, \beta_4)$ combinations as in Table 8-3, namely road network preferred:

1. $(d^+_{RN}, \sum flow^+)$: Remote to existing population and high existing flows;
2. $(d^+_{RN}, \sum flow^-)$: Remote to existing population and low existing flows;
3. $(d^-_{RN}, \sum flow^+)$: Close to existing population and high existing flows;

4. $(d_{RN}^{-}, \sum flow^{-})$: Close to existing population and low existing flows.

Each panel showed spatial decisions of choosing new road node location among the three candidate locations, marked in red and for a different $r_{flow}$. In the first column, $(\beta_3, \beta_4) = (1,1)$, i.e. $(\beta_3, \beta_4) = \left(d_{RN}^{+}, \sum flow^{+}\right)$, road network preferred large $d_{RN}$ and large $\sum flow$; the chosen new road node location was candidate location 1. Addition of a new road network node at location 1 did not change the population's total distance to the road network, while other locations reduced the distance. Location 1 was close to the existing road network, thus had high $\sum flow$. The advantage of location 1 under criteria preference $\left(d_{RN}^{+}, \sum flow^{+}\right)$ prevailed across all $r_{flow}$ values.

The measurement of criteria $C_3$ - $d_{RN}$ did not change with $r_{flow}$, changes with $r_{flow}$ in Road Network Dynamics criteria evaluation come from changes of $C_4$ measurement - $\sum flow$. The effect of $r_{flow}$ was shown in the third column when $(\beta_3, \beta_4) = (-1,1)$, i.e. $(d_{RN}^{-}, \sum flow^{+})$. When $r_{flow} = 50, 150$, location 1 and 2 shared the same evaluation score $U = 0.5$. Location 2 was close to population thus had preferable small $d_{RN}$. Location 1 was close to all road network links, thus had a preferable large $\sum flow$. After $r_{flow}$ increased to 250, the neighbourhood for flow calculation expanded, location 2's $\sum flow$ increased and became more desirable than location 4.

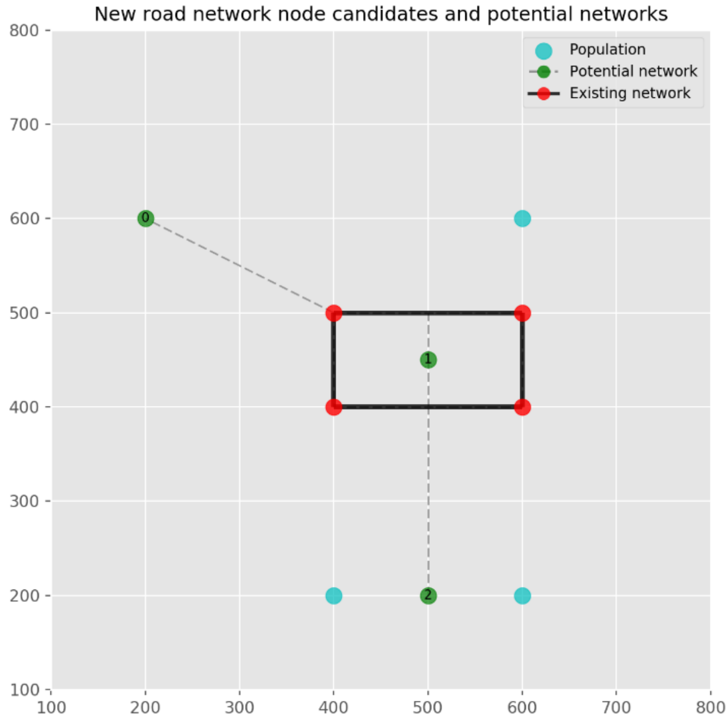



**Figure 8.7 Demonstrate Road Network Dynamics – Network and Population Example**: Green points represent candidate road network node locations. Grey dashed lines represent new links candidate connected if they were added.

$r_{flow} = 50$

| β3, β4 | 1,1 | | | 1,-1 | | | -1,1 | | | -1,-1 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Normalized | C3 | C4 | Uj | C3 | C4 | Uj | C3 | C4 | Uj | C3 | C4 | u |
| Candidates | | | | | | | | | | | | |
| 0 | 1 | 0 | 0.5 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 0.5 |
| 1 | 1 | 1 | 1 | 1 | 0 | 0.5 | 0 | 1 | 0.5 | 0 | 0 | 0 |
| 2 | 0 | 0 | 0 | 0 | 1 | 0.5 | 1 | 0 | 0.5 | 1 | 1 | 1 |

$r_{flow} = 150$

| β3, β4 | 1,1 | | | 1,-1 | | | -1,1 | | | -1,-1 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Normalized | C3 | C4 | Uj | C3 | C4 | Uj | C3 | C4 | Uj | C3 | C4 | Uj |
| Candidates | | | | | | | | | | | | |
| 0 | 1 | 0 | 0.5 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 0.5 |
| 1 | 1 | 1 | 1 | 1 | 0 | 0.5 | 0 | 1 | 0.5 | 0 | 0 | 0 |
| 2 | 0 | 0 | 0 | 0 | 1 | 0.5 | 1 | 0 | 0.5 | 1 | 1 | 1 |

$r_{flow} = 250$

| β3, β4 | 1,1 | | | 1,-1 | | | -1,1 | | | -1,-1 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Normalized | C3 | C4 | Uj | C3 | C4 | Uj | C3 | C4 | Uj | C3 | C4 | Uj |
| Candidates | | | | | | | | | | | | |
| 0 | 1 | 0 | 0.5 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 0.5 |
| 1 | 1 | 1 | 1 | 1 | 0 | 0.5 | 0 | 1 | 0.5 | 0 | 0 | 0 |
| 2 | 0 | 0.75 | 0.375 | 0 | 0.25 | 0.125 | 1 | 0.75 | 0.875 | 1 | 0.25 | 0.625 |

$r_{flow} = 350$

| β3, β4 | 1,1 | | | 1,-1 | | | -1,1 | | | -1,-1 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Normalized | C3 | C4 | Uj | C3 | C4 | Uj | C3 | C4 | Uj | C3 | C4 | Uj |
| Candidates | | | | | | | | | | | | |
| 0 | 1 | 0 | 0.5 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 0.5 |
| 1 | 1 | 1 | 1 | 1 | 0 | 0.5 | 0 | 1 | 0.5 | 0 | 0 | 0 |
| 2 | 0 | 1 | 0.5 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 0 | 0.5 |

**Figure 8.8 Demonstrate Road Network Dynamics – Spatial Decision of New Road Network Node in One Time Step**: This example demonstrates spatial decisions of new road network node location under different $\beta_k$ and $r_{flow}$ combinations.

This example showed that the proposed criteria evaluation process could choose candidate locations properly according to the specified criteria for Road Network Dynamics. It also demonstrated how the spatial decision of new road network node location in one time step changed under different $(\beta_3, \beta_4)$ combinations and with different $r_{flow}$.

### 8.2.3 Computer Model

Following the proposed co-evolution mechanism – Population Dynamics and Road Network Dynamics 8.2.1, as well as the explained Criteria evaluation process to implement the co-evolution mechanism 8.2.2, this section described the hybrid generative network model of population and urban road network co-evolution.

This model proposed to represent the population and the urban road network as two inter-dependent urban system layers, addressing previous GNMs' design limitation of population and road network in one network. Road network was represented by a network $G = (V, E)$, as in the proposed GNM of urban road network evolution in Chapter 6. The population was represented by a point set $V_{pop}$, which consisted of abstract points where population concentrated.

As described in 8.2.1, this model proposed population and road network co-evolved with two iterative processes, Population Dynamics and Road Network Dynamics. The population increased at each iteration by adding new population; new population made spatial decision to locate in the urban area. Population's spatial decisions considered the existing population and road network. Growth and spatial decision constituted the process of Population Dynamics. Road network also increased at each iteration by adding new road network components and made spatial decision to locate in the urban area. Road network's spatial decisions considered existing population and road network as well. After making the spatial decision for new road network nodes, road network performed Node Addition and Link Connection. Growth, spatial decision, Node Addition and Link Connection constituted the process of Road Network Dynamics.

At each time step, Population Dynamics happened first: $j^*$ new population locations were chosen from $j$ generated candidate locations, and new population were added. The spatial decision to locate new population was made by evaluating two criteria - $C_1$ measured impacts of factor $d_{pop}$ – a population location candidates' distance to the road network and $C_2$ measured factor $\rho$ - a population location candidate's local density within radius $r_{density}$. All $j$ population candidate locations' $C_1$ and $C_2$ measurement values were calculated and evaluated using Equation 1 with weights $\alpha_1$, $\alpha_2$ and value preference $\beta_1$, $\beta_2$. Population Dynamics of a time step then completed by choosing candidate locations with the most desirable evaluation score $U$ and adding new population to these locations.

Road Network Dynamics then happened: $j'^*$ new road node locations were chosen from $j'$ generated candidate locations by evaluating two criteria. Candidate locations were compared by the potential network provided they were connected. $C_3$ measured the impact of factor $d_{RN}$ - total distance from the potential road network to all existing population. $C_4$ measured the impact of factor $\sum flow$ – total link flows of a subnetwork within radius $r_{flow}$ to the candidate in the potential road network. All $j$ road node candidate locations' $C_3$ and $C_4$ measurement values were calculated and evaluated using Equation 1. The evaluation was controlled by $C_3$, $C_4$'s weights $\alpha_3$, $\alpha_4$ and value preference $\beta_3$, $\beta_4$. Road Network Dynamics of a time step completed by choosing candidate locations with most desirable evaluation score $U$ and performing Node Addition and Link Connection at these locations.

### 8.2.4 Algorithm

1. Initialisation:
   a. Generate initial population points $V_{pop}$;
   b. Generate initial road network $G$;
2. While iteration number $i \leq \text{Total iteration number } N$:
   a. Population dynamics:
      i. Generate $j$ population candidates;
         1. For each population candidate:
            a. Calculate $C_1$ Population location candidate's distance to road network $d_{pop}$;
            b. Calculate $C_2$ Population location candidate's local density $\rho$ within radius $r_{density}$;
         2. Evaluate $(C_1, C_2)$ of all population candidate locations with $(\alpha_1, \alpha_2)$ and $(\beta_1, \beta_2)$;
         3. Choose $j^*$ new population points and add to $V_{pop}$;
   b. Road Network Dynamics:
      i. Generate $j'$ road node candidates;
         1. For each road node candidates:
            a. Calculate $C_3$ Potential distance to population $d_{RN}$;
            b. Calculate $C_4$ potential link flows $\sum \text{flow}$ within radius $r_{flow}$;
         2. Evaluate $(C_3, C_4)$ of all road node candidate locations with $(\alpha_3, \alpha_4)$ and $(\beta_3, \beta_4)$;
         3. Choose $j'^*$ new population points;
         4. For each new road node:
            a. Node Addition to $G$;
            b. Link Connection;
   c. $i = i + 1$;

## 8.3 Simulation Experiments

By modelling microscopic road network and population behaviours and interactions, this simulation study attempted to explore emerging road network and urban system spatial structures as well as their relationships, by conducting experiments with parameters $\beta_k$ and radius $r_{density}$, $r_{flow}$ combinations. Previous models often assumed fixed one-way influence from the transport system to population and vice versa. However, empirical findings as reviewed in Chapter 3 have suggested that urban road networks and urban systems exhibited diverse spatial structures and changed in various directions, e.g. the existence and emergence of monocentric and polycentric spatial structures, the suburbanization and urban sprawl processes. The influences between the road network and population on each other behind the diverse urban spatial structure and dynamics required further understanding. Thus, the co-evolution mechanism might not assume fixed mutual influences between population and urban road network and of shall be able to give rise to different spatial structures. Following this idea, this simulation study attempted to explore with different combinations of parameters for various population and urban road network co-evolution scenarios.

As explained in 8.2.1, $\beta_k \in \{-1,1\}$ and controlled the impact of co-evolution mechanism criteria $\mathrm{C_k}$'s measurement values, on spatial decisions of new population and new road node locations in Population Dynamics and Road Network Dynamics respectively. The simulation study planned to experiment with all 16 $\beta_k$ combinations in Population Dynamics and Road Network Dynamics, namely $(\beta_1, \beta_2, \beta_3, \beta_4) =$

1. $(d_{pop}^{-}, \rho^{+}, d_{RN}^{-}, \sum flow^{+})$;
2. $(d_{pop}^{-}, \rho^{+}, d_{RN}^{-}, \sum flow^{-})$;
3. $(d_{pop}^{-}, \rho^{-}, d_{RN}^{-}, \sum flow^{+})$;
4. $(d_{pop}^{-}, \rho^{-}, d_{RN}^{-}, \sum flow^{-})$;
5. $(d_{pop}^{-}, \rho^{+}, d_{RN}^{+}, \sum flow^{+})$;
6. $(d_{pop}^{-}, \rho^{+}, d_{RN}^{+}, \sum flow^{-})$;
7. $(d_{pop}^{-}, \rho^{-}, d_{RN}^{+}, \sum flow^{+})$
8. $(d_{pop}^{-}, \rho^{-}, d_{RN}^{+}, \sum flow^{-})$;
9. $(d_{pop}^{+}, \rho^{+}, d_{RN}^{-}, \sum flow^{+})$;
10. $(d_{pop}^{+}, \rho^{+}, d_{RN}^{-}, \sum flow^{-})$;
11. $(d_{pop}^{+}, \rho^{-}, d_{RN}^{-}, \sum flow^{+})$;
12. $(d_{pop}^{+}, \rho^{-}, d_{RN}^{-}, \sum flow^{-})$;
13. $(d_{pop}^{+}, \rho^{+}, d_{RN}^{+}, \sum flow^{+})$;
14. $(d_{pop}^{+}, \rho^{+}, d_{RN}^{+}, \sum flow^{-})$;
15. $(d_{pop}^{+}, \rho^{-}, d_{RN}^{+}, \sum flow^{+})$;
16. $(d_{pop}^{+}, \rho^{-}, d_{RN}^{+}, \sum flow^{-})$.

Simulation trials happened on a $1000\, unit * 1000\, unit$ square area. The initial road network was a small rectangle in the geographical centre of the simulation area. The initial population were three units of the population (three points), distributing from the geographical centre according to the exponential distribution. $\alpha_\mathrm{k} = (\alpha_1, \alpha_2, \alpha_3, \alpha_4) = (1,1,1,1)$; this assumed all four criteria to have the same weight in the Population Dynamics and Road Network Dynamics spatial decision making. $\mathrm{r_{density}} = \mathrm{r_{flow}} = r$ were assumed with three experimental values: $r = 50$, $150$, $250$ units.

For each simulation trial, at each time step, Population Dynamics generated $j = 5$ population candidate locations and chose $j^* = 1$ location to add new population; and Road Network Dynamics generated $j' = 5$ and chose $j'^* = 1$ new location to add new road node and connect to the existing road network. Spatial decisions were performed with one combination of $\beta_k$ and $r$: for instance, $(d_{pop}^{-}, \rho^{+}, d_{RN}^{-}, \sum flow^{+})$ and $r = 50$. One simulation trial terminated when reaching a user-specified number of time steps. Each $\beta_k$ combination set was experimented with all three $r$ values and for 30 trials. Table 8-4 summarised the setting of simulation experiments.

**Table 8-4 Simulation Parameter Setting Summary**

| Parameters | Setting |
|---|---|
| *Initial Road Network* | $200\ unit * 100\ unit$ rectangle at the centre of the simulation area |
| *Initial Population and Distribution* | 3 Units; Following Exponential distribution from geographical centre of simulation area |
| *Population Growth Rate* $\boldsymbol{j^*}$ | One Unit per time step |
| *Population Candidates Generation Rate* $\boldsymbol{j}$ | Five Unit per time step |
| *Road Growth Rate* $\boldsymbol{j'^*}$ | One Location per time step |
| *Road Candidates Generation Rate* $\boldsymbol{j'}$ | Five Locations per time step |
| *Spatial Distribution of Candidate Location* | Uniformly Random |
| *Simulation Terminate Condition* | Time step $t = 150$ |
| *Number of Simulation Trials* | 30 |

### 8.3.1 Sensitivity Analysis

First, population and road network growth rate – the number of locations to add new population $j^*$ and new road nodes $j'^*$, at each time step, were both set to 1. The number of population $j$ and road node $j'$ candidate locations generated at each time step were both set to 5. When candidate generation rate $j$ and $j'$ were very large, for instance, $j \to +\infty$ and $j' \to +\infty$, simulation equalled computing analytical solutions at each time step for the co-evolution mechanism. Large $j$ and $j'$ shall speed up the process of revealing the simulated structure but would exhaust the computational power. On the other hand, when candidate generation rate $j$ and $j'$ were very small, for instance, $j = j' = 1$, the designed new population and road node selection mechanism were disabled. New population and road node locations followed the distribution of candidate generation location and were uniformly random. Therefore, the ratio between population growth rate $j^*$ and candidate location generation rate $j$, as well as between road network growth rate $j'^*$ and candidate location generation rate $j'$, were set by balancing the capacity to utilise the proposed model and the computational power.

Second, the ratio between $j^*$ and $j'^*$ were set as equal in simulation experiment – adding one new location for population and road network each. In the urban system, the rate between population and road network growth may indicate the relationship between population and the required amount of transport infrastructure, like with the urban scaling relations. It may as well indicate time scale differences between urban Population Dynamics and road infrastructure construction. In the proposed model, the population were represented with abstract units. Rate between $j^*$ and $j'^*$ did not suggest scaling relations or time scales of Population Dynamics and Road Network Dynamics. When $j^* \gg j'^*$, for road network at a time step, Population Dynamics added new population until exhausting locations over the existing road network. This setting led to the disabling of designed $d_{RN}$ impact in Road dynamics. Because new population exhausted locations over road network, $d_{RN}$ was homogeneous for road node candidate locations and made no difference on new road infrastructure locations. Similarly, when $j'^* \gg j^*$, for the population at a time step, Road Network Dynamics performed until exhausting new road node locations, relative to population distribution. This setting led to the disabling of designed $d_{pop}$ impact on the population, as new population candidate locations were homogeneous when measured by $d_{pop}$. Change of this ratio may be explored in future work to simulate more realistic Population Dynamics and Road Network Dynamics relationships.

Third, to explore emerging spatial structures of simulated population and road network under the designed co-evolution mechanisms, candidate locations were generated as uniformly random. Population and road network spatial structures emerged would result from spatial decisions made according to the co-evolution mechanism, instead of predetermined candidate distribution.

Forth, each simulation trial terminated at time step $t = 150$. For 16 $\beta_k$ combinations and 3 $r$ values, 30 trials were performed for each of 48 sets of $\beta_k$ and $r$ combinations. Simulation results of $t = 350$ were compared with that of $t = 150$ to show $t = 150$ simulated structure were significant to represent the proposed model's results.

## 8.4 Chapter Conclusions

This chapter addressed the third research question of this thesis and proposed a hybrid model of population and urban road network co-evolution in 8.2, with co-evolution mechanism 8.2.1 consisting of Population Dynamics 8.2.1.1 and Road Network Dynamics 8.2.1.2. Using the synthesized layered urban system representation from Chapter 3, the proposed model considered explicitly the urban road network structure, which positioned it with alternative modelling approaches that involved RNE such as transport demand modelling, land use and transport models, urban models. At the same time, the proposed model coupled urban road network and population, which integrated GNM into the urban system, as illustrated in Figure 8.1. 8.2.2 explained the implementation of the co-evolution mechanism, and 8.2.3, 8.2.4 summarised the model and algorithm.

This model addressed two limitations in previous GNMs, as reviewed in chapter 4 section 4.3.4.4. First, the proposed model represented population and road network as two inter-dependent urban system layers, addressing previous GNMs' limitation in modelling population and road network using one network, with nodes representing population concentrated locations and links representing roads. The proposed model treated population and road network as independent urban system layers; thus, the two systems would not be inherently related being one network's nodes and links as in previous representations. The modelled population and road network structure, as well as their relationship, would only be influenced by the proposed co-evolution mechanisms and not by the built-in network connectivity between nodes and links. This model design helped disentangle and understand mutual relationships and interactions between population and road network.

Second, the proposed co-evolution mechanism did not assume fixed population and road network mutual influences but proposed to explore all potential population and road network spatial decision possibilities. This model and simulation experiment design attempted to relate to the diverse urban road network spatial structures and urban spatial structures reported in recent empirical research. Diverse spatial structures of simulated road networks may emerge, addressing previous studies' limitation in exploring the urban road network spatial structure and its relationship to the urban spatial structure.

