

The Resilience of Road Transport Networks
Redundancy, Vulnerability and Mobility characteristics

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Submitted in accordance with the requirements for the degree of
Doctor of Philosophy

The University of Leeds

Institute of Transport Studies, Faculty of Environment

September 2014

Declaration

The candidate confirms that the work submitted is her own, except where work which has formed part of jointly-authored publications has been included. The contribution of the candidate and the other authors to this work has been explicitly indicated below. The candidate confirms that appropriate credit has been given within the thesis where reference has been made to the work of others.

List of the jointly-authored publications and the contributions of the candidate and the other authors are as this below statement.

- El-Rashidy, R.A. and Grant-Muller, S.M. “The evaluation of redundancy for road traffic networks”, Transport, Taylor & Francis, accepted for publication in December 2014.
- El-Rashidy, R.A. and Grant-Muller, S.M. (2014), “An assessment method for highway network vulnerability”, Journal of Transport Geography, 34, pp. 34–43.
- El-Rashidy, R.A. and Grant-Muller, S.M.(2015), “An operational indicator for network mobility using fuzzy logic”, Expert Systems with Applications available online, DOI information: 10.1016/j.eswa.2014.12.018.
- El-Rashidy, R.A. and Grant-Muller, S.M. “A composite resilience index for road transport networks”, Transportmetrica A – Special issue on Resilience in Transportation Networks, submitted in September 2014.

Above journal papers are part of the candidate’s thesis that she mainly wrote in the following Chapters, respectively:

- Chapter 5 Redundancy of Road Transport Networks.
- Chapter 6 Vulnerability of Road Transport Networks
- Chapter 7 Mobility of Road Transport Networks.
- Chapter 8 A composite resilience index and ITS influence on the road transport network resilience.

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Acknowledgments

I am deeply grateful to my supervisor, Dr Susan Grant-Muller, for her help, encouragement and friendship throughout this project. I shall always remember her excellent advice and invaluable support. I am also grateful to Dr Riccardo Mogre, Hull University, my second supervisor for useful discussions and support.

The assistance and co-operation of the staff of the Institute for Transport Studies are gratefully acknowledged. I would also like to thank the OmniTRANS IT team, particularly Mr. Feike for their technical support.

I am grateful to White Rose Network for providing me with the financial support. Finally, I want to share my happiness with my family. Their love, patience and full support enriched my life and made this study possible.

Abstract

This thesis is concerned with the development of a composite resilience index for road transport networks. The index employs three characteristics, namely redundancy, vulnerability and mobility, measuring resilience at network junction, link and origin-destination levels, respectively. Various techniques have been adopted to quantify each characteristic and the composite resilience index as summarised below.

The redundancy indicator for road transport network junctions is based on the entropy concept, due to its ability to measure the system configuration in addition to being able to model the inherent uncertainty in road transport network conditions. Various system parameters based on different combinations of link flow, relative link spare capacity and relative link speed were examined. The developed redundancy indicator covers the static aspect of redundancy, i.e. alternative paths, and the dynamic feature of redundancy reflected by the availability of spare capacity under different network loading and service level.

The vulnerability indicator for road transport network links is developed by combining vulnerability attributes (e.g. link capacity, flow, length, free flow and traffic congestion density) with different weights using a new methodology based on fuzzy logic and exhaustive search optimisation techniques. Furthermore, the network vulnerability indicators are calculated using two different aggregations: an aggregated vulnerability indicator based on physical characteristics and the other based on operational characteristics.

The mobility indicator for road transport networks is formulated from two mobility attributes reflecting the physical connectivity and level of service. The combination of the two mobility attributes into a single mobility indicator is achieved by a fuzzy logic approach.

Finally, the interdependence of the proposed characteristics is explored and the composite resilience index is estimated from the aggregation of the three characteristics indicators using two different approaches, namely equal weighting and principal component analysis methods. Moreover, the impact of real-time travel information on the proposed resilience characteristics and the composite resilience index has been investigated.

The application of the proposed methodology on a synthetic road transport network of Delft city (Netherlands) and other real life case studies shows that the developed indicators for the three characteristics and the composite resilience index responded well to traffic load change and supply variations. The developed composite resilience index will be of use in various ways; first, helping decision makers in understanding the dynamic nature of resilience under different disruptive events, highlighting weaknesses in the network and future planning to mitigate the impact of disruptive events. Furthermore, each developed indicator for the three characteristics considered can be used as a tool to assess the effectiveness of different management policies or technologies to improve the overall network performance or the daily operation of road transport networks.

Key words: Resilience, Road traffic networks, Redundancy, Vulnerability, Mobility, Fuzzy Logic.

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List of Abbreviations

Each abbreviation has been defined when it is first appeared in the thesis.

Below is a list of abbreviations and their meaning.