Following the proposed model, the next chapter performs the planned simulation experiments in 8.3 and examines the emerging road network and population spatial structures, as well as their mutual influences, under different parameter combinations of the proposed co-evolution mechanism.

# Chapter 9 Hybrid Model of the Population and Urban Road Network Co-evolution - Simulation Results

## 9.1 Chapter Introduction

Implementing the hybrid model of population and urban road network co-evolution proposed in the previous chapter, this chapter examines results of performed simulation experiments, explores the emerging road network spatial structure, population spatial structure, as well as their relationships.

The proposed co-evolution mechanism iterated Population Dynamics and Road Network Dynamics, both making spatial decisions to add new components based on preferences for the distance between population and road network and existing population density or network flow situation. Population Dynamics made the spatial decision by two criteria $C_1$ and $C_2$. $C_1$ measured the impact of candidate population location's distance to existing road network $d_{pop}$ and was controlled by the parameter $\beta_1$. $\beta_1 = d_{pop}^{+}$ and $\beta_1 = d_{pop}^{-}$ represented population's preferences for being away from or close to the road network. $C_2$ measured the impact of existing local population density $\rho$ within radius $r_{density}$ of the candidate population location and was controlled by the parameter $\beta_2$. $\beta_2 = \rho^{+}$ and $\beta_2 = \rho^{-}$ represented population's preferences for densely or sparsely populated areas. Road Network Dynamics made the spatial decision of the location to add new road network nodes, then performed Node Addition and Link Connection. Road Network Dynamics had two criteria $C_3$ and $C_4$. $C_3$ measured the impact of total distance $d_{RN}$ from the road network to all existing population, provided a candidate new node was connected; $C_3$ was controlled by the parameter $\beta_3$. $\beta_3 = d_{RN}^{+}$ and $\beta_3 = d_{RN}^{-}$ represented the road network's proximity preferences for being away from or being close to the population. $C_4$ measured the impact of total link flows $\sum flow$ of a subnetwork within radius $r_{flow}$, provided a candidate node was connected; $C_4$ was controlled by the parameter $\beta_4$. $\beta_4 = \sum flow^{+}$ and $\beta_4 = \sum flow^{-}$ represented road network's preferences for areas with high or low existing network flow.

Simulation experiments in the chapter explore various population and road network spatial decision combinations, instead of assuming fixed ones, by experimenting parameters $\beta_k$ and r. Each $\beta_k$ in $(\beta_1, \beta_2, \beta_3, \beta_4)$ had two possible values - positive and negative. The radius of spatial decisions in Population Dynamics and Road Network Dynamics in each simulation trial was set to the same value $r_{density} = r_{flow} = \mathrm{r}$, and each $\beta_k$ set experimented with three radius values $\mathrm{r} \in \{50{,}150{,}250\}$. Thus, there were a total number of 48 $\beta_k$ and $\mathrm{r}$ combinations to explore. Each $\beta_k$ and $\mathrm{r}$ combination had with 30 simulation trials, from which the parameter combination's effects on the simulated structure were concluded. This chapter attempts to answer the fourth research question of this thesis, as proposed in Chapter 1 and specified in Table 5-2:

4 What road network spatial structure may arise during the co-evolution of road network and population? How do the simulated road network and population relate?

a) How to characterise the spatial structure of urban road networks?

This chapter first examines the simulated network spatial structure 9.2 by visual inspection 9.2.1, network characterisation 9.2.2, and the relationship between network spatial structure and connectivity 9.2.3. Second, the simulated population-road network spatial structure 9.3 is examined, which identifies the combined population-road network spatial structures 9.3.1, as well as the mutual influences between population and road network 9.3.2, 9.3.3. Finally, 9.4 concludes the modelling and simulation findings under the proposed hybrid model of population and urban road network co-evolution.

## 9.2 The Spatial Structure of Simulated Networks

### 9.2.1 Visual Examination of Simulated Network Spatial Structures

Figure 9.1 - Figure 9.4 show one sample set of simulation results under the 48 $\beta_k$ and $\mathrm{r}$ combinations. Together with the other 29 trials conducted under different random seeds, simulation experiments yielded 30 such simulation result sets in total.

The shown set of 48 $\beta_k$ and $\mathrm{r}$ combination simulation results were organised into the four tables Figure 9.1 - Figure 9.4, first by parameters $(\beta_1, \beta_3)$ - the preference of population and road network for being close to or away from each other. Simulated results in each table shared a same $(\beta_1, \beta_3)$ combinations, and there were four combinations, namely $(\beta_1, \beta_3) = (d_{pop}^{-}, d_{RN}^{-})$, $(d_{pop}^{-}, d_{RN}^{+})$, $(d_{pop}^{+}, d_{RN}^{-})$, $(d_{pop}^{+}, d_{RN}^{+})$. For example, simulations in Figure 9.1 shared $(\beta_1, \beta_3) = (d_{pop}^{-}, d_{RN}^{-})$, when population and road network both chose to be near each other in spatial decision making; and this table shows the simulation result visualizations with varied $(\beta_2, \beta_4)$ and $\mathrm{r}$ under the same $(\beta_1, \beta_3) = (d_{pop}^{-}, d_{RN}^{-})$. Each table has three vertical panels with parameter $\mathrm{r} = 50,\ 150,\ 250$. Each $\mathrm{r}$ panel shows the same simulated structure at two time steps $t = 150, 350$ in two rows.

Visual inspections yielded two findings. First, the simulated networks exhibited a spectrum of diverse spatial structures. In particular, the simulated networks exhibited centralising, decentralising, clustering, and dispersing trends in the spatial structure, for instance, with simulated networks in Figure 9.1 column 1 $\mathrm{r} = 250$, column 4 $\mathrm{r} = 250$, column 1 $\mathrm{r} = 50$, and column 4 $\mathrm{r} = 50$ respectively. Second, differences in simulated network spatial structures resulted from varied parameter combinations, namely the population and road network spatial decision combinations enabled by the proposed co-evolution mechanism. According to each parameter's influences on the simulated network spatial structure, the parameters were separated into three groups.

#### 9.2.1.1 The Influences of $\boldsymbol{\beta_4}$ and $\mathbf{r}$ on the simulated network spatial structure

First, the parameter $\beta_4$, whether new road network preferred area with large or small network flow $\sum flow$ in criteria $C_4$ of the Road Network Dynamics mechanism, led simulated networks to centralise or decentralise, which was observable in all simulated networks. When $\beta_4 = \sum flow^+$ , namely column 1, 3 in all tables, new road network preferred area with large $\sum flow$, the simulated network spatial structure tended to centralise. When $\beta_4 = \sum flow^-$ , namely column 2, 4 in all tables, new road network preferred area with small $\sum flow$, the simulated network spatial structure tended to decentralise.

Further, when $\beta_4 = \sum flow^+$ and the network spatial structure had the centralising tendency, large $\mathrm{r}$, e.g. the third panels in all tables with $\mathrm{r} = 250$, led to centralised spatial structures with a single centre; and small $\mathrm{r}$, e.g. the first panels in all tables with $\mathrm{r} = 50$, led to clustered spatial structures with multiple potential centres. This could be shown by Figure 9.1 column 1 at $\mathrm{r} = 250$ and $\mathrm{r} = 50$, respectively, as well as by Figure 9.2 column 1 at $\mathrm{r} = 250$ and $\mathrm{r} = 50$. When $\beta_4 = \sum flow^-$ and the network spatial structure had the decentralising tendency, large $\mathrm{r}$, e.g. the third panels in all tables with $\mathrm{r} = 250$, led to decentralised spatial structures; and small $\mathrm{r}$, e.g. the first panels in all tables $\mathrm{r} = 50$, led to dispersed spatial structures. This impact could be shown in Figure 9.1 column 4 at $\mathrm{r} = 250$ and $\mathrm{r} = 50$, as well as in Figure 9.2 column 4 at $\mathrm{r} = 250$ and $\mathrm{r} = 50$.

Centralising and decentralising tendencies in the simulated network spatial structures under $\beta_4 = \sum flow^+$ and $\beta_4 = \sum flow^-$ respectively, suggested $\beta_4$ modelled opposite centralisation and decentralisation processes that pushed and pulled simulated road network spatial structures, by spatial decision preferences for areas with high or low existing network flow. Preference for high flow $\sum flow^+$ modelled simulated networks' centralising behaviour and centralisation process, while preference for low flow $\sum flow^-$ modelled the road networks' decentralising behaviour and decentralisation process.

$\mathrm{r}$ modelled the scope of centralisation and changed the simulated structure between centralised to clustered resulted. Centralising globally within a large radius $\mathrm{r}$ resulted in the centralised spatial structure with a single centre while centralising locally within a small radius $\mathrm{r}$ resulted in the clustered spatial structure with multiple potential centres. The tendency between decentralised to dispersed resulted from the spatial scope of decentralisation. Decentralising globally within a large radius $\mathrm{r}$ resulted in the decentralised spatial structure while decentralising locally within a small radius $\mathrm{r}$ resulted in the dispersed spatial structure.

Combining $\beta_4$ and $\mathrm{r}$, two dimensions of road network spatial structure – centralised to decentralised on the global scale, clustered to dispersed on the local scale were modelled. Overall, this suggested the spectrum of diverse simulated network spatial structures resulted from simulated networks' centralisation and decentralisation processes on the global scale and clustering and dispersion processes on the local scale, behind the formation of these spatial structures as modelled by $\beta_4$ and $\mathrm{r}$.

The observation and characterisation of simulated network spatial structures were consistent with the characterisation of urban spatial structure. As reviewed in 3.3.1, the urban spatial structure has been characterised by two dimensions centralisation to decentralisation on the global scale, clustering to dispersion on the local scale. The urban spatial structure has been attributed to push and pull processes, including economies and diseconomies of agglomeration on the economic urban spatial structure, coalescence and diffusion in physical urban growth, attraction and repulsion between land use categories, centripetal and centrifugal forces of transport accessibility, spatial interaction potentials on the functional urban spatial structure.

Characterisation by the centralised to decentralised, clustered to dispersed dimensions, associated simulated network spatial structures and the push and pull processes behind their formation as modelled by $\beta_4$ and $\mathrm{r}$, with the urban spatial structure and push and pull processes behind its formation. Economic agglomeration encourages the spatial concentration of physical capital; urban road network spatial structures have been reported to correlate with population and urban spatial structure, by empirical research reviewed in 3.4. The correlations may suggest the presence of related push and pull processes behind their formation, respectively. Meanwhile, the urban spatial structure has socioeconomic, physical, functional components, as synthesised in 3.3.4; spatial structures of different urban system layers may correlate but should not be equated to each other. Hence, simulated network spatial structures were first characterised independently from the simulated population.

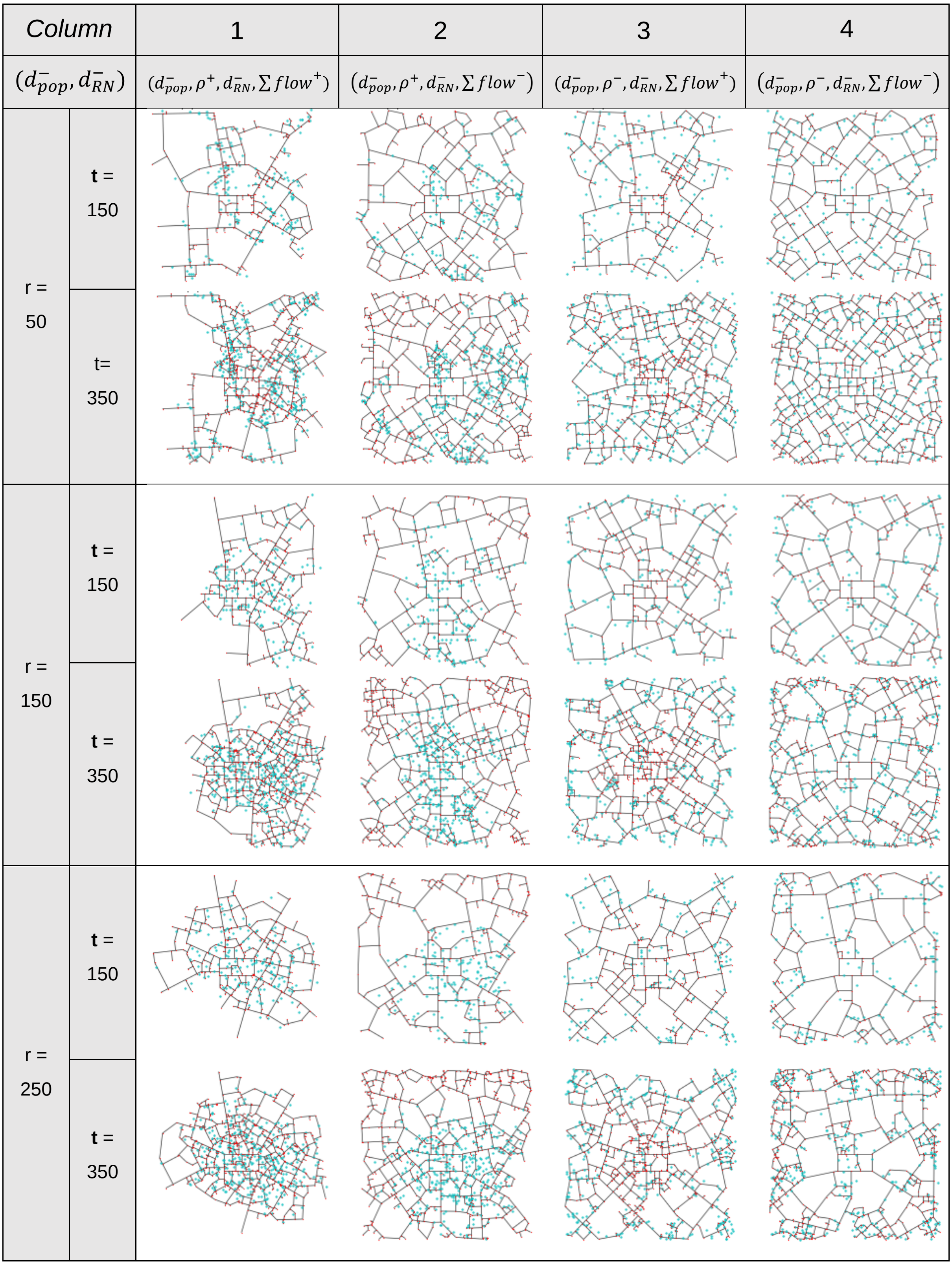



**Figure 9.1** **Simulated Structures under $(\beta_1, \beta_3) = (d_{pop}^{-}, d_{RN}^{-})$ with $r = 50, 150, 250$ at $t = 150, 350$**: This figure shows the simulated population and road networks. Blue points represent population concentrated locations. Red points represent road network nodes and black lines represent road network links.

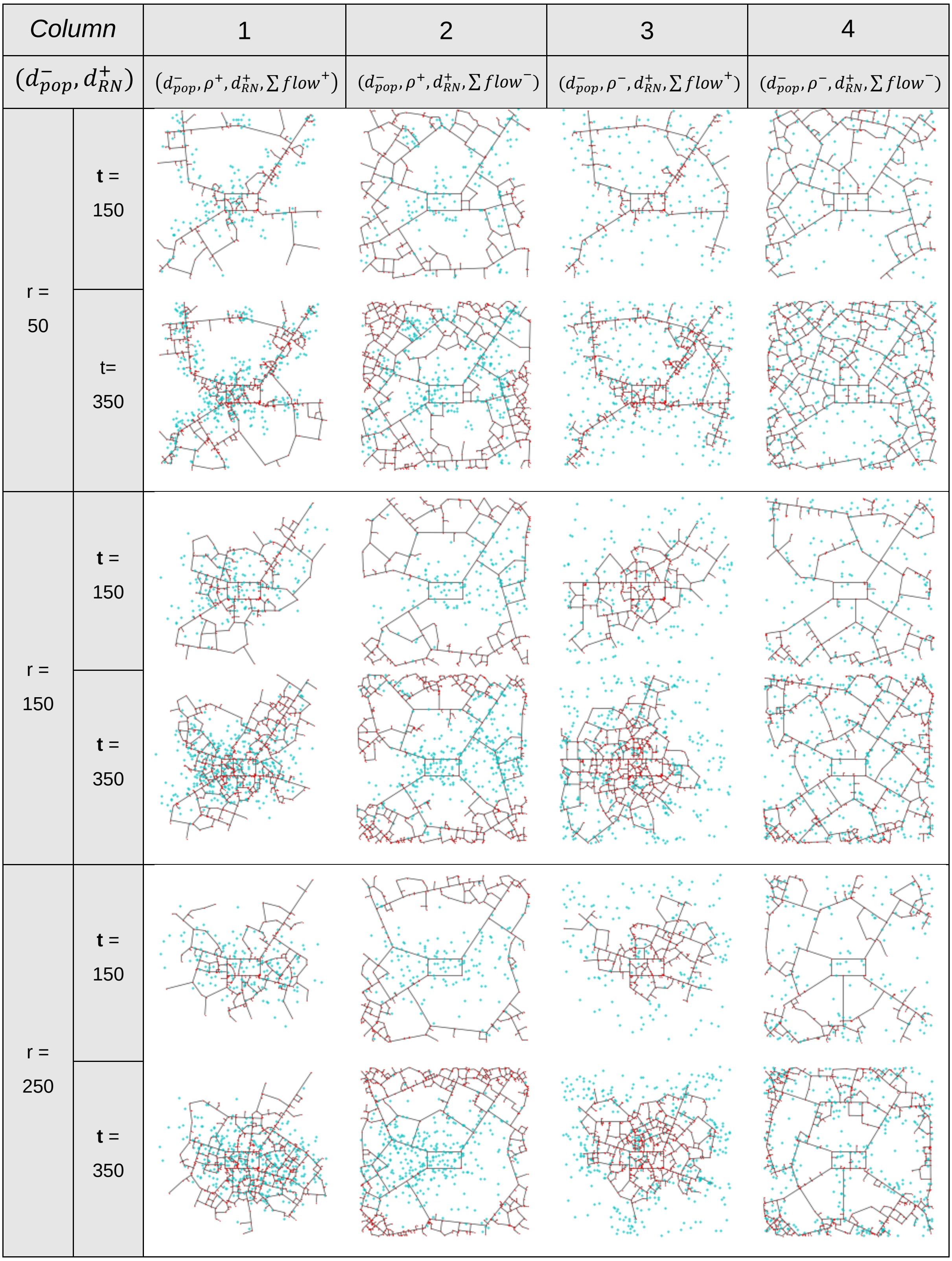



**Figure 9.2 Simulated Structure under $(\boldsymbol{\beta_1}, \boldsymbol{\beta_3}) = (\boldsymbol{d^-_{pop}}, \boldsymbol{d^+_{RN}})$ with $\boldsymbol{r} = \mathbf{50}, \mathbf{150}, \mathbf{250}$ at $\boldsymbol{t} = \mathbf{150}, \mathbf{250}$**: This figure shows the simulated population and road networks. Blue points represent population concentrated locations. Red points represent road network nodes and black lines represented road network links.

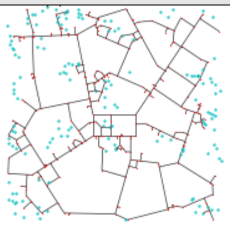
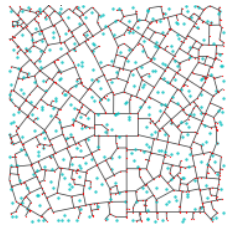
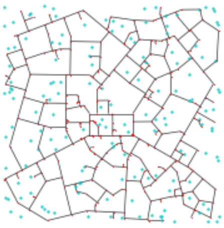
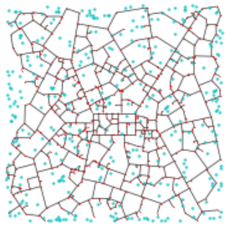
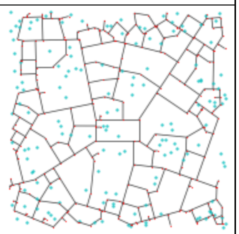
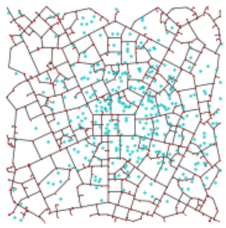
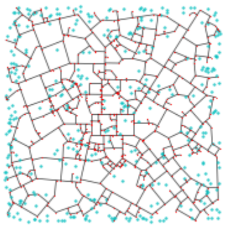
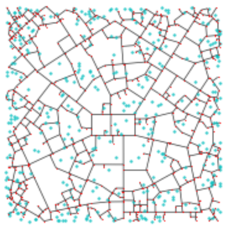
| Column | | 1 | 2 | 3 | 4 |
|---|---|---|---|---|---|
| $(d^+_{pop}, d^-_{RN})$ | | $(d^+_{pop}, \rho^+, d^-_{RN}, \sum flow^+)$ | $(d^+_{pop}, \rho^+, d^-_{RN}, \sum flow^-)$ | $(d^+_{pop}, \rho^-, d^-_{RN}, \sum flow^+)$ | $(d^+_{pop}, \rho^-, d^-_{RN}, \sum flow^-)$ |
| r = 50 | t = 150 |  |  |  |  |
| | t= 350 |  |  |  |  |
| r = 150 | t = 150 |  |  |  |  |
| | t = 350 |  |  |  |  |
| r = 250 | t = 150 |  |  |  |  |
| | t = 350 |  |  |  |  |

**Figure 9.3 Simulated Structure under $(\beta_1, \beta_3) = (d^+_{pop}, d^-_{RN})$ with $r = 50, 150, 250$ at $t = 150, 250$**: This figure shows the simulated population and road networks. Blue points represented population concentrated locations. Red points represent road network nodes and black lines represent road network links.

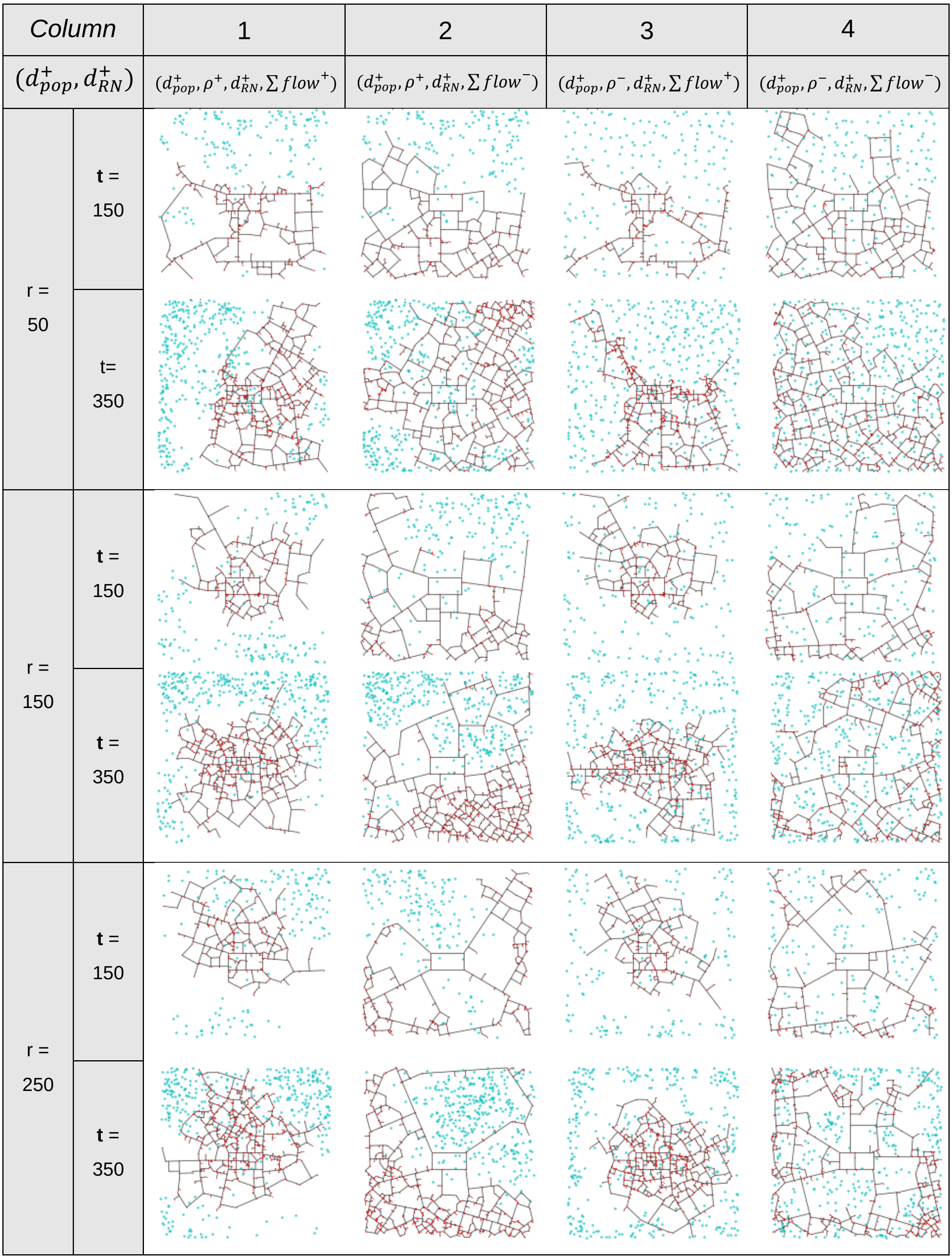



**Figure 9.4 Simulated Structure under $(\beta_1, \beta_3) = (d^+_{pop}, d^+_{RN})$ with $r = 50, 150, 250$ at $t = 150, 250$**: This figure shows the simulated population and road networks. Blue points represented population concentrated locations. Red points represent road network nodes and black lines represent road network links.

#### 9.2.1.2 The Influences of $(\boldsymbol{\beta_1}, \boldsymbol{\beta_3})$ and $\boldsymbol{\beta_2}$ on the simulated network spatial structure

The second group of parameters were $(\beta_1, \beta_3)$, namely population and road network's preferences for the distance to each other. These two parameters intensified or counteracted the influences of $\beta_4$ and $\mathrm{r}$ on the simulated network spatial structure, rather than giving rise to systematic differences on their own. Figure 9.1 - Figure 9.4 each corresponds to one combination of $(\beta_1, \beta_3)$. There was no persistent pattern of differences among simulated networks of the four figures; however, their centralised, decentralised, clustered, and dispersed spatial structures were intensified or counteracted. In comparison to $(\beta_1, \beta_3) = (d_{pop}^-, d_{RN}^-)$ of Figure 9.1, $(\beta_1, \beta_3) = (d_{pop}^-, d_{RN}^+)$ in Figure 9.2 intensified centralising and decentralising of simulated network spatial structures, as population chose to be close to the road network while road network chose to be away from the population. $(\beta_1, \beta_3) = (d_{pop}^+, d_{RN}^-)$ in Figure 9.3 counteracted centralising and decentralising of simulated network spatial structures, as population chose to be away from road network while road network chose to be close to population, and all simulated networks had dispersed spatial structures, exceeding other parameters' influences. $(\beta_1, \beta_3) = (d_{pop}^+, d_{RN}^+)$ in Figure 9.4 both intensified and counteracted centralising and decentralising of simulated network spatial structures, leading to asymmetric spatial distributions of simulated networks.

The last parameter was $\beta_2$, which controlled the population's preference for areas with high or low existing population density. $\beta_2$ exerted indirect influences on the simulated road network spatial structure, as it controlled the behaviour of the population. $\beta_2$ intensified or counteracted influences of $\beta_4$ and $\mathrm{r}$ as $(\beta_1, \beta_3)$ did, which could be observed by comparing each figure's columns 1 and 3 as well as columns 2 and 4. Columns 1 and 3 of each figure shared the same value of parameters $(\beta_1, \beta_3, \beta_4)$, but had opposite $\beta_2$ values; same applied to columns 2 and 4. The spatial structure of the population might intensify and counteract simulated networks' centralisation, decentralisation, clustering, and dispersion.

#### 9.2.1.3 Visual Examination Summary

In summary, visual inspection suggested the proposed model is capable of giving rise to a spectrum of network spatial structures, which could be characterised by the processes behind their formation - centralisation and decentralisation on the global scale, clustering and dispersion on the local scale. Simulated networks' spatial structures being a spectrum, rather than a few fixed and clear-cut types, resulted from centralising, decentralising, clustering, dispersion processes that pushed and pulled the simulated network spatial structures as modelled by $\beta_4$ and $\mathrm{r}$, as well as from further intensification or counteraction by influences of the simulated population as modelled by $(\beta_1, \beta_2, \beta_3)$.

To be more specific, parameters $\beta_4$, the spatial decision preference for areas with large or small network flow $\sum flow$ to locate new network nodes, modelled the centralisation and decentralisation processes of simulated networks. And radius $\mathrm{r}$ of the area within which road network and population made spatial decisions, controlled the scale - global or local, on which centralisation and decentralisation happened. Centralisation on the global scale led to centralised monocentric spatial structures, centralisation on the local scale led to clustered spatial structures with multiple potential centres; decentralisation on the global scale led to decentralised spatial structures, and decentralisation on the local scale led to dispersed spatial structures. The rest of parameters $(\beta_1, \beta_3)$ - population and road network's preferences of the distance to each other, and $\beta_2$ - population's preference for areas with high or low existing population density, intensified or counteracted centralisation and decentralisation, clustering and dispersion processes, together contributing to the emergence of the diverse spectrum of simulated network spatial structures.

After identifying the two dimensions of simulated network spatial structures, the next section used network characteristics to characterise these spatial structures.

### 9.2.2 Network Characterisation of Simulated Network Spatial Structures

Existing research has characterised road network spatial structure by dominant geometric connection patterns, continuity patterns, and density distributions, as reviewed in 3.2. Dominant geometric connection patterns such as ring, star, web, hub-and-spoke, and stroke-based or street-based patterns have captured the inherent hierarchy of urban road networks, but defined fixed types of road network spatial structures, and have insufficiently considered these patterns' relationship to the urban system. Spatial analysis of road network density has related the road network spatial structure to the urban spatial structure yet treated only road network nodes or road infrastructure quantities under certain space division, while neglecting the network nature of the road network spatial structure. Because of its network nature, measures of the urban spatial structure may not be directly applicable to characterise road network spatial structure. Network science perspective empirical and modelling RNE research, as reviewed in Chapter 2, 4 has had limited characterisation of road network spatial structure. Since road networks have been a significant data source of urban form, the road network structure has often been equated to urban form and urban spatial structure, without discussions of the relationship between them.

5.3.2.1 proposed to use two network characteristics - total link length $L_{tot}$ and maximum shortest path $l_{max}$, to characterise the road network spatial structure from centralised to decentralised and from clustered to dispersed. On areas of the same size, centralised network structures concentrated around a single centre and should be characterised by relatively small network diameter and small total length. On the contrary, decentralised network structures spanned to the fringe of the area and should be characterised by a large diameter. Compared to decentralised network structures, dispersed network structures not only had a relatively large diameter but also had large total length, spanning over an area with high coverage. Compared to centralised network structures, clustered network structures had larger diameter but smaller coverage.

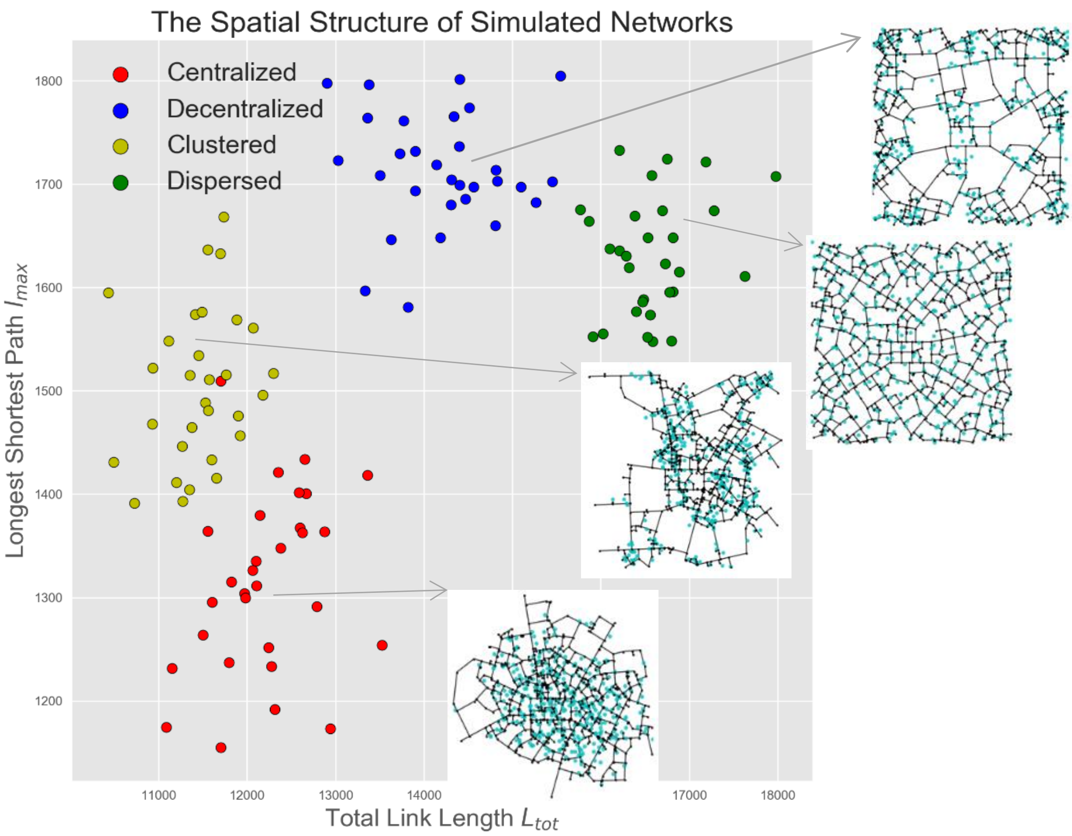



**Figure 9.5 Network Characterisation of Simulated Network Spatial Structure**: This plot shows the total link length $L_{tot}$ and maximum shortest path $l_{max}$ separated simulated networks under parameter combinations $(\beta_1, \beta_2, \beta_3, \beta_4) = (d_{pop}^{-}, \rho^{+}, d_{RN}^{-}, \sum flow^{+})$ at $r = 250$, $50$ and $(d_{pop}^{-}, \rho^{-}, d_{RN}^{-}, \sum flow^{-})$ at $r = 50$, $250$ to benchmark the centralised to decentralised, clustered to dispersed dimensions. The x-axis represents $L_{tot}$; the y-axis represents $l_{max}$. Sample simulated network visualizations of the corresponding parameter combination are marked with spatial structures.

Figure 9.5 demonstrated $L_{tot}$ and $l_{max}$ separated centralised, decentralised, clustered, and dispersed network spatial structures. Simulated networks under four parameter combinations $(\beta_1, \beta_2, \beta_3, \beta_4) = \left(d_{pop}^{-}, \rho^{+}, d_{RN}^{-}, \sum flow^{+}\right)$ at $r = 250$, $50$ and

$\left(d_{pop}^{-}, \rho^{-}, d_{RN}^{-}, \sum flow^{-}\right)$ at $r = 250$, $50$, corresponding to Figure 9.1 column 1 $\mathrm{r} = 50$, $250$ and column 4 $\mathrm{r} = 50$, $250$, were selected to benchmark the two spatial structure dimensions. Each group of simulated networks had data of 30 simulation trials.

In the lower left corner, simulated networks under $(\beta_1, \beta_2, \beta_3, \beta_4) = \left(d_{pop}^{-}, \rho^{+}, d_{RN}^{-}, \sum flow^{+}\right)$ at $r = 250$ had centralised spatial structures and formed a point cluster with smallest $l_{max}$ and small $L_{tot}$ among the two spatial structure dimensions, indicating a compact layout and low construction cost. Simulated networks under $(\beta_1, \beta_2, \beta_3, \beta_4) = \left(d_{pop}^{-}, \rho^{+}, d_{RN}^{-}, \sum flow^{+}\right)$ at $r = 50$ had clustered spatial structures and formed a point cluster with smallest $L_{tot}$ on average but larger $l_{max}$ than centralised spatial structures. In other words, centralised network spatial structures with a single centre resulted from centralising globally over a large area, had the smaller $l_{max}$ but larger $L_{tot}$ than clustered network spatial structures with multiple potential centres resulted from centralising locally within small areas. This finding showed clustered spatial structures with multiple local centres had the advantage of smaller construction cost than centralised spatial structures with a single centre, but also had the disadvantage of larger traversing diameter. This result may relate to empirical observations of the transformation from monocentric to polycentric urban spatial structure, in which polycentricity has been regarded as keeping benefits of agglomeration while avoiding diseconomies of agglomeration, as reviewed in 3.3.1.

On the top, simulated networks under $(\beta_1, \beta_2, \beta_3, \beta_4) = \left(d_{pop}^{-}, \rho^{-}, d_{RN}^{-}, \sum flow^{-}\right)$ at $r = 250$ had decentralised spatial structures and formed a point cluster with the longest $l_{max}$, demonstrating the largest diameter among the two spatial structure dimensions. To the right, simulated networks under $(\beta_1, \beta_2, \beta_3, \beta_4) = \left(d_{pop}^{-}, \rho^{-}, d_{RN}^{-}, \sum flow^{-}\right)$ at $r = 50$ had dispersed spatial structures and formed a point cluster with the maximum $L_{tot}$, demonstrating the highest coverage over the simulation area among the two spatial structure dimensions. Decentralised network spatial structures resulted from decentralising globally over a large area, while dispersed road network spatial structures resulted from decentralising locally within small areas. This result may further relate to empirical observations of the transformation from polycentric to dispersion, as reviewed in 3.3.1 when benefits of agglomeration have been regarded as failed to excel the negatives and have been characterised by increasing costs in infrastructure construction and travel.

Compared to existing characterisation methods of the road network spatial structure, such as dominant geometric connection patterns or continuity hierarchy patterns, characterisation by processes behind road network spatial structure formation captured the potential diversity of urban road network spatial structures. The spatial structure of urban road networks emerged as a spectrum, agreeing with the findings of empirical pattern recognition of global urban road networks as reviewed in 3.2.3. The centralised to decentralised, clustered to dispersed dimensions related more closely the spatial structure of the road network to the urban system. Compared to spatial analysis methods such as road network density, characterisation by network characteristics emphasised on the network structure, instead of treating network nodes spatial distribution or road infrastructure quantities in specific space division.

In summary, this section combined two network characteristics, total link length $L_{tot}$ and maximum shortest path $l_{max}$, and characterised simulated network spatial structures by centralisation to decentralisation, clustering to dispersion processes, behind the formation and dynamics of these spatial structures. For simulated networks of the same size, the centralisation tendency was characterised by small $L_{tot}$ and $l_{max}$, whereas the decentralisation tendency was characterised by large $L_{tot}$ and $l_{max}$. The changes among simulated network structures and the generative mechanisms behind may relate to empirical urban spatial structure transformations from monocentric, to polycentric and dispersed, with accompanying changes in costs of road network infrastructure and travel. Compared to alternative methods, the proposed network characterisation of urban road network spatial structure using processes behind the formation and dynamics of spatial structures had the potential to capture a diverse spectrum of network spatial structures. Using the centralisation to decentralisation, clustering to dispersion processes related road network spatial structure to the urban spatial structure; using network characteristics emphasised on the network nature of the urban road network spatial structure.

### 9.2.3 Simulated Network Spatial Structures and Connectivity

Existing empirical and modelling RNE research, as reviewed in Chapter 2, 4, have limited consideration of urban road networks' spatial structure; therefore, they have not related network characteristics' differences to different spatial structures of the studied road networks, as well as their underlying urban spatial structure at large. The reported network characteristics differences may result from studied networks' variation in the spatial structure, thus signalling different network spatial structures, rather than a general variation of network characteristics. Existing research has reported network characteristics without consideration of the spatial structural cause behind characteristic differences. For instance, current network science research might assume a monocentric spatial structure. Following the two dimensions of the network spatial structure, this section examines the variation in simulated networks' connectivity, resulted from the variation of their spatial structures.

Two network characteristics were used to characterise simulated networks' connectivity: average node degree $\bar{k}$ and treeness $\varphi_{tree} = \frac{L_{tree}}{L_{tot}}$. $\varphi_{tree}$ measured the ratio between Euclidean length of a network's tree structure and the total Euclidean network length. Figure 9.6 and Figure 9.7 show $\bar{k}$ and $\varphi_{tree}$ of simulated networks under the four benchmark parameter combinations $(\beta_1, \beta_2, \beta_3, \beta_4) = (d_{pop}^{-}, \rho^{+}, d_{RN}^{-}, \sum flow^{+})$ at $r = 250$, $50$ and $(d_{pop}^{-}, \rho^{-}, d_{RN}^{-}, \sum flow^{-})$ at $r = 250$, $50$, of centralised, clustered, decentralised, dispersed spatial structures. Each group of simulated networks had 30 simulation trials' data.