AMI	=	Advanced Motorway Indicator.
AMS	=	Advanced Motorway Signs.
ANPR	=	Automatic Number Plates Recognition.
AON	=	All Or Nothing.
ATMS	=	Advanced Traffic Management System.
ATM	=	Active Traffic Management.
CCTV	=	Closed-Circuit Television.
CEDR	=	Conference of European Directors of Roads.
DaSTS	=	Delivering a Sustainable Transport System.
DECC	=	Department of Energy and Climate Change.
Defra	=	Department for Environment, Food and Rural Affairs
DfT	=	Department for Transport.
DMS	=	Dynamic Message Signs.
DNL	=	Dynamic Network Loading.
DRGS	=	Dynamic Route Guidance System.
DTA	=	Dynamic Traffic Assignment.
DUE	=	Dynamic User Equilibrium.
ETS	=	Electronic Toll Systems.
EWM	=	Equal Weighting Method.
FEHRL	=	Forum of European National Highway Research Laboratories.
FEMA	=	Federal Emergency Management Agency.
FHWA	=	Federal Highway Administration.
FL	=	Fuzzy Logic.
FW	=	Frank-Wolfe.
GDP	=	Gross Domestic Product.
HA	=	Highway Agency.
HADECS	=	Highways Agency Digital Enforcement Camera System.
HAR	=	Highway advisory Radio.

HATRIS	=	Highway Agency Traffic Information System.
HM	=	Her Majesty's Government.
Government		
ITS	=	Intelligent Transport Systems.
JTDB	=	Journey Time Database.
KPI	=	Key Performance Indicators.
LCF	=	Low Carbon Future.
ICT	=	Information and Communication Technology.
MaDAM	=	Macroscopic Dynamic Assignment Model.
MIDAS	=	Motorway Incident Detection and Automatic Signaling.
MJTSCR	=	Motorway Junction's Traffic Signal Controlled Roundabout.
MSA	=	Method of Successive Averages.
NATA	=	New Approach to Appraisal.
PCA		Principal Component Analysis.
PCL		Paired Combinatorial Logit.
PTZ	=	Pan Tilt and Zoom.
cameras		
RM	=	Ramp Metering.
RTTIS	=	Real Time Travel Information Systems.
RWS	=	Road Weather Stations.
SACS	=	Semi-Automatic Control System.
TAC	=	Transportation Association of Canada.
TAG	=	Transport Analysis Guidance.
RTIC	=	Regional Traffic Information Centre.
UE	=	User Equilibrium.
USDHS	=	United States Department of Homeland Security.
VDL	=	Vehicle Detector Loops.
VMS	=	Variable Message Sign.
VPDS	=	Vehicle Proximity Detection System.
3L-VMSL	=	3 lanes - Variable Mandatory Speed Limit.
4L-VMSL	=	4 lanes - Variable Mandatory Speed Limit.
VSL	=	Variable Speed Limits.

List of Notations

Each notation has been defined when it is first appeared in the thesis. Below is a list of notations and their definitions.

a	=	A link in the road transport network.
C_{am}	=	The design capacity of link a for travel mode m (vehicles/hour).
C_{max}	=	The maximum capacity of all network links (vehicles/hour).
d_{ij}	=	The demand between zone i and zone j (vehicles/hour).
f_{am}^i	=	The traffic flow of link a during time interval i using a travel mode m (vehicles/time unit).
f_{bm}^i	=	The traffic flow of link b during time interval i using a travel mode m (vehicles/ time unit).
$FFGDpM$	=	The free flow Geo-distance per minute.
GD_{ij}	=	The Geo-distance between zone i (origin) and zone j (destination) (distance unit).
$GDpM$	=	The Geo-distance per minute (distance unit/ time unit).
i	=	An origin in the road transport network.
j	=	A destination in the road transport network.
$JD_{in}^i(o)$	=	The junction delay (time unit) for node o during time interval i .
$JVCR_{in}^i(o)$	=	The junction volume capacity ratio for node o during time interval i .
k_{am}^j	=	The congestion density for link a (vehicles/distance unit).
l_a	=	The length of link a (distance unit).
L_a	=	The total network length without link a length (distance unit).
MOR	=	A measure of resilience.
n_a	=	the number of lanes of link a that have been used by travel mode m .

NMI	=	The network mobility indicator.
NVI_{PH}	=	The physical based aggregated vulnerability index.
NVI_{OP}	=	The operational based aggregated vulnerability index.
p	=	The percentage of unsatisfied demand.
PC_j	=	The principal component j .
PCA	=	The physical connectivity attribute.
PI_{before}	=	A performance indicator before the disruptive event.
PI_{after}	=	A performance indicator after the disruptive event.
CRI_{eq}	=	The composite resilience index based on equal weighting method.
CRI_{pc}	=	The composite resilience index based on principal component analysis method.
$RI1_{in}$	=	An inflow redundancy index.
$RI1_{out}$	=	An outflow redundancy index.
RLS	=	The relative link speed.
s_{ij}	=	The number of times the link is a component of the shortest path between different OD pairs.
t_{am}^i	=	The actual travel time for inbound link a during time interval i using travel mode m (time unit).
T_{am}^i	=	The free flow travel time of a link a during time interval i using travel mode m (time unit).
TCA	=	The traffic condition attribute.
$TD_{ij(r)}$	=	The actual travel distance between zone i and zone j using route r (distance unit).
TS_{ij}	=	The travel speed between zone i and zone j for a route r (distance unite /time unit)
$TT_{ij}(r)$	=	The actual travel time between zone i and zone j for a route r (time unit).
$TTpT_a$	=	The total travel time per trip during the closure of link a (time unit).
$UnSDI$	=	The unsatisfied demand impact.
VA_x	=	The vulnerability attribute.

V_{am}		The free flow speed of link a for a travel mode m (distance unit /time unit).
VI_a		The vulnerability index of link a .
ρ_{am}^i	=	The percentage of the link spare capacity with respect to the node total spare capacity for a during time interval i using travel mode m .
τ	=	The link closure period (time unit).

List of Publications and Awards

Below are publications produced from this work and awards given to parts of work.

Journal papers:

- El-Rashidy, R.A. and Grant-Muller, S.M. (2014), "An assessment method for highway network vulnerability", *Journal of Transport Geography*, Vol. 34, pp. 34–43.
- El-Rashidy, R.A. and Grant-Muller, S.M. "An operational indicator for network mobility using fuzzy logic", *Expert Systems with Applications: Transport available online, DOI information: 10.1016/j.eswa.2014.12.018*.
- El-Rashidy, R.A. and Grant-Muller, S.M. "The evaluation of redundancy for road traffic networks", *Transport*, Taylor & Francis, accepted for publication in December 2014.
- El-Rashidy, R.A. and Grant-Muller, S.M. "A composite resilience index for road transport networks", *Transportmetrica A – Special issue on Resilience in Transportation Networks*, submitted in September 2014.

Conference papers and posters

- El Rashidy, R.A. and Grant-Muller, S.M. (2014), "A network mobility indicator using a fuzzy logic approach", *the 93rd Annual Meeting of the Transportation Research Board (TRB)*, Washington D.C, USA, January 12-16, 2014.
- El Rashidy, R.A. and Grant-Muller, S.M. (2014) "A network mobility indicator using a fuzzy logic approach", Poster presentation at *the 93rd Annual Meeting of the Transportation Research Board (TRB)*, Washington D.C, USA, January 12-16, 2014.
- EL Rashidy, R.A., 2012, " Resilience evaluation of transport networks under disruption" Poster presentation at *Mobilities, Infrastructures and Resilience Research day*, Institute of Transport Studies, Leeds University, 10 December 2012.

- EL Rashidy, R.A., 2012, " Resilience Assignment Framework using System Dynamics and Fuzzy Logic: an illustration using motorway traffic data", Poster presentation at *the Faculty of Environment Conference 2012*, University of Leeds.
- EL Rashidy, R.A. (2012), "Resilience Assignment Framework using System Dynamics and Fuzzy Logic: an illustration using motorway traffic data", Poster presentation at *TRA 2012*, Athens, April 23-26, 2012.
- EL Rashidy, R.A. and Grant-Muller, S.M. (2012), "A Resilience Assignment Framework using System Dynamics and Fuzzy Logic", *the 44th Universities' Transport Study Group Conference (UTSG)*, Aberdeen, January 4 - 6, 2012.

Awards

- Rawia El Rashidy featured in the University's celebration of International Women's Day 2014, including a profile on the website celebrating the University's women of achievement.
- The author has been selected as a celebrant in the University of Leeds 2013 Women of Achievement awards. The awards recognise women who have achieved an external prize or award in their field for outstanding research, teaching, scholarship or technical work.
- Rawia El-Rashidy was awarded a gold medal in the 'Year 2012' European young researchers' competition, at the Transport Research Arena (TRA) conference in Athens. The competition, supported by the European Union, profiles promising young researchers specialising in surface transport.
- Institute for Transport Studies Researcher of the Year (2012).
- Award for the best poster presentation, Research Day on Mobilities, Infrastructures and Resilience, University of Leeds, Dec. 2012.

Chapter 1: Introduction

1.1 Background

The transport sector plays a leading role in enhancing economic growth and societal welfare in addition to its influence on various types of human activities. However, its environmental impact cannot be ignored, as it is a major contributor to greenhouse gas emissions. The Department of Energy and Climate Change (DECC, 2010) reported that road transport accounted for 26% of total UK carbon dioxide emissions. Consequently, there is a need to increase the efficiency of the transport system to enlarge the positive economic impact and decrease the negative environmental impact.

Moreover, recent years showed that efficiency of transport systems can be adversely affected by climate change related problems, such as floods and heavy snowfall in addition to different type of disruptive event as it will be explained in Section 3.2. For example, the estimated road traffic costs for the 2007 summer floods in the UK was around £191 million as reported by the Environment Agency (2010). Half of these costs were due to traffic delays because of road closures and the other half were used on repairing damage.