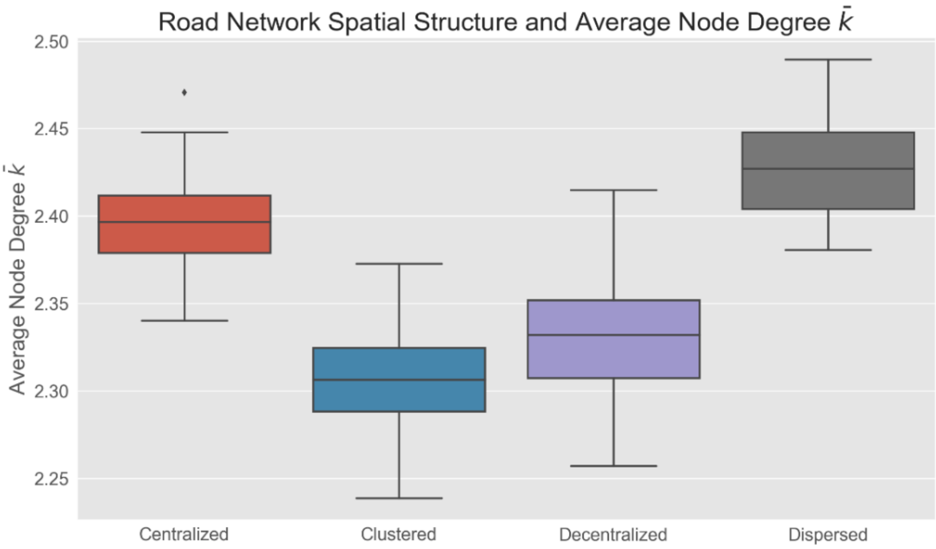



**Figure 9.6 Road Network Spatial Structure and Average Node Degree $\bar{k}$**: This boxplot shows average node degree $\bar{k}$ of centralised, clustered, decentralised, and dispersed simulated networks, generated under $(\beta_1, \beta_2, \beta_3, \beta_4) = (d_{pop}^{-}, \rho^{+}, d_{RN}^{-}, \sum flow^{+})$ at $r = 250$, $50$ and $(d_{pop}^{-}, \rho^{-}, d_{RN}^{-}, \sum flow^{-})$ at $r = 250$, $50$ respectively.

Figure 9.6 shows how average node degree $\bar{k}$ varied with simulated networks' spatial structures. On average, $\bar{k}_{Dispersed} > \bar{k}_{Centralized} > \bar{k}_{Decentralized} > \bar{k}_{Clustered}$. Dispersed simulated networks, such as Figure 9.1 column 4 $\mathrm{r} = 50$, had nodes spanning over the simulation area and links of typical lengths; their connectivity shared the highest similarity with a grid layout among the two spatial dimensions, as discussed in 5.3.2.1, and had the highest connectivity among simulated networks, as measured by $\bar{k}$. Centralised simulated networks had the second largest $\bar{k}$; 30 simulation trials' $\bar{k}_{Centralized} \approx 2.39$, larger than $\bar{k} \approx 2.36$ of simulate networks in Chapter 7 under the same Link Connection mechanism but without the population and road network co-evolution mechanism in Node Addition. Clustered and decentralised simulated networks exhibited lower $\bar{k}$ than simulate networks in Chapter 7. $\bar{k}$ showed the spatial structure of simulated networks influenced their network characteristics, and different network spatial structures had different levels of network connectivity. Thus, empirical research should consider the studied networks' spatial structure when investigating network characteristics, as the spatial structure may be one potential cause of network characteristic variations.

Meanwhile, the modelled network elementary connection patterns were also characterised by a majority of $k_3$ nodes and low $k_4$ node proportion, as the simulated networks from Chapter 7. Chapter 7's simulated networks with random positioning of new nodes and without the co-evolution mechanism that influenced new node locations, had similar $\bar{k}$ to urban road networks that have been recognised as organic, such as Worcester with $\bar{k} = 2.36$, as reviewed empirical findings in 2.3.2. Among the simulated network structures under the co-evolution mechanism, dispersed and centralised simulated spatial structures' $\bar{k}$ were close to Edinburgh with $\bar{k} = 2.43$, Sheffield with $\bar{k} = 2.42$. Decentralised and clustered simulated spatial structures' $\bar{k}$ was close to Oxford with $\bar{k} = 2.32$. However, compared to urban road networks with planned grid patterns, such as Barcelona with $\bar{k} = 3.42$, $\bar{k}$ of simulated networks by the hybrid model of population and road network co-evolution still lower, showing that grid patterns would not emerge with the spatial structure variations under the proposed co-evolution mechanism. Thus, the hybrid model is likely to model as well self-organised urban road network structures and supported Chapter 7's simulation finding that planned and self-organisation regimes coexist in the urban road network evolution.

Figure 9.7 shows how treeness $\varphi_{tree}$ varied with simulated networks' spatial structures. On average, $\varphi_{tree\_Clsutered} > \varphi_{tree\_Centralized} > \varphi_{tree\_Decentralized} > \varphi_{tree\_Dispered}$. Clustered simulated networks, such as Figure 9.1 column 1, $\mathrm{r} = 50$, had the highest tree structure length proportion among the two dimensions of network spatial structures. Compared to the centralised simulated networks which had a single centre, clustered simulated networks exhibited multiple potential centres, suggesting the transformation from single to multiple centres may increase network's tree structure and lower the network connectivity. This result agreed with the empirically observed increase of tree structures in the London road network evolution, which have been interpreted as increasing self-organisation with the urban road network evolution, as reviewed in 2.3.2.2. The simulation suggested such increase of tree structure may relate to a transformation from monocentric to polycentric road network spatial structures.

Together with Figure 9.6, negative correlations between $\bar{k}$ and $\varphi_{tree}$ were demonstrated, namely simulated networks with low $\bar{k}$ had high $\varphi_{tree}$, suggesting dead-ends' effect on the network connectivity. The network connectivity variation among spatial structures mainly resulted from the changing proportion of dead-ends.

Clustered and decentralised spatial structures encouraged more emergence of dead-ends, thus having lower connectivity than dispersed and centralised spatial structures. Considering the similarity between simulated networks' average node degree $\bar{k}$ and empirical urban road networks that have been regarded as organic, mechanisms behind the $\bar{k}$ variations between simulated spatial structures may find parallels in real-world processes that led to the observed empirical $\bar{k}$ variations. The exception of $\varphi_{tree\_Centralized} > \varphi_{tree\_Decentralized}$ was because $\varphi_{tree}$ measured Euclidean length. Decentralised simulation networks had larger total length $L_{tot}$ while their tree structure were mainly short links near the fringe of the simulated area.

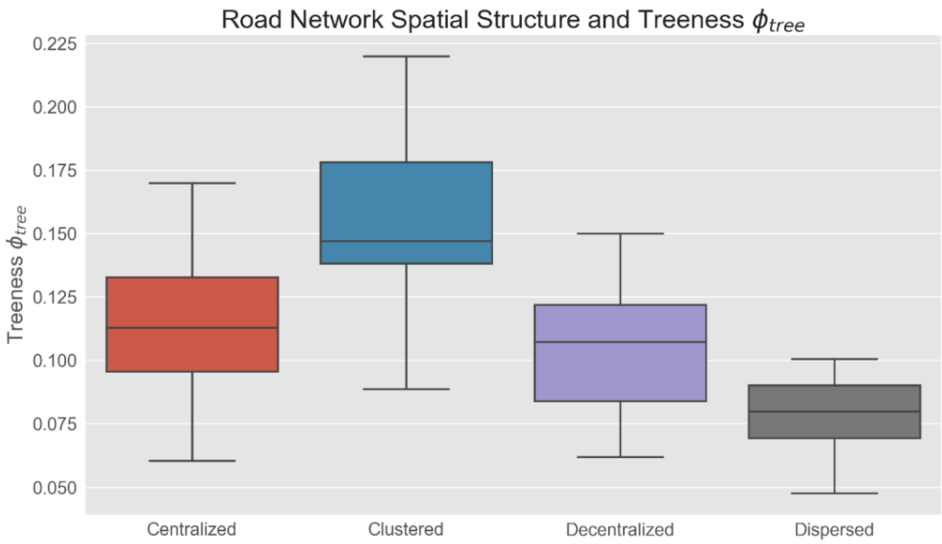



**Figure 9.7 Road Network Spatial Structure and Treeness $\boldsymbol{\varphi_{tree}}$**: This boxplot shows treeness $\varphi_{tree}$ of centralised, clustered, decentralised, and dispersed simulated networks, generated under $(\beta_1, \beta_2, \beta_3, \beta_4) = (d_{pop}^{-}, \rho^{+}, d_{RN}^{-}, \sum flow^{+})$ at $r = 250, 50$ and $(d_{pop}^{-}, \rho^{-}, d_{RN}^{-}, \sum flow^{-})$ at $r = 250, 50$, respectively.

2.4.4 reviewed empirically reported RNE phenomena Densification and Exploration (DE), which categorised two types of new links based on their influences on average network Betweenness Centrality (BC). Densification links have been associated with new links that bridged two existing roads while exploration links have been associated to dead-ends. Exploration links have been reported to gradually decrease and disappear in the observed urban road network evolution. DE new links have been associated with two RNE processes, namely densification and exploration. Because DE characterised two only possible Link Connection patterns in planar networks, 2.4.4.1 concluded the broad observation of DE suggested DE's existence is a planar network property. To describe RNE processes, DE shall include temporal and spatial characterisation.

Simulation results in this section showed that different simulated network spatial structures had different new link proportions. Compared to centralised and dispersed spatial structures, clustered and decentralised spatial structures encouraged more emergence of $k_1$ nodes and dead-ends. Thus, the proportions of new DE links related to the underlying network spatial structures. Transformations, such as from clustered to centralised, decentralised to dispersed, would witness decreasing exploration links, which may relate to the empirical observations made between polycentric and monocentric, decentralised and dispersed urban road networks. Observations made of the urban road network transformation from centralised, dispersed to clustered, decentralised may witness increasing exploration links, as reported by the empirical findings. Simulation suggested DE may relate to and characterise the transformation of observed road networks' spatial structure.

In summary, this section showed simulated networks of different spatial structures had quantitative differences in network connectivity. These simulation findings showed the spatial distribution and organisation of simulated networks are likely to influence their network characteristics, as demonstrated by $\bar{k}$ and $\varphi_{tree}$. Therefore, empirical and modelling research of network characteristics shall consider the underlying urban road network spatial structure, so that the variation of network characteristics caused by the variation of network spatial structures would not be overlooked.

In general, dispersion and centralisation resulted in higher connectivity than the simulated networks modelled in Chapter 7 without the population and road network co-evolution mechanism. Clustered spatial structures had the lowest connectivity and highest proportion of tree structure, suggesting empirically observed decrease of network connectivity and increase of tree structure with urban road network evolution may result from a transformation from monocentric to polycentric road spatial structure. Dispersed spatial structure networks had the highest connectivity but required a trade-off with high construction cost, shown by the largest total link length $L_{tot}$ in the last section. In comparison, the centralised spatial structure achieved high connectivity without high construction cost, suggesting a compact and efficient network structure. Finally, the variation in simulated network connectivity with different spatial structures mainly resulted from the change of dead-end or $k_1$ node proportions. This finding suggested simulated network spatial structures with lower connectivity, the clustered and decentralised spatial structures, encouraged more emergence of dead-ends, whereas centralised and dispersed spatial structures did not. This finding may share similarity with the processes that led to empirical $\bar{k}$ variations; namely, empirical changes of $\bar{k}$ may as well result from the changing network spatial structures, which differ in the level of network connectivity. This result may further relate to empirical observations of Densification and Exploration; that is, DE may have characterised the transformation of the road network spatial structure.

## 9.3 Combined Population-Road Network Spatial Structures and Relationships

The spatial structure of simulated networks was expected to be independent from as well as interrelated to the spatial structure of the population. Thus, the spatial structure of simulated networks was characterised first in the last section, which found a spectrum of spatial structures under the proposed population and road network co-evolution mechanism. The simulated network spatial structures resulted from global centralisation and decentralisation as well as local clustering and dispersion processes in simulated networks' dynamics. Network characteristics of different network spatial structures differed quantitatively. This section looked into the combined spatial structure of simulated population and road network 9.3.1, and established relationships between simulated population and road network spatial structures, regarding their correlations and mutual influences 9.3.2, 9.3.3.

### 9.3.1 The Combined Population-Road Network Spatial Structure

Like the simulated networks, visual examination of Figure 9.1 to Figure 9.4 suggested the spatial structure of simulated population could be characterised by the global centralisation and decentralisation, local clustering and dispersion processes behind the formation of these spatial structures, as shown by the benchmark population spatial structures in Figure 9.8. Simulated population's spatial structure was mainly influenced by parameters $\beta_2$ and $r$, namely population's spatial decision preference for new locations with high or low existing population density and the area radius within which spatial decisions were made.

When $\beta_2 = \rho^+$ and new population locations preferred high population density area, the population spatial structure tended to centralise. Centralisation within a large radius, e.g. $r = 250$, led to centralised population spatial structure with a single centre; centralisation within a small radius, e.g. $r = 50$, led to clustered spatial structure with multiple potential centres. On the other hand, when $\beta_2 = \rho^-$ and new population locations preferred low population density area, the population spatial structure tended to decentralise. Decentralisation within large radius $r$ led to decentralised population spatial structure; decentralisation within small radius $r$ led to dispersed spatial structure. The rest of parameters $(\beta_1, \beta_3)$ – population and road network's preferences for the distance to each other and $\beta_4$ – road network's preference for high or low flow area, intensified or counteracted $\beta_2$ and $r$'s influences on the population spatial structure, and contributed to forming a diverse spectrum of population spatial structures. $\beta_2$ and $r$'s influences on simulated population spatial structure were demonstrated in the differences of population spatial structures between columns 1, 2 and columns 3, 4 of Figure 9.1 to Figure 9.4. Columns 1, 2 shared $\beta_2 = \rho^+$ and exhibited centralised spatial structure at large $r = 250$ and clustered spatial structure at small $r = 50$. Columns 3, 4 shared $\beta_2 = \rho^-$ and exhibited decentralised spatial structure at large $r = 250$ and dispersed spatial structure at small $r = 50$.

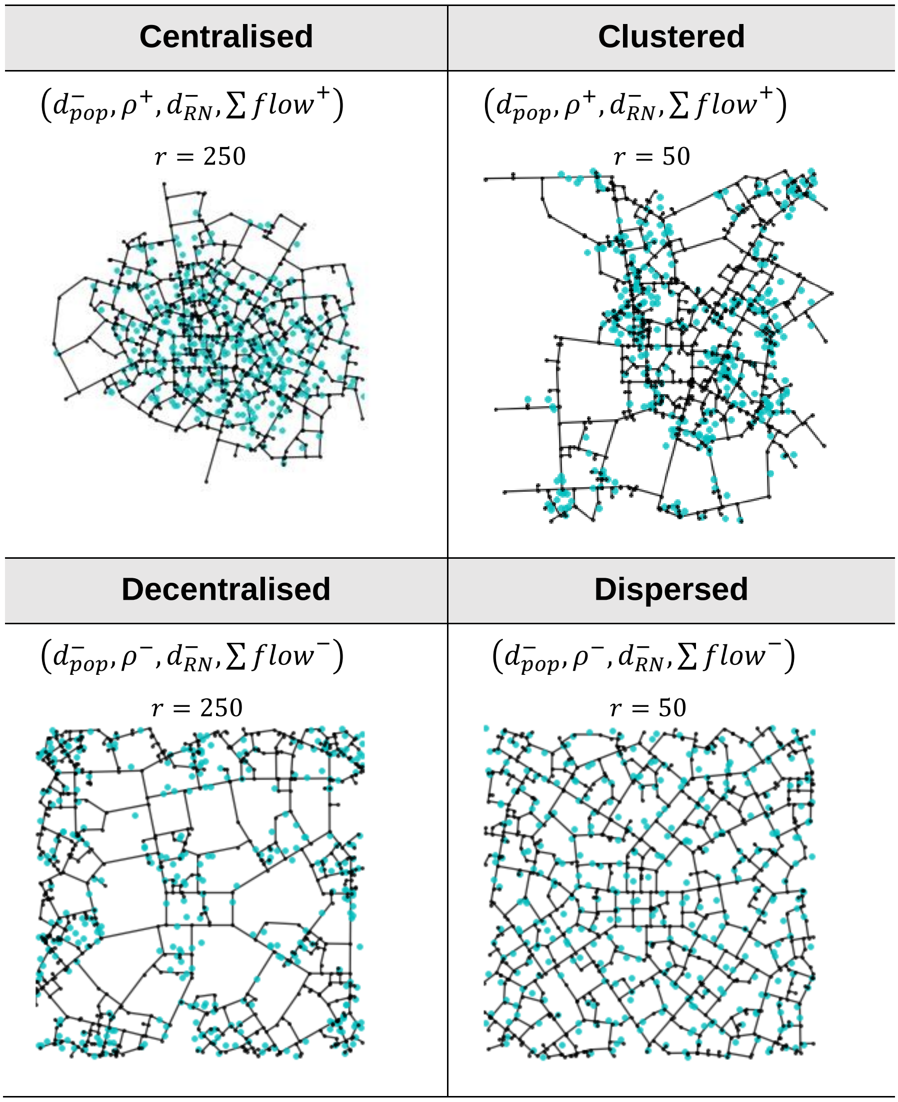



**Figure 9.8 Population-Road Network Spatial Structure**: four benchmark population-road network spatial structure - centralised, clustered, decentralised, or dispersed when the spatial structure of population and of road network agreed under parameter combinations $(\beta_1, \beta_2, \beta_3, \beta_4) = (d_{pop}^{-}, \rho^{+}, d_{RN}^{-}, \sum flow^{+})$ at $r = 250$, $50$ and $(d_{pop}^{-}, \rho^{-}, d_{RN}^{-}, \sum flow^{-})$ at $r = 250$, $50$.

Together the simulated population and road network constituted a combined spatial structure, resulted from global centralisation and decentralisation, local clustering and dispersion processes of population and road network, respectively. Simulated population-road network structures in Figure 9.8 benchmarked the combined centralised, decentralised, clustered and dispersed spatial structures, under parameter combinations $(\beta_1, \beta_2, \beta_3, \beta_4) = (d_{pop}^{-}, \rho^{+}, d_{RN}^{-}, \sum flow^{+})$ at $r = 250$, $50$ in Figure 9.1 column 1 and $(d_{pop}^{-}, \rho^{-}, d_{RN}^{-}, \sum flow^{-})$ at $r = 250$, $50$ in column 4. Under these parameter combinations, behaviours of population and road network modelled by the co-evolution mechanism coordinated. Population and road network preferred to locate near each other and both preferred high existing density and flow or low existing density and flow areas. These emerged combined spatial structures agreed, both exhibiting centralised, decentralised, clustered or dispersed spatial structures, suggesting coordinated spatial processes behind their formation. Other parameter combinations intensified or counteracted each other's influences and contributed to forming a diverse spectrum of simulated population-road network spatial structures.

Simulated population and road network structures supported the possible population and road network correlations, modelled more potential correlated population-road network spatial structures as in Figure 9.8, as well as specified the correspondent generative mechanisms. Empirical research has found spatial correlations between urban road network and population, and between road network and the urban spatial structure, as reviewed in 3.4. For instance, empirical research has reported exponential density decay of both population and road network from the CBD, suburbanization of population caused by highway development. The empirically observed exponential population and road network density decay from the CBD may relate to the simulated centralised combined population-road network spatial structure. Empirically observed suburbanization of population caused by highway development may relate to the simulated clustered combined spatial structure, which indicates the relocation of the population from a single urban centre to sub-centres. Besides, correlated population and road network may display potential decentralised and dispersed spatial structures as in the simulation, which may relate to dispersion of residence and work, low or high-density urban sprawl.

As synthesised in 3.3.4, the urban spatial structure may be viewed as having socioeconomic, physical, and functional levels, and the urban system as consisting of overlaid layers such as urban spatial structure, land use, transport. Related push and pull forces are likely to present across urban system layers. For example, the economies and diseconomies of agglomeration influence the economic urban spatial structure; physical urban growth goes through coalescence and diffusion; land uses categories exert attraction and repulsion; transport accessibility serves as both centripetal and centrifugal forces in influencing the urban spatial structure; spatial interaction potentials influence the functional urban spatial structure.