This mechanism between transport and climate change creates two types of impact; the influence of the transport sector on climate change and the impact of climate change extremes on transport. Literature shows the availability of many investigations including academic (e.g. Chapman, 2007; Meyer et al., 2007) and governmental (DfT, 2009) that quantify the role of transport in climate change. These investigations have led to the creation of sustainability and low carbon future (LCF) initiatives to avoid the adverse effects of transport without restricting its pilot role in development. Recent approaches to dealing with transport challenges have been innovative. For example, a number of potential trials have been introduced to decarbonise the transport sector such as electric vehicles. Conversely, the effect of climate change extremes on transport has not received similar attention (HM Government, 2011; Koetse and Rietveld, 2009; Shon, 2006). Sohn (2006) also called for the development of

various assessment frameworks that are able to quantify the impact of different climate change related events on transport systems. In line with this, the current research is intended to contribute to a better understanding of the performance of road transport networks under disruptive events. In particular, the current thesis examines the resiliency of road transport networks in order to improve its functionality under disruptive events. This aim is achieved by investigating the resilience characteristics that most influence the functionality of road transport networks under different disruptive events. Moreover, the role of intelligent transport systems (ITS) in enhancing transport networks performance under climate change extremes is also explored.

1.2 Climate Change Extremes

Climate change related challenges are unavoidable events in short term. Therefore, resilient transport networks are essential to mitigate the adverse impacts of such events. The effects of climate change related challenges on transport systems could arise from the increasing frequency of extreme events, such as heavy snowfall and floods, for example, Defra report (2012) highlighted that road transport networks and railways in the UK at a significant risk of flooding. The need to alleviate climate change impacts on road transport networks performance has been highlighted by various researchers (Koetse and Rietveld, 2009; Pisano and Goodwin, 2004). Weather conditions have a great impact on both supply and demand sides of road transport networks. The impact on the supply side can be represented by a deterioration in the road surface and the functionality of some links or the availability of certain modes (DfT, 2014). Whereas, the effect on the demand side could be shown by the variation in traffic flow patterns, mode choice and average speed. For example, the welfare cost of domestic transport disruption from severe winter weather is around £280 million per day in England alone (DfT, 2011). An integration between adaptation and mitigation policies is needed to decrease the adverse effects of current extreme events and their future likelihood, as highlighted in the recent HM Government report (2011). Figure 1.1 explains the integration mechanism between adaptation and mitigation policies. The real impacts of LCF strategies, which are applied now, will be harvested within 50 years owing to the long life of greenhouse gases in the

atmosphere in addition to the complexity of the chemical processes in the atmosphere. Therefore, adaptation strategies are necessary to decrease the adverse impacts of climate change related challenges.

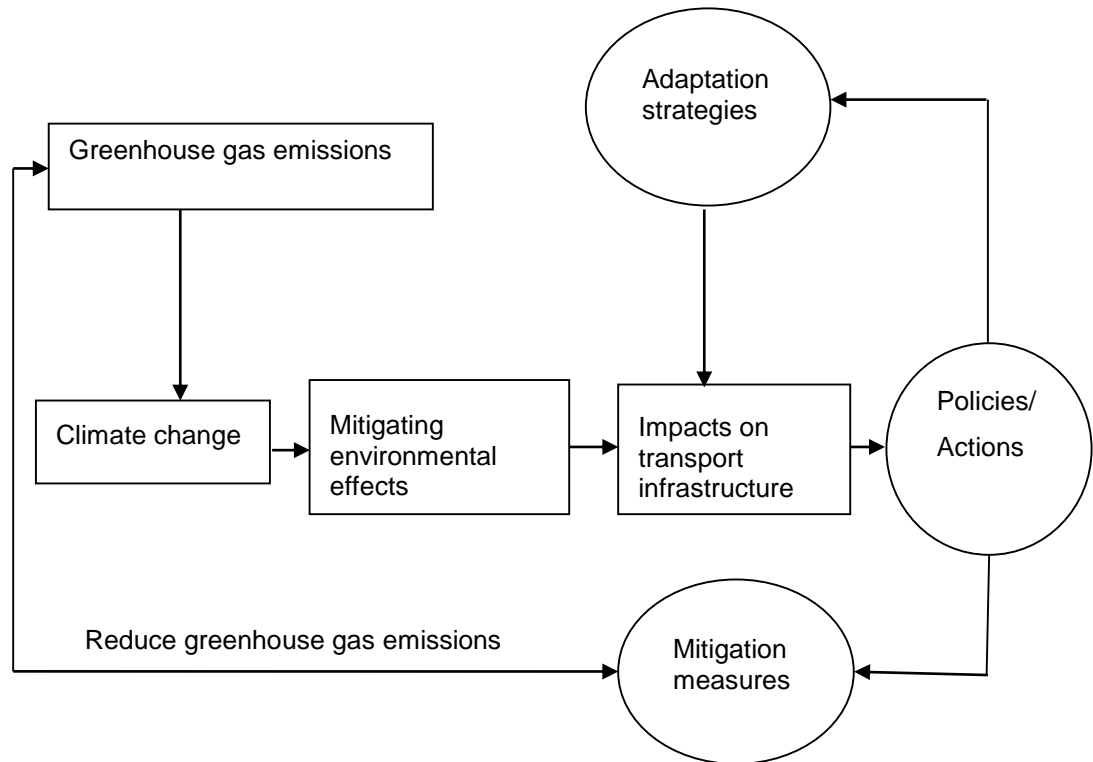


Figure 1.1 Role of mitigation measures and adaptation strategies in tackling climate change impacts (Source: National Academy of Science, USA, 2008).

1.3 Research Significance

The increasing number of climate change extremes worldwide and the UK has drawn the attention to the impact of such events on road transport networks. These impacts depend on the severity of the event and the ability of road transport networks to mitigate, respond and recover. Recently, this multilevel ability has been introduced as the resilience concept. Although NATA (DfT, 2009) introduced resilience as a measure of the climate change impacts on transport, there is no guidance provided on how resilience can be evaluated. The problem is driven by a lack of agreement on resilience measures (Cimellaro et al., 2010; Mansouri et al., 2010; Madni and Jackson, 2009; Murray-Tuite, 2006).

An assessment of the resilience of a road transport network could cover several issues, some related to the configuration of the road transport network and available capacity. This may include the number of routes between origin-destination pairs and the road capacity under different scenarios. Other issues are related to the impact of demand variations on the functionality of the road transport network. The availability of an assessment of resilience could increase understanding of how management policies and/or technologies can improve the overall performance of the road network under disruptive events, or improve daily operation of the network. It could be used, for example, to assess the effect of pre-trip travel information or en-route travel information on driver decisions during disruptive events.

The research presented here could have three different levels of impact, namely academic, strategic and operational levels as shown in Figure 1.2. From an academic point of view, this research has four main areas of importance:

- introducing a holistic approach for exploring the performance of road transport networks under disruptive events;
- proposing of resilience characteristics that helps in outlining the impact of different types of disruptive events at different levels;
- developing a resilience index to aggregate the influence of resilience characteristics to gauge of the overall resiliency level of road transport networks;
- exploring the role of ITS on enhancing the resilience of road transport networks.

At a strategic level, the main outcome of this research will be a development of a new evaluation and decision support tool for decision makers. Resilience characteristics indicators and the composite resilience index will allow decision-makers to evaluate the effect of a proposed transport scheme (new technology or policy) on road transport networks performance under several conditions. Furthermore, developing a technique to measure the resilience of road transport network could have a significant impact at the operational level.

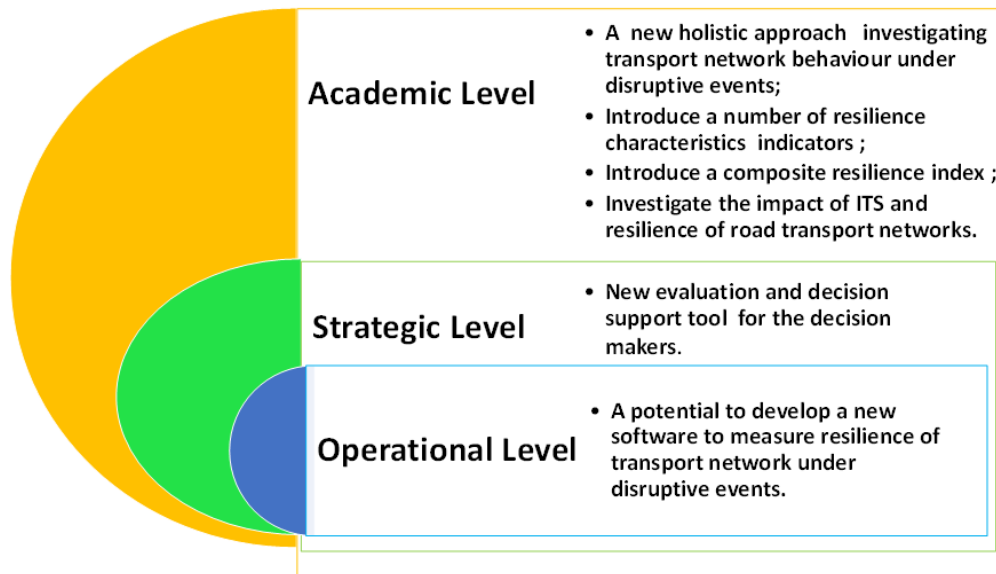


Figure 1.2 Research project impacts (Source: the author).