Parameter combinations that modelled these agreed spatial structures required coordinated preferences of population and road network, making spatial decisions to locate near each other, as well as both centralise, decentralise, cluster or disperse. The necessity to coordinate population and road network behaviours modelled by the co-evolution mechanism, to simulate the spatially agreed combined spatial structures as in empirical findings, suggested empirical population and road network may experience such coordinated processes as well. Namely, there may be coordinated centralising, decentralising, clustering, or dispersing processes on the population layer and the road network layer, respectively, that formed their correlated spatial structures. Meanwhile, both empirical road network and urban spatial structure exhibited a diverse spectrum, indicating that both push and pull forces existed, which intensify or counteract each other's influences. This finding of the necessity to coordinate Population Dynamics and Road Network Dynamics to simulate agreed combined spatial structures supported the proposed coevolution hypothesis that the population and road network spatial structures are the interaction result of push and pull forces across the urban system. The existence of both push and pull forces form a diverse spectrum, rather than fixed and clear-cut types.

In summary, simulation results showed the proposed co-evolution model is capable of modelling a diverse spectrum of population and road network spatial structures. Simulated population exhibited global centralisation to decentralisation, local clustering to dispersion spatial structures, as the simulated road networks. Under the co-evolution mechanism when population and road network chose to be near each other and had coordinated behaviours, agreed population-road network spatial structures emerged as empirically observed, suggesting similar coordinated processes behind the formation and dynamics of real-world population and road network spatial structures, respectively. These processes may result from the push and pull forces across urban system layers that intensify and counteract each other's influences, together contributing to the diverse spectrum of urban spatial structures.

### 9.3.2 Population's Influence on Road Network

#### 9.3.2.1 The Correlation between Population Density and Road Network Connectivity

Empirical research investigating the relationship between population and urban road network, as reviewed in 3.4.2, has reported correlations between population density and urban road network characteristics, such as network length, connectivity, density. Among these studies, most have reported positive population density and road network connectivity correlations and proposed hypotheses of population and urban road network's mutual relationship. Large cities with higher population density might have better-connected road network; road network might serve as the framework of population growth and land use changes, which in turn might attract more population and increase the population density. On the other hand, a few studies have found low correlations between population density and road network connectivity.

The relationship between simulated population density and road network connectivity was examined under the parameter combination $(\beta_1, \beta_2, \beta_3, \beta_4) = (d^-_{pop}, \rho^+, d^-_{RN}, \sum flow^+)$, with the variations of population and road network spatial decision radius $r = 250$, $150$, $50$, which were simulated structures in Figure 9.1 column 1. Under this parameter combination, the simulated population and road network had the spatial decision preference to be near each other, and both had the centralising tendency. When centralising globally within a large radius $r = 250$, both population and road network exhibited centralised spatial structures with a single centre; when centralising locally within a small radius $r = 50$, both population and road network exhibited clustered spatial structure with multiple potential centres.

The changes of $r$ from large to small under $(d^-_{pop}, \rho^+, d^-_{RN}, \sum flow^+)$ led the emergence of simulated population-road network spatial structures from monocentric to polycentric, as shown in the upper panel of Figure 9.9. During this transformation, the simulated population density decreased, as population spread from the single centre to the multiple potential sub-centres. At the same time, the simulated network's connectivity decreased, as shown by the two plots in the lower panel, which reported 30 simulation trials' results at each radius $r$. In the left plot, average node degree $\bar{k}$ of the simulated networks decreased as $r$ decreased from $250$, $150$ to $50$, namely as the simulated network changed from centralised to clustered. In the right plot, network efficiency $E^{geom}$, which measured the ratio of the Euclidean linear distance and network distance between network nodes, decreased as well.

The decreases of $\bar{k}$ and $E^{geom}$ with $r$ supported the empirical findings of positive correlations between population density and network connectivity. The centralised population-road network structures had higher population density and road network connectivity, while the clustered structures had lower population density and road network connectivity. This positive correlation between population density and road network connectivity was persistent as $r$ decreases during the transformation from centralised to clustered spatial structures. In other words, population density and network connectivity positively correlated when studying the simulated centralised and clustered population-road network spatial structures.

Meanwhile, there were also simulation scenarios that did not agree with the positive population density and road network connectivity correlation. For example, when the centralised and dispersed spatial structures in Figure 9.8 were compared, the dispersed structure had lower population density than the centralised structure, as the simulated population spread from a single centre to dispersion. However, the dispersed simulated network connectivity was higher than the centralised networks as discussed in Figure 9.6.

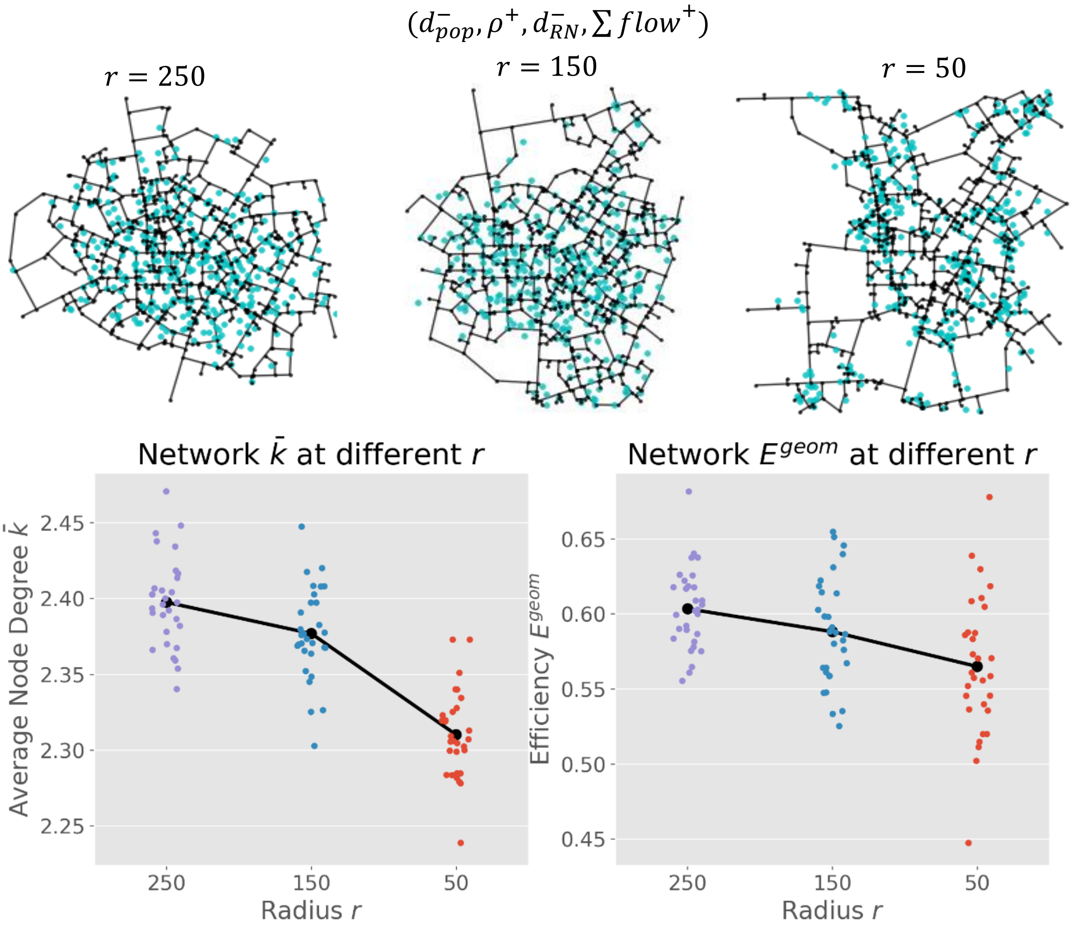



**Figure 9.9 Population Density and Road Network Connectivity**: The upper panel shows simulated population and road network under parameters $(\beta_1, \beta_2, \beta_3, \beta_4) = (d_{pop}^{-}, \rho^{+}, d_{RN}^{-}, \sum flow^{+})$ at $r = 250, 150, 50$ accordingly. The three illustrations demonstrate the spatial structure changed from centralised with a single centre to clustered with multiple potential centres with the decrease of $r$; during this change, simulated population density decreased. The lower panel shows average node degree $\bar{k}$ and network efficiency $E^{geom}$ decreased with $r$, namely with the variation of the network spatial structure. Population density and network connectivity were positively correlated in this example, as centralised spatial structure with high population density had higher network connectivity than clustered spatial structure with low population density.

In summary, whether simulated population density and network characteristics correlated resulted from the underlying population-road network spatial structure. The variation of simulated combined spatial structures was associated with variations of the road network and population spatial structures accordingly. There were potential positive correlations between simulated population density and road network connectivity, such as when comparing centralised and clustered population-road network spatial structures. This positive correlation between centralised and clustered combined spatial structures may relate to the empirically reported positive correlations between population density and road network connectivity, in the European studies. There were also scenarios in which such positive correlations could not be established, such as when comparing simulated centralised and dispersed spatial structures. The empirically reported non-correlated population density and road network connectivity, in the US studies, may have compared such population-road network spatial structures. Therefore, correlations between population density and road network structure shall be studied with the consideration of the underlying urban spatial structure, or both correlations and non-correlations may be found depending on the underlying urban spatial structure studied.

#### 9.3.2.2 Population's Influence on Road Network

Besides the correlation between population density and network connectivity, influences of the simulated population on the simulated road networks also showed under population-road network distance preference $(\beta_1, \beta_3) = (d_{pop}^{+}, d_{RN}^{-})$. Under $(d_{pop}^{+}, d_{RN}^{-})$, the new population made spatial decision to be away from the existing road network, while new road network nodes made spatial decision to be close to the existing population. As mentioned in 9.2.1.2, $(\beta_1, \beta_3)$ counteracted other parameters' influences on the simulated networks' spatial structures. This population-road network distance preference played the dominant role in the generation of dispersed simulated population and road networks, which exceeded $\beta_4$ and $r$'s centralising, decentralising, clustering influences on the simulated network spatial structures, as well as $\beta_2$ and $r$'s centralising, decentralising, clustering influences on the simulated population spatial structures. Though there were traits of other spatial structure tendencies resulted from $(\beta_2, \beta_4)$ and $r$, all simulated population and road networks had overall dispersed spatial structures.

Figure 9.10 shows the simulated population and road network structures which had the same $(\beta_2, \beta_4)$ and $r$ with the four benchmark parameter combinations for centralised, decentralised, clustered combined spatial structures in Figure 9.8, but with $(\beta_1, \beta_3) = (d_{pop}^{+}, d_{RN}^{-})$.

Simulation demonstrated the effectiveness of $(\beta_1, \beta_3) = (d_{pop}^{+}, d_{RN}^{-})$ in causing dispersion. Because of the network nature, simulated networks could span the simulated area more easily; population's spatial decision preference to locate away from the existing network easily led to the dispersion of the simulated population; road network's spatial decision to locate near the dispersed population then led to the dispersion of te simulated network spatial structures. This simulated feedback relationship suggested $(\beta_1, \beta_3) = (d_{pop}^{+}, d_{RN}^{-})$ may model a scenario in which population do not consider the transport access as a priority but seek space and avoid noise. At the same time, transport infrastructure is supplied unlimitedly to provide accessibility to all population; or roads, formal or informal, will follow population settlements to satisfy basic transport demand in any case. In such scenarios, population drive the population-road network co-evolution by locating away from the existing road network and forming dispersed population spatial structures, which further lead to dispersed simulated network structures, since the road network serves the dispersed population despite construction costs.

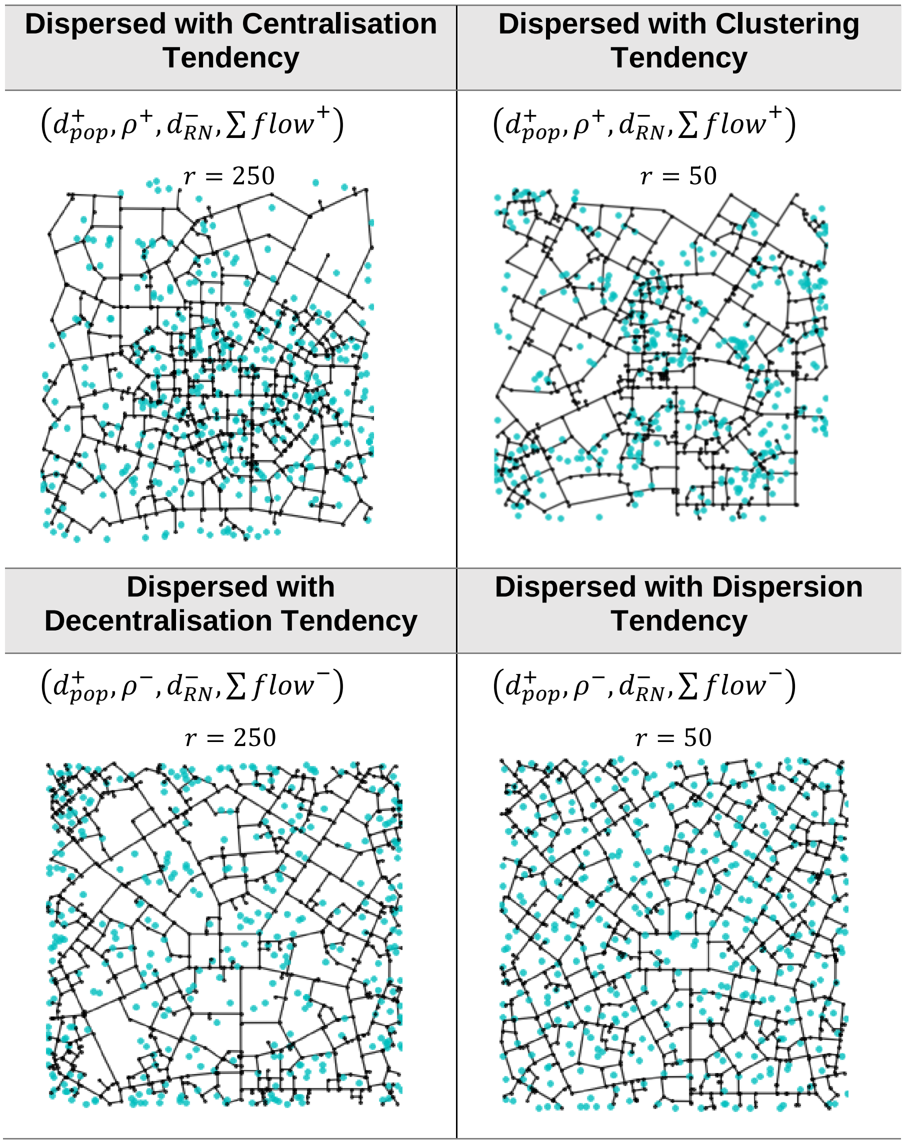



**Figure 9.10 Population's Influence on Road Network**: Four simulated population and road network structure under parameter combinations $(\beta_1, \beta_2, \beta_3, \beta_4) = (d^+_{pop}, \rho^+, d^-_{RN}, \sum flow^+)$ at $r = 250$, $50$ and $(d^+_{pop}, \rho^-, d^-_{RN}, \sum flow^-)$ at $r = 250$, $50$ are arranged in the same order with the benchmark centralised, clustered, decentralised, dispersed population-road network spatial structures in Figure 9.8. Though there were traits of each corresponding spatial structure under the influences of $(\beta_2, \beta_4)$ and $r$, these simulated population and road networks were dispersed because of the population-road network distance preference $(\beta_1, \beta_3) = (d^+_{pop}, d^-_{RN})$.

Dispersed simulated network structures, as discussed in 9.2.2, had the highest total length $L_{tot}$ and average node degree $\bar{k}$ among the two spatial structure dimensions, which suggested highest network connectivity and construction cost. In comparison, the simulated centralised spatial structures had high connectivity and low total length. There was a trade-off between providing increasing network connectivity and the increasing construction cost in dispersed network spatial structures.

Empirical findings, as reviewed in 3.3.2 have reported both high and low-density urban sprawl with dispersion characteristics. Low-density urban sprawl, such as in the US, and high-density urban sprawl, such in the Middle East, South America, and China, have been attributed to population growth, urban economics spatial decisions with increasing income and decreasing transportation costs, land use policies and regulation, urban planning, central urban problems and transport congestion, residential preferences. Urban dispersion has been attributed to the suburbanization of residence under the spatial decisions balancing land prices and transportation cost, which have further led to the dispersion of both residence and work.

Simulation suggested urban sprawl and dispersion may relate to population's spatial decisions to locate away from the existing road network, for reasons such as the trade-off between income, land price, and transportation cost, residential preference, urban planning. If such spatial decisions were all enabled by land use policies and regulations, urban sprawl and dispersion may occur, which are likely to be characterised by the dispersion of both population and road network. In comparison, the co-evolution mechanism under other parameter combinations, such as spatial decisions of the population to locate away from existing high population density area or road network locate away from existing high flow area, may not necessarily give rise to the dispersion of both simulated population and network.

In summary, population's influences on road network showed in the population-road network distance preference $(\beta_1, \beta_3) = (d_{pop}^{+}, d_{RN}^{-})$, which exceeded other parameters' influences and modelled a population driven co-evolution process, which led to both dispersed population and road network spatial structures. This parameter combination modelled a feedback relationship in which locating away from an existing road network effectively dispersed population, and road network followed the dispersed population to dispersion as well. This co-evolution mechanism that gave rise to dispersed population and road network spatial structures may relate to empirical urban sprawl and urban spatial structure dispersion, suggesting new settlements away from the existing urban road network's effect on the dispersion of urban spatial structure. Locating away from existing road network may quickly disperse population; formal and informal road network may follow the dispersed population and develop into a reinforcing feedback relationship of dispersion.

### 9.3.3 Road Network's Influence on Population

Simulated road networks' influences on the population spatial structures were identified by comparing two pairs of parameter combinations' simulation results. The first pair was $(\beta_1, \beta_2, \beta_3, \beta_4) = (d_{pop}^{-}, \rho^{+}, d_{RN}^{-}, \sum flow^{+})$, $r = 50$ and $(d_{pop}^{-}, \rho^{+}, d_{RN}^{+}, \sum flow^{+})$, $r = 50$, which were Figure 9.1 column 1 $r = 50$ and Figure 9.2 column 1 $r = 50$. The second pair was $(d_{pop}^{-}, \rho^{-}, d_{RN}^{-}, \sum flow^{-})$, $r = 250$ and $(d_{pop}^{-}, \rho^{-}, d_{RN}^{+}, \sum flow^{-})$, $r = 250$, which were Figure 9.1 column 4 $r = 250$ and Figure 9.2 column 4 $r = 250$. Two panels of illustrations are shown together in Figure 9.11 accordingly.