1.4 Aims and Objectives of the Research

The principal aim of the current research is to quantify the resilience of road transport networks under disruptive events. It will be achieved through identification of the main characteristics of the road transport network resilience and then proposing an indicator to gauge each characteristic. A composite resilience index will be also developed. The main objectives of the research project can be summarized as follows:

1. To carry out a critical review of the resilience concept and its measurement in a transport context and, hence, recognise the resilience dimensions and characteristics of road transport networks in an operational way;
2. To propose a number of resilience characteristics to outline the main elements that influence the resiliency level of road transport networks under different types of disruptive events;
3. To develop a redundancy indicator that is able to account for the topological characteristics of road transport networks and the dynamic nature of traffic flow, whilst maintaining the advantages of easy implementation;
4. To propose a methodology to assess the level of vulnerability of road transport networks;

5. To introduce a road transport network mobility indicator accounting for both the network configuration and traffic flow conditions, to allow for the inclusion of different types of disruptive events and their impacts on network mobility;
6. To develop a composite resilience index that is able to aggregate the influence of the three characteristics;
7. To investigate the role of available ITS technologies (such as real-time travel information) in enhancing the resilience of road transport networks under different types of disruptive event.

1.5 Research Questions

In line with the research objectives, the research questions, which the current research will address, are as follows:

Question 1: What does the resilience concept mean in the transport context?

The first research question aims to understand the resilience concept and outlines its definition in a transport context. It also attempts to explore its interrelated relationships with other commonly used concepts such as sustainability and risk management. Identification of resilience dimensions is very essential as a way to outline the main potential factors and measure for the progress towards resilient road transport networks. A good understanding of the resilience concept would help in developing a conceptual framework for resilience as a tool to achieve resilient road transport networks.

Question 2: What are the main characteristics and their indicators of the road transport network resilience?

Identifying the main characteristics of the resilience will help in converting the concept into measurable indicators. Each characteristic indicator can be used as a tool to assess the effectiveness of different management policies or technologies to improve the overall road transport networks performance or for the daily operation of road transport networks. Furthermore, it can also identify the main barriers to achieve a highly resilient road transport network.

Question 3: Could it be possible to develop a single resilience index?

The development of a resilience index could be used to measure the resilience of road transport networks under different scenarios. It can also be used to assess the effectiveness of different management policies or technologies to improve the overall network resilience in a similar way to each characteristic indicator.

Question 4: Could ITS improve the resilience of road transport networks?

The availability of a wide spectrum of ITS suggests that it could be used to improve the resiliency of road transport networks. A synthetic Delft city road transport network is used to investigate the impact of real-time travel information, as an example of ITS, on the developed resilience characteristics and composite resilience index.

1.6 Proposed Research Methodology

Figure 1.3 highlights the main elements implemented to define and quantify the resilience of road transport networks in addition to the case studies. The resilience dimensions and characteristics will be identified by conducting a comprehensive literature review as presented in Chapters 2 and 3, fulfilling the first and second research objectives. To quantify the resilience, a number of resilience characteristics indicators are developed using different approaches, i.e. the entropy concept for redundancy indicator (Chapter 5), the fuzzy logic approach and exhaustive optimisation search for vulnerability indicator (Chapter 6) and a fuzzy logic approach for mobility indicator (Chapter 7). The evaluation of the three characteristics indicators are mainly achieving the third, fourth and fifth research objectives, respectively. Furthermore, the composite resilience index of the road transport networks based on the three characteristics indicators is calculated using two weighting methods, namely equal weighing and principal component analysis accomplishing the sixth research objective (Chapter 8). Chapter 8 also investigates the role of real-time travel information in enhancing the resilience of road transport networks, fulfilling the seventh objective. The developed characteristics indicators and composite resilience index will be applied to road transport networks to examine their validity and applicability, for example a synthetic Delft City road

transport network, junction 3a on M42 motorway and routes among seven British cities as presented in Figure 1.3.

1.7 Limitations

A number of real life case studies have been used for the validation of the developed characteristic indicators, i.e. the redundancy indicator for Junction 3a on M42 motorway and the mobility indicator for 7 British cities. However, a full traffic data set linked to road transport network conditions and a database of disruptive events along with the available intelligent transport system is not currently available. Consequently, road transport network modelling using available software OmniTRANS has been adopted to generate traffic data under different scenarios. A synthetic Delft city road transport network (available with OmniTRANS software) is used in different scenarios to investigate the impact of demand/ supply variations in addition to the level of real-time travel information. The synthetic Delft city network can be considered as representative of road transport networks as explained in Section 4.5 but it is not possible to make direct validation for obtained links traffic data as the used network is a synthetic network. Furthermore, there is also a limitation of the road transport network modelling approach in general, as only a limited number of attributes/parameters can be changed in the simulation, decreasing potentially a significant number of combinations with the case-based reasoning. Consequently, some relevant combinations could be ignored (Chen and van Zuylen, 2014). However, it is important to understand that the intention of this research is to quantify the resilience of road transport network; therefore, intensive calibration of road transport network modelling is not the focus here.

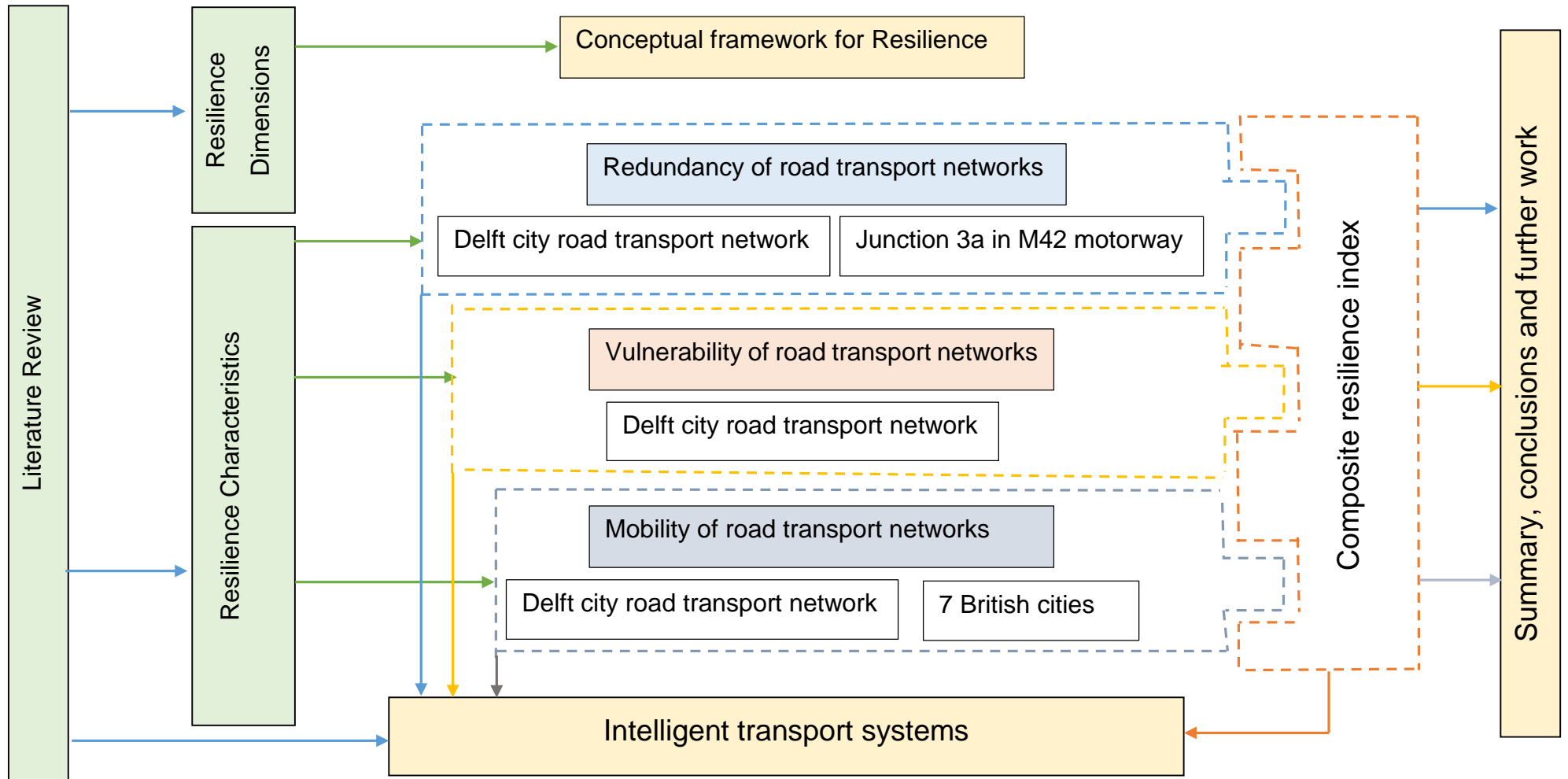


Figure 1.3 Research direction and case studies.

1.8 Thesis Outline

To give an overview of the structure of the remainder of this thesis, a brief description of each chapter is presented below:

- Chapter 2 discusses the definition of resilience from the perspective of various disciplines and in the transport context, in addition to a critical review of existing work in the area of resilience including academic, governmental and operational sources.
- Chapter 3 introduces the conceptual framework for resilience of road transport networks considering physical and organizational dimensions. Furthermore, different disruptive event types have been highlighted along with their significant impacts on the road transport network. Furthermore, the role of road transport network management is briefly investigated to explore its effect through different resilience stages. Finally, three resilience characteristics are proposed.
- Chapter 4 introduces an overview of road transport network modelling along with a description of the case study network. In addition, different traffic assignment methods as well as junction modelling are discussed. The presentation is mainly focused on OmniTRANS software as it has been used as a tool to generate data under different scenarios.
- Chapter 5 examines various system parameters based on different combinations of link flow, relative link spare capacity and relative link speed and then introduces two redundancy indicators using the entropy concept. An aggregated redundancy indicator for the whole network has been also developed. The ability of the proposed redundancy indicators to reflect various levels of network capacity and flow has been tested on the synthetic Delft city network. Moreover, Junction 3a in M42 motorway near Birmingham is also considered as a real live case study to investigate the ability of the proposed indicators to reflect the impact of active traffic management implementation.
- Chapter 6 investigates the vulnerability of road transport networks. It proposes a methodology to assess the level of vulnerability of road transport networks based on fuzzy logic and exhaustive search

optimisation techniques. The network vulnerability indicator is then developed using two different physical and operational aggregations. A synthetic Delft city road transport network is also used in this chapter to test the ability of the technique to show variations in the level of vulnerability under different scenarios.