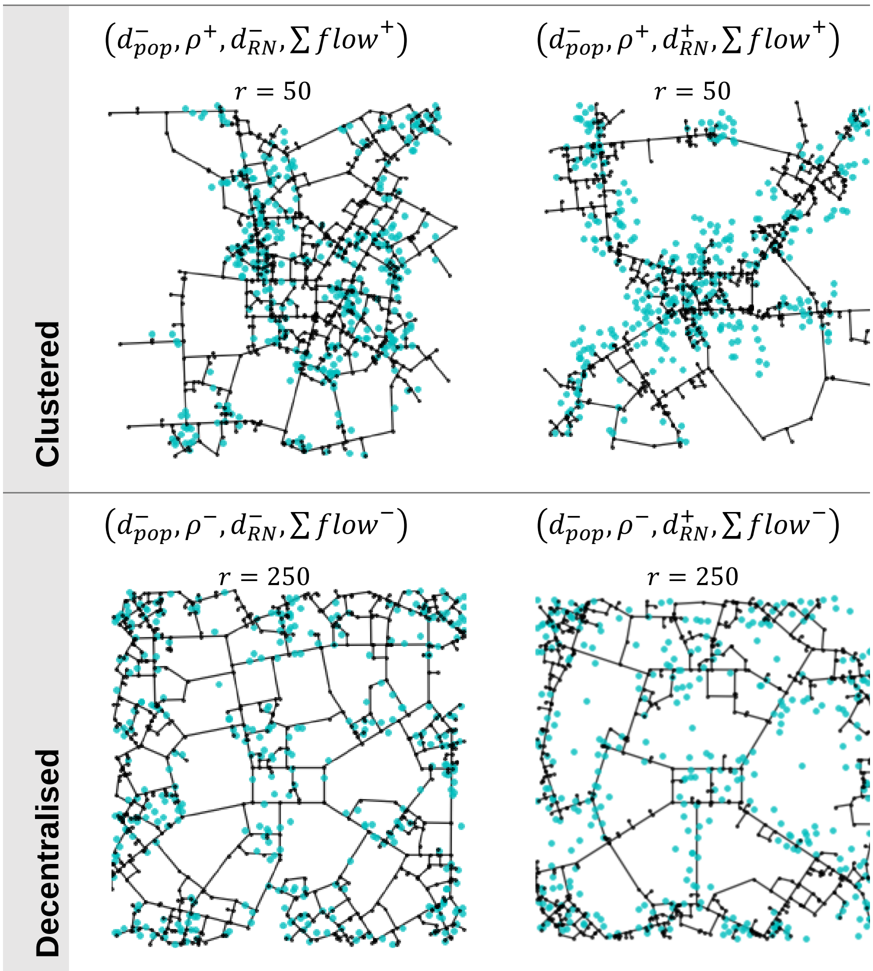



**Figure 9.11 Road Network's Influence on Population**: The upper panel shows the simulated population and road network under parameter combinations $(\beta_1, \beta_2, \beta_3, \beta_4) = (d_{pop}^{-}, \rho^{+}, d_{RN}^{-}, \sum flow^{+})$, $r = 50$ and $(d_{pop}^{-}, \rho^{+}, d_{RN}^{+}, \sum flow^{+})$, $r = 50$. The lower panel shows the simulated population and road network under $(d_{pop}^{-}, \rho^{-}, d_{RN}^{-}, \sum flow^{-})$, $r = 250$ and $(d_{pop}^{-}, \rho^{-}, d_{RN}^{+}, \sum flow^{-})$, $r = 250$. Changing the parameter $\beta_3$ from $d_{RN}^{-}$ to $d_{RN}^{+}$, as from the left column to the right, simulated population and road network exhibited linear spatial structure.

In the upper panel of Figure 9.11, the left simulated structure resulted from $(d_{pop}^{-}, \rho^{+}, d_{RN}^{-}, \sum flow^{+})$ and $r = 50$; under this parameter combination, population and road network both preferred to be near each other and centralised locally with a small area, and the simulated structures exhibited clustered spatial structure with multiple potential centres. The right simulated structure changed one parameter $\beta_3$ from $d_{RN}^{-}$ to $d_{RN}^{+}$, which changed the road network's proximity preference from being close to the population to being far away from the population. This opposite value of $\beta_3$ changed the simulated combined population and road network spatial structures from clustered to linearly clustered, in which population located alongside the road network and road network exhibited an elongated structure with a few major roads and many minor roads.

Similarly in the lower panel of Figure 9.11, the left simulated structure resulted from $(d_{pop}^{-}, \rho^{-}, d_{RN}^{-}, \sum flow^{-})$ and $r = 250$; under this parameter combination, population and road network both preferred to be near each other and decentralised globally within a large area, and the simulated structure exhibited decentralised population and road network spatial structures. The right simulated structure changed one parameter $\beta_3$ from $d_{RN}^{-}$ to $d_{RN}^{+}$, and this opposite value of $\beta_3$ changed the simulated structure from decentralised to linearly decentralised, in which population located alongside the road network and road network exhibited an elongated structure with a few major roads and many minor roads.

Empirical research on urban road networks' influences on the spatial structure of population have found road network construction stimulated population relocation to the urban periphery. Linear urban growth along the highway have constituted a large proportion of urban growth patterns, together with infill, independent new development, as reviewed in 3.4.1. In the urban planning history, linear city models have been proposed, in which urban development has been designed to orient around transport development.

The linear features emerged in simulated population and network spatial structures may relate to empirical linear urban growth patterns, in which transport development lead the urban development and urban settlements to locate along the major transport routes. The population-road network distance preference $(\beta_1, \beta_3) = (d_{pop}^{-}, d_{RN}^{+})$ modelled a feedback relationship in which road network did not serve population as a priority but probed into new urban areas away from existing populated areas, whereas population followed the growth and simulated network and located alongside the road segment, which further led to the further branching out of the simulated network. In Road Network Dynamics, parameter $\beta_3 = d_{RN}^{+}$ - new road network's preference of being away from population, generated many minor road segments along the major paths, leading to the linear simulated network spatial structures. In Population Dynamics, parameter $\beta_1 = d_{pop}^{-}$ - population's preference to be near the road network, generated linear population distribution alongside the simulated major road segments. Iterating Population and Road Network Dynamics, the linear elementary growth of road network and population spatial structures accumulated and were reinforced.

Besides, the linear population-road network spatial structures only emerged under the clustering and decentralisation processes of population and road network, respectively. This result suggested the potential clustering process on a local scale and decentralisation process on the global scale, as well as the lack of centralisation and dispersion processes, behind empirically observed linear urban growth. Empirical observations have been made with edge cities, which are sub-centres formed during the transformation from monocentric to polycentric urban spatial structures, often located at intersections of major transport routes. Simulated clustering and decentralising processes may find parallels in such empirical urban spatial structure transformation.

In summary, road network's influences on population showed in the population-road network distance preference $(\beta_1, \beta_3) = (d_{pop}^{-}, d_{RN}^{+})$, which modelled a road network driven co-evolution process and led to linear population-road network spatial structures. Under these co-evolution mechanism parameter combinations, population chose to be close to road network while road network chose to be away from population, both population and road network clustered on the local scale or decentralised on the global scale. These simulated scenarios may relate to the empirically observed linear urban growth, suggesting local clustering or global decentralising processes with the road network's priority in probing new urban areas instead of serving the existing population.

**Table 9-1 Findings and Conclusions – Hybrid Model of Population and Urban Road Network Co-evolution**

| **The Spatial Structure of Simulated Networks** | |
|---|---|
| **1. The co-evolution mechanism of Population Dynamics $(\boldsymbol{\beta_1}, \boldsymbol{\beta_2})$ and Road Network Dynamics $(\boldsymbol{\beta_3}, \boldsymbol{\beta_4})$ and the emergence of simulated networks' spatial structure**<br><br>• $\beta_1 = (d^+_{pop}, d^-_{pop})$ - population's distance preference for being far away from or close to road network;<br>• $\beta_2 = (\rho^+, \rho^-)$ - population's preference for densely or sparsely populated areas;<br>• $\beta_3 = (d^+_{RN}, d^-_{RN})$ - road network's distance preference for being away from population or being close to population;<br>• $\beta_4 = (\sum flow^+, \sum flow^-)$ - road network's preference for low flow or high flow areas.<br>• $\mathrm{r}$ – Spatial decision radius | • $\beta_4$ and $\mathrm{r}$ modelled two dimensions of simulated road network processes<br>○ Centralisation to Decentralisation on the global scale<br>  ○ Centralisation: preference for high flow $\sum flow^+$ globally within a large radius $\mathrm{r}$ modelled the centralisation process and resulted in centralised spatial structures with a single large centre;<br>  ○ Decentralisation: preference for low flow $\sum flow^-$ globally within a large radius $\mathrm{r}$ modelled the decentralisation process and resulted in decentralised spatial structures;<br>○ Clustering to Dispersion on the local scale<br>  ○ Clustering: preference for high flow $\sum flow^+$ locally within a small radius $\mathrm{r}$ modelled the clustering process and resulted in clustered spatial structures with multiple potential centres;<br>  ○ Dispersion: preference for low flow $\sum flow^-$ locally within a small radius $\mathrm{r}$ modelled the decentralisation process and resulted in the dispersed spatial structures.<br>• $(\beta_1, \beta_2, \beta_3)$ intensified or counteracted centralisation, decentralisation, clustering, and dispersion processes and resulted in a spectrum of simulated network spatial structures, rather than fixed and clear-cut types. |
| **2. Characterisation of simulated networks' spatial structures**<br><br>• Total link length $L_{tot}$<br>• Maximum shortest path $l_{max}$ | • Characterised simulated networks' spatial structures by processes behind their formation and dynamics: centralisation to decentralisation on the global scale and clustering to dispersion on the local scale;<br>○ Centralised network spatial structures were characterised by the smallest $l_{max}$;<br>○ Clustered network spatial structures were characterised by larger $l_{max}$ but smaller $L_{tot}$ than centralised spatial structures;<br>○ Decentralised network spatial structures were characterised by the largest $l_{max}$;<br>○ Dispersed road network spatial structures were characterised by the largest $L_{tot}$.<br>• The proposed characterisation method by processes behind network spatial structure formation<br>○ Captured the diverse spectrum of network spatial structures;<br>○ Related road network spatial structure to the urban spatial structure;<br>○ Captured the network nature of road network spatial structure.<br>• Transformation from centralised to clustered and dispersed simulated network spatial structures may relate to the transformation from monocentric, to polycentric and dispersed urban spatial structure:<br>○ Centralised to clustered: Decreasing $L_{tot}$ and increasing $l_{max}$;<br>○ Centralised to dispersed: Increasing $L_{tot}$ and increasing $l_{max}$. |
| **The Relationships Between Simulated Network and Population** | |

| | |
|---|---|
| **3. The combined population-simulated network spatial structure** | • $(\beta_1, \beta_2, \beta_3, \beta_4) = (d_{pop}^{-}, \rho^{+}, d_{RN}^{-}, \sum flow^{+})$ and $(d_{pop}^{-}, \rho^{-}, d_{RN}^{-}, \sum flow^{-})$ modelled the agreed road network and urban spatial structures - the combined centralised, clustered, decentralised, and dispersed spatial structure.<br>• Conditions for the emergence of agreed population-road network spatial structures:<br>o The simulated population and network chose to be near each other;<br>o The simulated population and network coordinated to both centralise, decentralise, cluster, or disperse.<br>• Under other experimented spatial decision combinations, parameters intensified or counteracted each other's influences and resulted in a spectrum of simulated population-road network spatial structures;<br>• Empirical correlations between urban road network and population spatial structures may experience coordinated centralise, decentralise, cluster, or disperse processes, resulted from related push and pull forces across urban system layers. |
| **4. Correlations between simulated network connectivity and population density** | • Simulated networks' connectivity depended on network spatial structure: Dispersed > Centralised > Decentralised > Clustered.<br>• The comparison of centralised and clustered spatial structures yielded positive correlations between population density and network connectivity.<br>• The comparison of centralised and dispersed spatial structure did not yield positive correlations between population density and network connectivity.<br>• Empirical correlations or non-correlations between population density and network characteristics may result from the underlying urban spatial structure:<br>o Comparing monocentric and polycentric urban spatial structure may yield positive correlations;<br>o Comparing monocentric and dispersed urban spatial structure may not yield positive correlations. |
| **5. Population's influences on the road network** | • Mutual distance preferences $(\beta_1, \beta_3) = (d_{pop}^{+}, d_{RN}^{-})$ modelled a population-driven co-evolution and dispersed combined spatial structures:<br>o The feedback relationship in the dispersed spatial structure formation: population easily dispersed when locating away from existing road network, road network followed dispersed population into dispersion;<br>o Empirical urban spatial dispersion and urban sprawl may relate to enabled spatial decisions of population to locate away from existing road network. |
| **6. Road network's influences on the population** | • Mutual distance preferences $(\beta_1, \beta_3) = (d_{pop}^{-}, d_{RN}^{+})$ modelled road network-driven co-evolution and linear combined spatial structures:<br>o The feedback relationship in the linear spatial structure formation: road network located away from population when clustering or decentralising, formed a few major routes and many minor dead-ends, population followed alongside the elongated major paths;<br>o Empirical linear urban development along transport development may relate to spatial decisions to locate road network away from existing population. |

## 9.4 Chapter Conclusions

Through modelling the Node Addition mechanism of generative network model (GNM) and coupling population, the proposed hybrid model of population and urban road network co-evolution in Chapter 8 integrated GNM and RNE into the urban system. The proposed model represented the population and urban road network as two inter-dependent urban system layers, addressing previous models' limitation in representing the population and urban road network using the same network. The proposed co-evolution mechanism explored all population and road network spatial decision preferences for new locations, instead of assuming fixed spatial decisions. The proposed model gave rise to a diverse spectrum of road network spatial structures, as examined in this chapter, addressing network science research's lack of road network spatial structure consideration. The modelled road network spatial structures were characterised by the processes behind the formation of network spatial structures, which did not assume fixed road network spatial structure types, related road network spatial structure to the urban system but not equated the two, as well as emphasised on the network nature of urban road network spatial structure.

This chapter addressed the fourth research question of this thesis and examined the simulated network and population spatial structures, and their mutual influences, as summarised in Table 9-1. Simulation results suggested the spatial structure of urban road networks appear to be a spectrum, rather than fixed clear-cut types (Marshall, 2004; Huynh et al., 2017; Moosavi, 2017). Urban road network spatial structure may be characterised by two dimensions of processes behind their formation – centralisation and decentralisation on the global scale, clustering and dispersion on the local scale. These processes may result from related push and pull forces across the urban system, which intensify and counteract each other's influences and lead to the diverse spatial structure spectrum. The simulation also suggested different spatial structures of the urban road network have different quantitative network characteristics; the correlations between population density and road network characteristics shall be studied with the consideration of the underlying spatial structure. The spatial structure of urban road networks is likely to correlate with the urban spatial structure, both experiencing coordinated centralisation, decentralisation, clustering, or dispersion processes. Population's influence on road network spatial structure may show in the spatial decision of population to locate away from the road network, leading dispersed spatial structures. Road network's influence on population may show in the spatial decision of road network to locate away from the population, leading to linear spatial structures.

# Chapter 10 Conclusions, Originality, Limitations, and Future Research

## 10.1 Research Conclusions and Originality

This thesis proposed an original modelling and simulation framework to approach the urban road network evolution (RNE), using proposed generative network models (GNMs). This framework defined a feasible scope to study the evolution of urban road networks by the structure and dynamics of simulated networks. Following the proposed framework, this thesis addressed the evolution of urban road networks by modelling and simulation of two iterating RNE processes - Link Connection and Node Addition, considering RNE alone and in the urban system, respectively. The former connected new spatial locations to an existing road network and directed elementary connection patterns of the urban road network structure; the latter added new node and directed spatial structures of the road network and the urban system at large. Through two modelling and simulation studies, the thesis addressed the four research questions, as outlined in Figure 10.1.

First, this thesis generalised the Link Connection mechanism in the generative mechanism of the urban road network structure (section 10.1.1). Second, the proposed GNM of urban road network evolution with the generalised Link Connection mechanism yielded original simulation findings of both static urban road network structures and dynamics (section 10.1.2). Third, this thesis proposed an original hybrid model of population and urban road network co-evolution model (section 10.1.3). Fourth, the proposed hybrid model of population and urban road network co-evolution model yielded original simulation findings of the urban road network and population spatial structures and relationships between population and road network (section 10.1.4).

Combining modelling and simulation of the Link Connection and Node Addition processes, the proposed framework advanced the understanding of the network science perspective on urban road network evolution and led to a key original contribution of proposing the novel hybrid model of the population and the road network coevolution.

Proposed a modelling and simulation framework of urban road network evolution

- Proposed a feasible scope to study RNE
  - Network structure: Selected network characteristics;
  - Network evolution: Selected netowrk characteristics' dynamics.
- Generalised urban road network generative mechanism
  - Node Addition: Directed network spatial structure;
  - Link Connection: Directed elementary connection patterns.

**Research Question 1**

Modelling findings - Generalised the Link Connection mechanism, *section 10.1.1*

- Proposed a generative network model of urban road network evolution
  - Generalised the Link Connection mechanism;
  - Used the primal represetnation;
  - Proposed using GNM to model the dynamic RNE process beyond network generation.
- Designed and performed simulation experiment
  - Explored GNM's capacity in modelling the dynamic RNE process
    - Proposed a framework to quantify RNE based on elementary network component characteristics and dynamics
    - Integrated and compared empirical RNE findings;
    - Stored and investigated the whole network generation process;
  - Explored proximity relationship's role in urban road network generation.

**Research Question 2**

Simulation Findings - Modelling the Dynamic RNE Process

*section 10.1.2*

- Modelled both plausible static and dynamic urban road network structures and advanced understanding of empirical RNE findings
  - Node degree: urban road networks lie between centrally-planned grid patterns and not-centrally-planned self-organised growth patterns;
  - Link length, Block area: urban road networks evolve with multiplicative and additive spatial processes.
  - Betweenness centrality: urban road networks evolve with initial formation of major paths and later local changes.
- Modelled a broader range of road network structures than previous models by controlling parameter β, understood the role of proximity relationship.

**Research Question 3**

Modelling findings - Proposed a hybrid model of population and urban road network co-evolution

*section 10.1.3*

- Proposed a hybrid model of population and urban road network co-evolution
  - Proposed a representation of population and urban road network;
  - Proposed a population and urban road network co-evolution mechanism.
- Designed and performed simulation experiment
  - Explored the urban road network spatial strucutre;
    - Proposed a method to characterise the urban road netowrk spaital structure;
  - Explored relationships between population and the urban road network.

**Research Question 4**

Simulation findings - the spatial structure of urban road networks, the relationship between the road network and the urban system

*section 10.1.4*

- Modelled diverse road network spatial structures and advanced understanding of empirical findings
  - A spectrum of road network spatial structures: Centralised to decentralised on the global scale, clustered to dispersed on the local scale;
  - Different road network spatial structures have different network characteristics.
- Modelled mutual influences between population and the urban road network and advanced understanding of empirical findings
  - Related push and pull forces drive the co-evolution of urban road network and population;
  - Coordinated population and road network spatial decisions result in agreed urban spatial structures;
  - Population-driven co-evolution result in dispersed spatial strucutres;
  - Road network-driven cevolution result in linear spatial structures.

**Figure 10.1 Research Questions and Conclusions**

### 10.1.1 Modelling Findings: Generalisation of the Link Connection Mechanism in Generative Network Model of Urban Road Network Evolution

Chapter 6 answered the first research questions proposed in Chapter 1 and specified in Table 5-2:

1. What is the working mechanism of generative network models (GNMs) in generating the urban road network structure? Can previous models' generative mechanisms be generalised?

- Whether proximity relationships from proximity graphs other than Relative Neighbourhood Graph (RNG), like β-skeletons, play a role in modelling RNE?

GNMs propose generative mechanisms behind the formation and dynamics of complex networks, to generate complex network structures. This approach acknowledges the dynamic nature of urban road networks, namely the static network structure results from dynamic formation and changing processes. Understanding this dynamic structure is necessary for understanding the urban road network structure as a whole. The generative mechanism of spatial network generation model balances link length costs and the realised efficiency through Link Connection. The generative mechanism of planar network generation models maintains planarity.

As discussed in detail in 4.2.3.5, previous GNMs of urban road networks (Barthélemy and Flammini, 2008; Barthélemy and Flammini, 2009; Yang et al., 2011; Courtat et al., 2011; Rui et al., 2013; Zhao, F. et al., 2015) have generated network structures that statistically agreed with empirical urban road network characteristics, but have not compared their generative mechanisms horizontally, or considered the role of proximity relationships in generating the urban road network structure. Therefore, previous models have not generalised the Link Connection process. For example, previous models have described Link Connection as a process of connecting the new node first to the nearest point on the existing network, then to RNG neighbouring points. Previous models have also described Link Connection as a process of connecting the new node to points in the intersection point set of visible points that maintained planarity on the existing network, orthogonal projections of the new node, and RNG neighbours. In this way, previous models have generated network structures with RNG's proximity relationship in Link Connection, which was equal to the proposed Link Connection mechanism when $\beta = 2.0$. However, previous models have not considered the working mechanism of the RNG proximity relationship in generating the urban road network structure or used other proximity relationships, such as from β-skeletons, to model the urban road network structure.

Addressing this gap, the proposed generative network model of urban road network evolution in Chapter 6 generalised the generative mechanism of urban road networks as two iterative processes: Node Addition and Link Connection, in consistence with the spatial and planar network models. Node Addition directed the spatial structure of urban road networks, and Link Connection directed elementary network connection patterns. In particular, the proposed mechanism generalised Link Connection as a process of examining the proximity relationship between a new spatial location and the existing road network, using proximity relationships from β-skeletons with $\beta \in [1.0, 2.0]$. In doing so, Link Connection balanced link length cost and realised efficiency, as well as maintained planarity. Beyond spatiality and planarity, Link Connection further modelled connection patterns of urban road networks, which were characterised by local perpendicular intersections and a global structure between a tree and complete circuitous.

The generalised mechanism modelled both static and dynamic urban road network structures, in correspondence to empirical RNE findings, and generated more diverse road network structures than previous models, by changing the value of $\beta$. The modelled network structures' node, link, block, betweenness centrality (BC), by the proposed mechanism with $\beta \in [1.0, 2.0]$, exhibited characteristics and dynamics as reported in empirical findings. By changing the value of parameter $\beta$ in $[1.0, 2.0]$, the proposed mechanism modelled not only network structures generated in previous models with $\beta = 2.0$, but also a broader range of plausible urban road network structures. Network connectivity increased as $\beta$ decreased; network structures modelled with $\beta = 1.0$ exhibited the closest average node degree to empirical findings. $\beta < 1.0$ led to non-planar network structures while $\beta > 2.0$ led to unconnected network structures, hence the range $\beta \in [1.0, 2.0]$.

Addressing the first research question, this study generalised the Link Connection mechanism of the urban road network structure. In doing so, this study proposed a generalised GNM of urban road network evolution, designed an algorithm, implemented the model, and planned and performed simulation experiments. This study found that Link Connection could be generalised as examining the proximity relationship between a new spatial location and the existing urban road network, using β-skeletons proximity relationships with $\beta \in [1.0, 2.0]$. As will be discussed in 10.1.2, this original methodological contribution is significant, since the generalised Link Connection mechanism is capable of modelling a broader range of network structures and dynamics than previous GNMs, in correspondence with empirical findings. Therefore, the generalisation of the Link Connection mechanism has led to an improved understanding of modelling elementary urban road network connection patterns and the role of proximity relationships in urban road network generation.

### 10.1.2 Simulation Findings: Modelling the Dynamic RNE Process

Chapter 7 answered the second research question of this thesis:

2. Can the GNM model the dynamic RNE process?

- What is the relationship between the simulated static and dynamic network structures and the generative mechanism?
- Are the simulated networks' dynamic structure comparable to the RNE process?
- Can modelling and simulation provide insights on empirical RNE findings?

Previous GNMs of urban road networks (Barthélemy and Flammini, 2008; Barthélemy and Flammini, 2009; Yang et al., 2011; Courtat et al., 2011; Rui et al., 2013; Zhao, F. et al., 2015) have aimed at reproducing statistically empirical urban road network characteristics and examined only the final generated network structures, leaving a gap in understanding the simulated network dynamics. Empirical urban Road Network Dynamics quantified by empirical RNE research, as reviewed in Chapter 2, have shown potential parallels with the network generation process. Because of previous models' network generation objective, they have not integrated these empirical RNE findings into results examination or looked into the dynamic simulated network structure.

This study originally proposed using GNM to model the dynamic RNE process, beyond network generation. Simulation experiments demonstrated the proposed model's capacity in modelling the dynamic RNE process, by examining both static and dynamic network structures, in comparison to empirical RNE findings.

This study first synthesised empirical RNE findings in Chapter 2 and proposed a framework to quantify RNE, consisting of elementary road network component node, link, block characteristics and dynamics in Chapter 5 Table 5-3. In simulation experiments, data of the entire network generation processes were collected, instead of only the generated networks. The proposed model used the primal representation, in which nodes represented road intersections, and links represented road segments. This representation addressed the limitation of previous GNMs' modelled network structure using nodes to represent urban centres of population concentration and links to represent road network. The usage of primal representation enabled the comparison of simulated network structures with primal empirical RNE findings, which have constituted most empirical RNE research.

Chapter 7 explored the capacity of the proposed model in modelling the dynamic RNE process, by examining the modelled static and dynamic network structures, simulated network dynamics, in comparison to existing empirical and modelling RNE findings, based on the proposed RNE quantification framework of elementary component characteristics and dynamics. Interpretations of the simulation results were made relating to existing empirical findings, as summarised in the following paragraphs and Table 7-1.

First, simulated networks' node, link, block, and BC all exhibited characteristics and dynamics that corresponded with empirical findings, demonstrating that the proposed model is capable of giving rise to both plausible static and dynamic urban network structures, and potential parallels may exist in processes that lead to simulated network structures and empirical urban road networks.

Simulated networks had stable connection patterns with network growth, characterised by a majority of $k_3$ nodes, and resulted in an almost constant average node degree $\langle k \rangle$. Simulated networks under $\beta = 2.0$ had $\langle k \rangle \approx 2.36$, while simulated networks under $\beta = 1.0$ had $\langle k \rangle \approx 2.78$. Simulated $\langle k \rangle$ was similar to urban road networks that have been recognised as organic, such as Oxford with $\langle k \rangle = 2.32$, Worcester with $\langle k \rangle = 2.36$, Edinburgh with $\langle k \rangle = 2.43$, Sheffield with $\langle k \rangle = 2.42$, yet was lower than urban road networks that have been recognised as planned, such as Barcelona with $\langle k \rangle = 3.42$. All US urban road networks had $\langle k \rangle \approx 2.76$ in the range of $[2.22, 3.22]$, showing the diversity of real-world urban road network connectivity under potential planned and organic regimes. Simulated networks' $\langle k \rangle$ resulted from low $k_4$ node proportion, which could form under the proposed Link Connection mechanism given predetermined grid node distribution, as discussed in 5.3.2.1. $k_3$ nodes could emerge under random new node positioning as in the simulation. Previous models have reported similar node degree distributions, consisting of mainly $k_3$ and $k_1$ nodes. Empirical urban road networks' majority of $k_3$ nodes and higher $k_4$ proportion than simulated networks (Barrington-Leigh and Millard-Ball, 2015; Boeing, 2017; Chan et al., 2011; Strano et al., 2013), suggested that urban road networks lie between planned grid patterns and organic growth patterns (Wang, 2015; Buhl et al., 2006). Planned and organic urban form coexist (Kostof, 1991).

Simulated networks' link length $\mathrm{l}$ distribution and block area $\mathrm{A}$ distribution and dynamics suggested the existence of both multiplicative and additive processes during the simulated network dynamics, which were the continuous division of large network components into smaller components and addition of random size network components, respectively. Simulation suggested the inconsistency in empirical findings between heavy-tailed power-law, lognormal, and exponential distributions (Fialkowski and Bitner, 2008; Jiang and Liu, 2012; Lämmer et al., 2006; Long et al., 2016; Louf and Barthelemy, 2014; Riascos, 2017; Usui and Asami, 2018; Liu, 2012) may have characterised various potential spatial processes behind the formation of these network characteristic distributions, such as the continuous space division and random space addition.

The betweenness centrality distribution of simulated networks resulted from the simulated dynamics characterised by initial global changes, which formed a skeleton of major paths spanning over the simulation area, and later local minor changes. The proposed model gave rise to the empirically reported bimodal BC distribution in global urban road networks, separating large and small BC components at the BC value of network node number (Kirkley et al., 2017). This bimodal BC distribution differed from previous smaller individual road network studies' results (Lämmer et al., 2006; Crucitti et al., 2006b; Porta et al., 2006b; Porta et al., 2010), but supported the long-standing recognition of backbone in urban road networks (Scellato et al., 2006; Strano et al., 2012; Masucci et al., 2013). The simulation confirmed correlations between high BC and long-existing network components found the empirical backbone phenomenon, and further included geographically central network components into this correlation, suggesting the inherent hierarchy in planar networks because of the formation process. Densification and Exploration (DE) (Barthelemy et al., 2013; Corcoran and Mooney, 2013; Mohajeri and Gudmundsson, 2014; Mohajeri et al., 2015; Mohajeri et al., 2014; Patarasuk, 2013; Strano et al., 2012) which characterised two types of new link influences on average network BC was observed in the simulated networks. The simulation suggested DE is a planar network property, which are the only two Link Connection patterns in planar networks; DE shall include temporal and spatial information to be meaningful in characterising urban road network evolution. Modelling and simulation in Chapter 8, 9 found that the empirical DE phenomenon may relate to the change of road network spatial structure. For instance, the transformation from clustered or decentralised to centralised road network spatial structures may exhibit a decrease of exploration links and an increase of densification links in the central area with time, as empirically reported. Clustered and decentralised road network spatial structures encouraged more the emergence of dead-ends and $k_1$ nodes, compared to centralised spatial structures.

The simulation observed continuous simulated network dynamics under the proposed model and established a clear relationship between the generative mechanism and the emerged network structure. Observations of elementary network generation process portrayed a general network changing process. In comparison, empirical studies have inferred RNE mechanisms from static network structures at a few discrete historical snapshots, while previous GNMs have generated static network structures without considering the dynamic network structure. Look into the emerging process of network characteristics and the related generative mechanism, rather than reporting more observed individual differences, the proposed model and simulation gave rise to unintuitive characteristics like the combined probability distributions of link length $l$ and block area $A$. Inconsistency in empirical findings may have characterised network dynamics behind the formation of these probability distributions. The simulation also showed how complex macroscopic characteristics might emerge from a simple microscopic generative mechanism, and real-world urban road networks may experience similar processes.

Answering the second research question, this study used GNM to model the dynamic RNE process, yielding original simulation findings. Simulations using the proposed model established associations between the network generation process and the dynamic RNE process, advanced the understanding of urban road networks' structure and dynamics, and empirical RNE findings. Modelling and simulation in Chapter 6, 7 portrayed the formation and dynamics of a general urban road network structure, in particular, the emergence of elementary road network connection patterns under the Link Connection mechanism. The urban road network evolution alone may be characterised by stable connections, multiplicative and additive growth with continuous large component division and random component addition, the initial formation of a major path skeleton and later local minor changes. Nevertheless, modelling the dynamic RNE process did not mean reproducing step-by-step any urban road network evolution in particular but used GNM and computer simulation as a tool to improve the empirical and modelling understanding of urban road network evolution.

### 10.1.3 Modelling Findings: Proposing the Hybrid Model of Population and Urban Road Network Co-evolution

Chapter 8 answered the third research question of this thesis:

3. How to integrate GNM of urban road network evolution into the urban system?

- How to represent the urban road network and population?
- What population-urban road network co-evolution mechanism do the correlations between population and urban road network in terms of quantity, spatial structure, and network characteristics, as well as by mutual influences between road network and the urban system reflect?

Modelling of urban road network evolution is involved implicitly or explicitly in various transport and urban study topics; different research perspectives approach different urban system layers and components. Transport demand forecasting focuses on the transport layer (Levinson and Yerra, 2006; Xie and Levinson, 2009; Pagliara et al., 2016), urban models focus on the land use layer (Raimbault, 2017; Wu et al., 2016), land use and transport interaction models focus on the feedback relationship between transport and land use layers (Levinson and Huang, 2012; Levinson et al., 2007). The network science perspective GNMs were distinguished from alternative approaches by modelling the urban road network structure explicitly and having the flexibility to integrate with transport and urban theories.

As discussed in detail in 4.3.4.4, previous GNMs (Barthélemy and Flammini, 2009; Yang et al., 2011; Zhao, F. et al., 2015; Barthélemy and Flammini, 2008; Courtat et al., 2011; Rui et al., 2013) of urban road networks have shown limitations in the representation of the road network and population, and the consideration of road network spatial structure and its relationship to the urban system. In these studies, the modelled road network structure has not been sufficiently distinguished from and integrated into the urban system. Most of the previous GNMs have equated the road network to the urban system, by using nodes to represent population concentration locations and links to represent the road network. Under such a model design, the population and road network have been related inherently, being one network's nodes and links; thus, the potential explanatory power of the proposed population-road network co-evolution mechanisms has been weakened. The generated population and road network structure, as well as their relationship, have not only been influenced by the co-evolution mechanism, but also by the built-in network connectivity between nodes and links. Moreover, in the previous studies, simulation results have been evaluated by primal empirical urban road network structure findings, regardless of the difference in the modelled network structure and the primal urban road network representation.

Based on the synthesis of previous empirical studies reviewed in Chapter 3, this study proposed that the spatial structure of urban road networks is correlated with the economic, physical and functional urban spatial structure (Baum-Snow, 2007; Garcia-López, 2012; Giuliano et al., 2012; Sánchez-Mateos et al., 2014; Garcia-López et al., 2015; Batty and Kim, 1992; Hawbaker et al., 2005; Wang et al., 2014; Law, 2017; Porta et al., 2012; Wang et al., 2012; Agryzkov et al., 2014; Shen and Karimi, 2016; Shen and Karimi, 2018). These studies have suggested that the urban road network and the urban system may be driven by related push and pull forces across different urban system layers. For example, the economies and diseconomies of agglomeration on the economic urban spatial structure (Anas et al., 1998), coalescence and diffusion of physical urban growth (Dietzel et al., 2005), attraction and repulsion among different land use categories (Stanilov and Batty, 2011), centripetal and centrifugal forces of transport accessibility (Smith, 2011), and the influence of spatial interaction potentials on the functional urban spatial structure

(BERRY, 1968) have been identified. Chapter 3 proposed that the evolution of urban road networks depends on and is influenced the evolution of the urban system; road network and the urban system co-evolved.

This study originally identified the need to represent both the road network and the urban system, to integrate GNM into the urban system. Chapter 3 proposed to view the urban system as overlaid layers, such as urban spatial structure, land uses, and transport layers, each having socioeconomic, physical, and functional components. The road network resided on the transport layer and belonged to the physical built environment of the urban system. The population generated and represented socio-economic components across urban system layers, such as economic urban spatial structure, socio-economic activities, transport demand. The road network realised the spatial interactions of the population. The co-evolution of urban road network and population served as a starting point to understand the co-evolution of the road network and the urban system. Integrating GNM of urban road network evolution into the urban system required representation and modelling of these two inter-dependent systems.

Chapter 8 proposed a hybrid model of population and road network co-evolution. Node Addition in the generative mechanism of urban road network evolution directed the modelled network's spatial structure and further related to the urban system; Node Addition integrated GNM into the urban system. The co-evolution mechanism proposed an iterative process of Population and Road Network Dynamics on two inter-dependent urban system layers. Population and Road Network Dynamics both located new components by making spatial decisions, regarding preferences of the distance between them and for areas with high or low existing population density and road network flow respectively. Implementing the proposed model, simulation experiments explored all combinations of spatial decision preferences, rather than assuming fixed population and road network relationships. The proposed model was capable of giving rise to a diverse spectrum of both road network and population spatial structures, as well as the mutual influences between them.

Answering the third research question, this study made the third original contribution by integrating GNM and RNE into the urban system through Node Addition. The proposed model represented population and road network as inter-dependent urban system layers. Push and pull forces across urban system layers were hypothesized to drive the co-evolution of road network and population, which was designed into the co-evolution mechanism through population and road network's spatial decision preferences for mutual distance, existing population density and network flow.

### 10.1.4 Simulation Findings: The Spatial Structure of Urban Road Networks, the Relationship Between the Road Network and the Urban System

Chapter 9 addressed the fourth research question of this thesis:

4. What road network spatial structure may arise during the co-evolution of road network and population? How do the simulated road network and population relate?

- How to characterise the spatial structure of urban road networks?

Empirical and modelling RNE research has paid limited attention to the spatial structure of urban road networks and the relationship between the road network and the urban system.

This study originally modelled and examined the spatial structure of urban road networks and the relationship between the road network and the urban system. First, Chapter 3 reviewed existing research, which has studied road network spatial structure as geometric connection patterns and continuity hierarchy, by density spatial analysis and quantitative classification. Chapter 3 synthesised the relationship between urban road network and the urban system from empirically reported correlations, between population and road network quantity, spatial structure, and connectivity. Chapter 5 proposed an original method to characterise the spatial structure of urban road networks using network characteristics and by processes behind the formation of these spatial structures – centralisation and decentralisation on the global scale, clustering and dispersion on the local scale. This characterisation method was consistent with the characterisation of urban spatial structure, thus relating the road network spatial structure to urban spatial structure while emphasising on the network nature. A spectrum of spatial structures may be captured, rather than a few fixed types (Marshall, 2004; Huynh et al., 2017; Moosavi, 2017). The proposed hybrid model of population and road network co-evolution in Chapter 8 gave rise to a diverse spectrum of population and road network spatial structure as well as their mutual influences. Simulation experiments in Chapter 9 originally explored the emergence of the urban road spatial structure, and the relationship between the road network and population, in terms of the mutual influences on their spatial structures and network connectivity, as summarised in Table 9-1.

Diverse road network spatial structures emerged, which appear to be a spectrum, rather than a few clear-cut types, supporting empirical findings (Huynh et al., 2017; Moosavi, 2017). The spatial structures of simulated networks were characterised by processes of centralisation to decentralisation on the global scale, clustering to dispersion on the local scale, behind the generation of these spatial structures. Road network spatial decision preference for areas with high or low flows in the proposed Road Network Dynamics mechanism modelled the centralisation and decentralisation processes of the road network structure. Centralisation on the global scale led to centralised road network spatial structures with a single centre, and centralisation on the local scale led to clustered road network spatial structures with multiple potential centres. Decentralisation on the global scale led to decentralised road network spatial structures, and decentralisation on the local scale led to dispersed road network spatial structures. Other parameters, namely road network and population's spatial decision preferences for mutual distance and population's spatial decision preference for high or low existing population density, intensified or counteracted the centralisation, decentralisation, clustering, and dispersion processes, thus leading to the diverse spectrum of simulated network spatial structures.

The spatial structure of simulated networks was characterised by network characteristics total link length $L_{tot}$ and longest shortest path length $l_{max}$. Together $L_{tot}$ and $l_{max}$ separated network spatial structures under the centralisation and decentralisation processes. Centralised spatial structure networks had both small $L_{tot}$ and $l_{max}$, suggesting low construction cost and diameter. Clustered spatial structure networks had smaller $L_{tot}$ and larger $l_{max}$ than the centralised spatial structure networks, suggesting increasing traverse distance from monocentric to polycentric. Dispersed spatial structure networks had the highest $L_{tot}$, suggesting the largest coverage and construction cost. Decentralised spatial structure networks had the highest $l_{max}$, suggesting the largest traverse distance. Characterisation of the network spatial structure by network characteristics and by spatial structure formation processes, linked road network spatial structure to urban spatial structure, emphasised on the network nature, and captured a spectrum of spatial structures rather than fixed types (Marshall, 2004; Huynh et al., 2017; Moosavi, 2017).

A spectrum of population spatial structures emerged in the simulated co-evolution, which was also characterised by centralisation, decentralisation, clustering, dispersion processes. Joining the road network and population layers yielded combined population-road network spatial structures. Under road network and population's preferences to be near each other and coordinated processes to both centralise, decentralise, cluster, or disperse, agreed population-road network spatial structures emerged, in accordance with empirical correlated population and road network spatial distributions, which formed urban spatial structures such as monocentric and polycentric (Snellen et al., 2002; Borruso, 2003; Tsai, 2005; Chen et al., 2017; Quinn and Fernández, 2011; Jia and Jiang, 2010; Krehl et al., 2016).

Other road network and population spatial decision combinations intensified or counteracted the combined spatial structure and led to the diverse spectrum of simulated population-road network spatial structures. The necessity to coordinate road network and population processes and mutual distance to simulate correlated population and road network spatial structures, as in empirical findings, supported the co-evolution hypothesis. Dynamics of population and urban road network, respectively, which lead to the formation and dynamics of urban form and urban spatial structure, may be driven by related push and pull forces across urban system layers.

Besides the necessity to coordinate mutual distance and processes to form agreed spatial structures, relationships between simulated population and urban road network also showed in the quantitative correlation between population density and network characteristics, as well as the influences population and road network had on each other's spatial structures.

Simulations suggested the correlations between population density and road network characteristics may result from the underlying population-road network spatial structure. Comparing centralised monocentric spatial structures and clustered polycentric spatial structures may yield positive correlations (Peponis et al., 2007; Maniadakis and Varoutas, 2013; Patarasuk, 2013; Tsiotas and Polyzos, 2017) while comparison made with dispersed spatial structures may not (Weber, 2016). Thus, the study of correlations between urban road network characteristics and population density shall consider the underlying spatial structure. Clustered spatial structure networks showed the lowest connectivity and highest treeness among all spatial structures while dispersed spatial structure networks showed the lowest. Variation of network characteristics among different spatial structures may relate to empirical observations of increasing treeness and self-organisation as urban road network evolved with time (Masucci et al., 2013). Simulation suggested this empirical finding may characterise the transformation of the studied road network's spatial structure from monocentric to polycentric. Variation in network connectivity among simulated network spatial structures resulted from the proportion of $k_1$ nodes and dead-ends. Clustered and decentralised spatial structures encouraged more $k_1$ nodes and dead-ends than centralised and dispersed spatial structures.

Population's influence on the combined spatial structure showed in the spatial decision when population chose to be away from the road network while road network chose to be close to the population. Population's spatial decision to locate away from the existing road network exceeded other parameters and resulted in dominant dispersed spatial structures. This impact indicated a population-driven co-evolution and may relate to the empirical urban spatial structure dispersion (Gordon and Richardson, 1996; Lee, 2007), as well as urban sprawl (Schneider and Woodcock, 2008; Gouda et al., 2016).

Road network's influence on the combined spatial structure showed in the spatial decision when road network chose to be away from the population while population chose to be close to the road network. Road network's locating away from population resulted in linear simulated spatial structures with population locating alongside major road network segments. Such impact indicated a road network-driven co-evolution and may relate to empirical linear urban growth alongside major transport routes (Krehl and Siedentop, 2019; Inostroza et al., 2013; Ji et al., 2014; Kotavaara et al., 2011).

Answering the fourth research question, this study made the fourth original contribution with simulation findings of the road network spatial structure, urban spatial structure, and the relationship between the road network and the urban system. The proposed hybrid model of population and urban road network co-evolution demonstrated the possible existence of a spectrum of urban road network spatial structures, which may be characterised by processes centralisation to decentralisation on the global scale and clustering to dispersion on the local scale, behind the formation of these network spatial structures. The proposed road network spatial structure characterisation method may find broader applications in real-world road networks. Correlated centralised, decentralised, clustered, dispersed population-road network spatial structures in accordance with empirical findings emerged under coordinated population and road network spatial decisions, supporting the hypothesis of related push and pull forces across the urban system that drive the co-evolution of population and urban road network, as well as the evolution of urban spatial structure at large. Population-driven co-evolution gave rise to dispersed spatial structures, and road network-driven co-evolution gave rise to linear spatial structures, suggesting potential parallels between the simulated population-road network dynamics and real-world urban growth patterns. Variation of the simulated network spatial structure resulted in the variation of network characteristics, demonstrating the necessity to consider network spatial structure when studying network characteristics or correlating network structure to population.

## 10.2 Limitations

### 10.2.1 The Network Science Urban Road Network Evolution Perspective

Urban road network structure and evolution discussed in this study were limited to a network science perspective. RNE was regarded as a process of macroscopic network characteristics arising from microscopic network component behaviours and interactions, which followed a set of local rules rather than central control. Network structure was limited to selected network characteristics. Network evolution was limited to the changes of selected network characteristics and studied by characteristics' dynamics trajectories. Only incremental network growth was considered. Modelling and simulation of network evolution aimed at increasing understanding of the mechanism that gave rise to urban road network characteristics, instead of reproducing or predicting any road network evolution process in particular.

Compared to alternative research perspectives identified in Chapter 1, for instance, a transport studies perspective, the discussed network structure and evolution here lacked considerations for road network's transport function and performance. Meanwhile, this network science perspective also provided a feasible research scope to approach urban road network evolution. At this stage, empirical and modelling RNE research has accumulated a considerable number of findings and methods but with inadequate horizontal comparison and consensus. This study's research scope suited the objective to explore the emergence of observed urban road network characteristics, from elementary road network components' behaviours and interactions. At the same time, the proposed approach had the flexibility to integrate alternative research perspectives' factors of interest, through the design of generative mechanisms, as additional system components that participate in the interactions of urban system formation and dynamics.

Therefore, though the network science urban road network evolution perspective has limitations regarding insufficient consideration of alternative research perspectives' factors of interest, such as road network design and planning, transport function and performance, it satisfied the research objective to explore and further understand RNE and had the flexibility to integrate with transport and urban theories through designed generative mechanisms. This bottom-up generative complex network modelling and simulation approach demonstrated the potential to advance the understanding of the urban road network structure and dynamics, which positioned it with alternative research dimensions.

### 10.2.2 Generative Network Models

GNMs generate networks iteratively; spatial and temporal network structure and dynamics are limited to the designed generative mechanisms. With the modelling and simulation conducted, this study identified two limitations about the proposed GNMs.

First, the modelled network structure shared similar node degree characteristics with urban road networks that have been considered as self-organising but had lower $k_4$ node proportion than urban road networks that have been considered as planned. 5.3.2 discussed the potential emergence of grid connection patterns under the proposed Link Connection mechanism; given a grid node distribution, the proposed Link Connection mechanism would form $k_4$ connections and grid connection patterns. Thus $k_4$ connection patterns required predetermined grid node distributions, indicating design and planning. Meanwhile, $k_3$ connections patterns, which have been reported to make up a major proportion of empirical urban road network intersections, could emerge under random node positioning as in the simulation. This study concluded that urban road networks lie between centrally planned grid layouts and not-centrally-planned self-organised urban growth patterns, and GNM with randomness in Node Addition may model the self-organised road network structure with low $k_4$ proportion.

Assumed randomness in the Node Addition mechanism to avoid arbitrary assumptions of spatial decisions led to the low $k_4$ proportion. In the proposed generative network model of urban road network evolution, positions to add new nodes were modelled as random, since this model intended to explore network elementary connection patterns rather than spatial structure. In the proposed hybrid model of population and urban road network co-evolution, though the spatial distribution of network nodes was directed by the population-road network co-evolution mechanism, candidate locations among which spatial decisions to add new nodes were made were modelled as random. These settings did not interfere with this study's research objectives, as elementary connection patterns and diverse spatial structures emerged under proposed models. However, these settings caused the modelled network to exhibit low proportions of degree $k_4$ nodes and grid patterns, as discussed in 7.2 and 9.2.3.

The proposed GNMs perceived urban road network evolution as arising from elementary network components' behaviours and dynamics, which were numerous interactions among numerous urban factors. GNMs selected the urban factors of research interest to design into the generative mechanism for further exploration. If $k_4$ nodes were the primary concern, generative mechanisms should include a predetermined grid node distribution design.

Second, the propose road network generative mechanism consisting of Node Addition and Link Connection was always initiated by Node Addition. The addition of a new link only happened when a new spatial location was connected. However, in real urban road networks, new roads may be constructed not to connect a new location, such as adding a road segment intersecting two existing roads. This was discussed in the examination of Densification and Exploration (DE) in 7.5.4, which showed one densification link in simulated networks were, in fact, two new links from a new node extending to opposite directions and intersecting two existing links. Though this did not affect the identification of DE, there was still a difference between the formation of simulated networks and real urban road networks' densification links.

In summary, GNM showed limitations in modelling planned grid patterns and real-world bridge links. GNM was used as a tool for understanding; modelling and simulation using GNM did not mean reducing the real-world urban road networks and their evolution processes to the simulated network structures and dynamics.

### 10.2.3 Simulation Result Examination

This study examined the simulated network structure and dynamics by network characteristics and changes of a general urban road network structure, instead of by reproducing exact empirical urban road network characteristics or dynamics trajectories.

First, the syntheses of existing empirical and modelled urban road network structures were general, based on a proposed RNE quantification framework consisting of elementary network components node, link, block characteristics, betweenness centrality and dynamics, as in Table 4-1, Table 5-3. Chapter 2, 4 reviewed and compared horizontally empirical and modelling RNE research findings. Elementary components and betweenness centrality were selected to quantify RNE, which maximumly utilised existing findings for comparison and synthesis. Many sophisticated network characteristics were not selected because of the uniqueness of individual road networks and the limited number of findings for comparison. The synthesised general static and dynamic urban road network structures concerned variation ranges of node, link, block, betweenness centrality characteristics, as well as trends of their changes.

Simulated network structure and dynamics were examined according to the synthesised RNE quantification framework, as summarised in Table 7-1. Rather than reproducing specific network characteristic statistics, the plausibility of simulated network structure and dynamics were established by comparing simulated network characteristics' variation ranges and trends with empirical findings. Simulated network characteristics all found correspondence in empirical findings. For characteristics and dynamics with inconsistent empirical findings, simulation results were analysed regarding the emergence of empirical inconsistency and advanced the understanding of empirical research in this regard.

Second, Chapter 9 proposed simulated networks' spatial structures and characterisation method, as summarised in Table 9-1, since the spatial structure of urban road networks have had limited discussions in network science perspective studies. This simulation result examination was designed based on the synthesised understanding of the general urban road network spatial structure and urban spatial structure from Chapter 3. Simulation findings agreed with quantitative empirical findings of urban road network spatial structure as a spectrum and may guide future data collection of different spatial structure urban road networks.

The simulation result examination design was limited, given the current research stage of RNE. Empirical RNE research, as reviewed in Chapter 2, has accumulated a considerable number of findings but had inconsistent conclusions because individual urban road networks were studied with various research questions. Modelling RNE research, as reviewed in Chapter 3, has generated various network structures without horizontal comparison either. A general urban road network structure and dynamics understanding serve to bridge the empirical and modelling RNE research and guide future research.

Meanwhile, given specific network statistics and historical socio-economic development of a particular area and the accompanied spatial development history, road network structure and dynamics of particular numerical precision may be generated. If the research interests were network generation or road network development reproduction, the proposed models may be used to generate specified network structure and dynamics. In that case, simulation results examination shall compare specified network structure and dynamics.

## 10.3 Future Research

### 10.3.1 The Evolution of Self-organised Urban Road Networks

Modelling and simulation using the proposed GNM of urban road network evolution in Chapter 6, 7 portrayed the formation and dynamics of a general urban road network structure. Elementary road network connection patterns emerged from the Link Connection process and could be characterised by stable connections, multiplicative and additive growth with continuous large component division and random component addition, the initial formation of major path skeleton and later local minor changes leading to hierarchy in the network. A majority of $k_3$ nodes and low $k_4$ node proportion characterised simulated networks' elementary connection patterns because $k_4$ node required predetermined grid node distribution while $k_3$ nodes could emerge under random new node positioning as in the simulation. Empirical findings of the $k_3$ node majority and higher $k_4$ node proportion than the simulated networks suggested that urban road networks lie between centrally planned grid patterns and not-centrally-planned self-organised growth patterns.

Self-organised has been used to describe urban road networks and the urban form, in comparison to the centrally-planned. Self-organisation in the complex system means system components' behaviours follow local rules instead of the central control (Mitchell, 2009); external influences do not determine or cause system behaviours but instead trigger an internal and independent process (Portugali, 2012b). Self-organised road networks have been attributed to local natural environment and history, land division and increments without the preservation of continuity (Kostof, 1991), interactions of various urban forces (Batty and Longley, 1994), decentralised building processes and spatial decisions (Buhl et al., 2006). The spontaneous, grown organic road networks with representative narrow winding streets and cul-de-sacs (Kostof, 1991), have often been used as examples of self-organised urban road networks. In contrast, the centrally-planned has been used to refer to networks determined once and for all by some authority at one moment, with representative regular grids (Kostof, 1991).

Following this study's simulation findings, future research may look into the evolution of real-world self-organised urban road networks, for instance, the evolution of informal urban settlements road network. Increasing research has studied empirically and quantitatively informal settlements, as one primary ongoing urbanisation process. The uniqueness in informal settlements' morphology has been recognised regarding their blurred or absent typology of form, which has been attributed to their formation processes as a result of individual negotiation of space, rather than central planning (McCartney and Krishnamurthy, 2018). The road network of informal settlements has been regard to emerge as walking paths that connect residence, markets and street shops, transport hubs, meeting points and recreational area, which accommodate residents' demand directly (Roy et al., 2014). The road network has been identified as the central physical problem of informal settlements for the lack of accessibility (Brelsford et al., 2018) and as shaping the structure and growth of informal settlements (Roy et al., 2014).

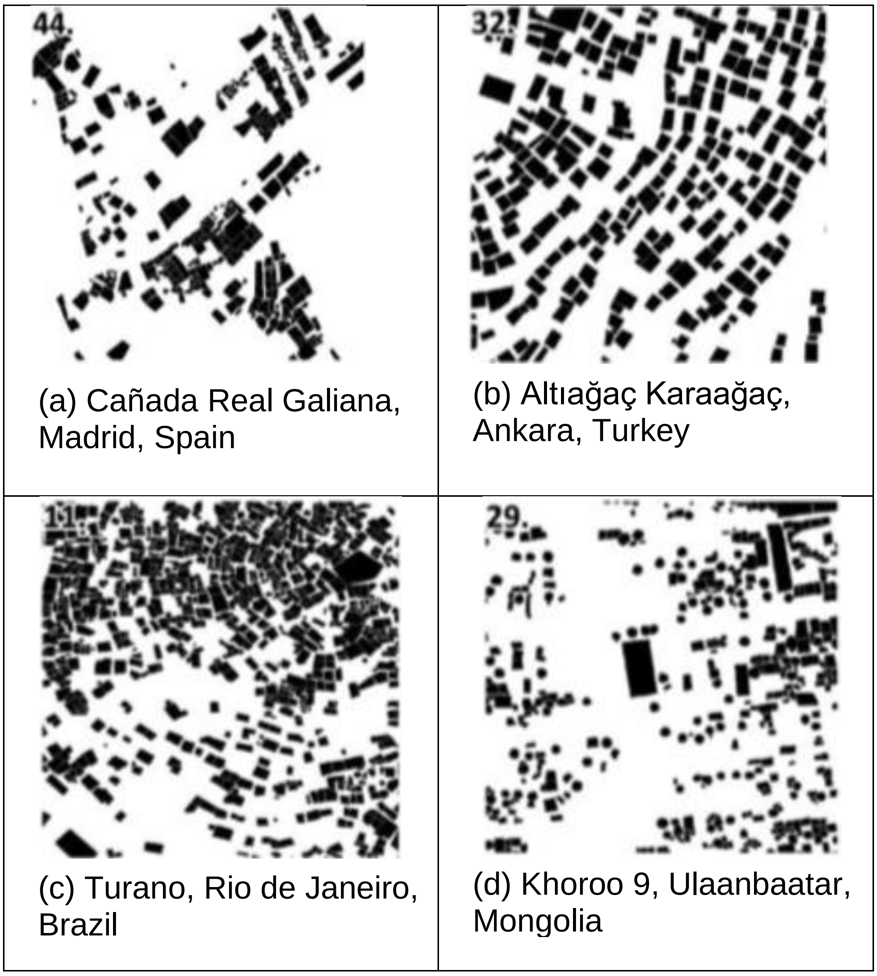
The structure of informal settlements consists of access – roads, streets, paths and places – buildings (Brelsford et al., 2018). The proposed GNM of the urban road network evolution in Chapter 6 can model the dynamics of these two systems. Informal settlements and their road networks form and change in response to local individual demands, rather than by the design of a central master plan. External influences, such as policies to upgrade infrastructure, do not determine informal settlements' future development but trigger complex internal responses, namely self-organisation. Local social and economic factors behind such self-organisation can be designed into the generative mechanism of the proposed model, which directs Node addition and Link connection. The simulated networks in Chapter 7 shared structural similarity with informal settlements' road networks, as shown in the high $k_3$, $k_1$ node proportions and the low $k_4$ node proportion. Identified evolutionary processes of the simulated networks including stable connection patterns, multiplicative and additive growth, the initial formation of a major path skeleton and later local minor changes, are likely to apply to the formation and dynamics of informal settlements' road networks as well.

Figure 10.2 shows one example of informal settlement evolution in I.S.Sadan, Hyderabad, India. The informal settlement developed in the central space of this area between 2003 and 2010, in contrast to the planned grid settlements around. Figure 10.3 shows the morphology of four informal settlements, which exhibited diverse spatial structures. The road network of informal settlements self-organised, following local rules rather than central control. The macroscopic structure of this road network structure displayed characteristics similar to urban road networks that have been recognised as organic. Compared to planned networks, these network structures have been reported to have high $k_3$, $k_1$ node proportions and low $k_4$ node proportion, irregular street segment lengths and block sizes. With the increasing data availability (Kuffer et al., 2016), empirical research regarding the characteristics and dynamics of informal settlement road networks may be conducted, investigating both static and dynamic network structures.

(a) 2003 imagery (b) 2010 imagery

**Figure 10.2 The Evolution of Informal Settlement** : The two images depict the evolution of informal settlement in I.S.Sadan, Hyderabad, India between 2003 and 2010. The informal settlement grew in the central empty area since 2003, in contrast to the planned grid settlements around. (Kit and Lüdeke, 2013)

Empirical and modelling research questions may be proposed regarding self-organised road networks' evolution, following this study's modelling and simulation findings and methodology. The evolution of informal settlements is happening rapidly, which provides data on self-organised RNE processes. Empirical research may explore whether real-world self-organised road networks exhibit RNE processes as concluded in Chapter 7: whether self-organised road networks evolve by stable connection patterns, multiplicative and additive growth corresponding to continuous large component division and addition of random size components, the initial formation of a major path skeleton and later local minor changes. Understanding of mechanisms behind the formation and dynamics of self-organised road networks may advance the understanding of informal settlement development.



(a) Cañada Real Galiana, Madrid, Spain

(b) Altıağaç Karaağaç, Ankara, Turkey

(c) Turano, Rio de Janeiro, Brazil

(d) Khoroo 9, Ulaanbaatar, Mongolia

**Figure 10.3 The Spatial Structure of Informal Settlement** : Empirical informal settlements that exhibited global centralisation and decentralisation and local clustering and dispersion (Taubenböck et al., 2018), in accordance with simulation findings of Chapter 9.

The empirical informal settlement dynamics may be studied by elementary network characteristics. For example, network characteristic dynamics of link length and block area may reveal the proportion of multiplicative and additive growth in the studied network; these two types of growth may further reveal different development in the informal settlement. Multiplicative growth, which corresponds to the continuous division of large network components, may suggest geographically constrained development and division of existing land use for more sophisticated land use. Additive growth, which corresponds to the addition of random size components, may suggest geographical expansion and new primitive land use. Availability of empirical data, such as in Figure 10.2 suggests research direction to investigate mechanisms behind real-world self-organised road networks' evolution.

Second, the proposed GNM of urban road network evolution in Chapter 6 may be used to model various self-organisation scenarios of informal settlements' development. Simulated network structure under the proposed model shared structural similarity with informal settlement road networks. Scenarios may be specified for informal settlements' development, and the proposed model can be used to simulate different network structure and dynamics accordingly. Various development scenarios may result in different network characteristics, such as network connectivity. Simulation findings from Chapter 7 suggested potential hierarchy in informal settlement road networks because of the initial major path skeleton and high BC road segments. Modelling and simulation of different development scenarios may be used to improve the function of informal settlement road networks by improving these key network components.

In summary, modelling and simulation findings from this study may increase the understanding of self-organised urban road networks' evolution, such as informal settlement road networks. Meanwhile, future empirical research on self-organised road network evolution may improve the quantification and enhance the theorisation of the modelled general urban road network structure and dynamics, as well as the identified evolutionary processes in Chapter 7.

### 10.3.2 Empirical Spatial Structure of Urban Road Networks

Characterisation of urban road networks' spatial structure in network science perspective research has been limited. Modelling and simulation findings from Chapter 8, 9 suggested that urban road networks are likely to have a diverse spectrum of spatial structures, rather than fixed types (Marshall, 2004; Huynh et al., 2017; Moosavi, 2017). This spectrum of urban road network spatial structures may be characterised by processes behind their formation: centralisation to decentralisation on the global scale, clustering and dispersion on the local scale. The spectrum of the urban road network spatial structure, rather than a few fixed and clear-cut types, may result from related push and pull forces across the urban system that drive the co-evolution of road network and the urban system.

Increasing quantitative empirical research, using approaches such as machine learning, have reported diverse road network spatial structures and urban form. Figure 10.3 and Figure 10.4 show empirical road networks that exhibited centralised to decentralised, clustered to dispersed spatial structures. Figure 10.3 selects four samples of informal urban settlements and Figure 10.4 selects four samples of urban road networks. Future empirical research may apply the proposed road network spatial structure dimensions and characterisation to explore the real-world urban road network spatial structures.

In summary, modelling and simulation findings from this study may guide the data collection and empirical investigation of the variation in real-world urban road network spatial structures, which has been limited in existing network science research. Future empirical research may improve the quantification and enhance the theorisation of identified centralisation, decentralisation, clustering, and dispersion processes, as well as improve the understanding of identified push and pull forces across the urban system behind the formation of such spatial structures in Chapter 8, 9.

**Figure 10.4 The Spatial Structure of Urban Road Networks**: Empirical urban road networks that exhibited global centralisation and decentralisation and local clustering and dispersion (Moosavi, 2017) in accordance with simulation findings of Chapter 9.

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