- Chapter 7 describes a mobility indicator for road transport networks. It presents a new methodology to assess the mobility of road transport networks from a network perspective. The mobility indicator developed is based on two mobility attributes, namely physical connectivity and road transport network level of service attributes. The chapter also introduces a flexible technique based on a fuzzy logic approach to estimate a mobility indicator from the two attributes. Two case studies were considered to validate the technique: the first case based on real traffic data between seven British cities and the synthetic Delft city road transport network to show the ability of the technique to estimate variation in the level of mobility under different scenarios.
- Chapter 8 discusses the interdependence relationships among the proposed resilience characteristics and how each characteristic could be implemented to gauge a certain ability of road transport networks. Moreover, the chapter also presents the composite resilience index as a way to obtain the aggregated influence of the proposed characteristics. The chapter proposes two methods to weight each resilience characteristics: equal weighting and principal component analysis. Furthermore, the impact of real-time travel information is explored on the resilience characteristics indicators and the composite resilience index under different road transport network conditions.
- Chapter 9 summarizes the research project and draws together some of the findings and issues discussed earlier. It also provides suggestions for future research.

Chapter 2: Literature Review

2.1 Introduction

This chapter discusses the definition of resilience from various disciplines' point of view and in the transport context. A condensed review is conducted to cover different disciplines' views on resilience, aiming to recognise the common dimensions of resilience and hence focusing on resilience in the transport sector. It also includes the characteristics of resilience as described in the literature. Current measures of resilience are also critically reviewed.

2.2 Resilience Definitions

According to Gibbs (2009), the first step towards achieving resilience is agreeing on a definition and performance measures of resilience of a certain system. Furthermore, Rogers et al. (2012) suggested that a clear resilience definition could facilitate a broader and more holistic understanding and, consequently, critical element infrastructure can be identified and improved. The word resilience is derived from the Latin word "resillo" which means, "to jump back" (Cimellaro et al., 2010). There are vast numbers of resilience definitions in the context of different disciplines such as ecosystems (e.g. Holling, 1973; Carpenter et al., 2001; Folke, 2006), industry (e.g. Hollnagel et al., 2006), economics (e.g. Rose, 2009), freight transport systems (e.g. Ta et al., 2008) and transport (e.g. Murray-Tuite, 2006; Ip and Wang, 2009; Henry and Ramirez-Marquez, 2012a and 2012b) available in the literature.

The first appearance of the resilience concept was by an ecology researcher called Holling in his seminal work in 1973. He defined resilience as a "measure of perseverance of systems and their capability to absorb changes and disturbances, and still sustain the same relationships between populations or state variables". Following this, a number of researchers (Holling, 2001; Carpenter et al., 2001; Walker et al., 2004) within the ecological science, including Holling himself, redefined resilience in the light of the severity of

events and system capacity. They (Carpenter et al., 2001) defined it as “the amount of interruption that can be mitigated before the need to restructure the system or the ability of the system to deal with unexpected events without losing its characteristics”. However, both definitions might be combined to fully represent the resilience concept of the system. For example, the ability of the system to absorb changes is highly affected by the amount and types of consequences arising from the disruptive event.

In addition to the metaphoric meaning of resilience, Carpenter et al. (2001) introduced two dimensions to the definition, firstly as a characteristic of the dynamic system and as a quantifiable measurement that can be gauged performance. They also highlighted the importance of system configurations and the nature of the event, as the system could be resilient under a certain event and not resilient under another one.

In 2006 from an industrial safety point of view, resilience engineering was introduced by Hollnagel et al. (2006). They defined resilience as “the property of the system which gives the ability to recoup with system complication and sustaining its functionality under expected or unexpected event”. Furthermore, Hollnagel, et al. (2006) argued that this ability should be judged against its time scale for recovery to measure the system’s elements efficiency to spring back quickly after being distributed. In contrast, Park et al. (2013) defines resilience as “an emergent property of what an engineering system does, rather than a static property the system has”.

Peeta et al. (2010), in line with Heaslip et al. (2010), defined resilience in relation to a time dimension as the system could have multi-phases: pre-event, during the event and recovery phase. Every phase represents part of the system resilience. This multi-stage process implies that resilience is a “multi-faceted capability” of a system, including avoiding, absorbing, adjusting and recuperating from disturbance (Madni and Jackson, 2009). Any stage could be tackled in different ways as shown in Figure 2.1. For example, for manmade events such as accidents, the resilience of the network should be carefully improved at the initial network design stage in addition to imposing a set of policies and new technologies in avoidance and mitigation stages, then

in responding and recovery stages. Whereas in natural events such as floods and snow, the responding and recovery stages are the crucial stages.

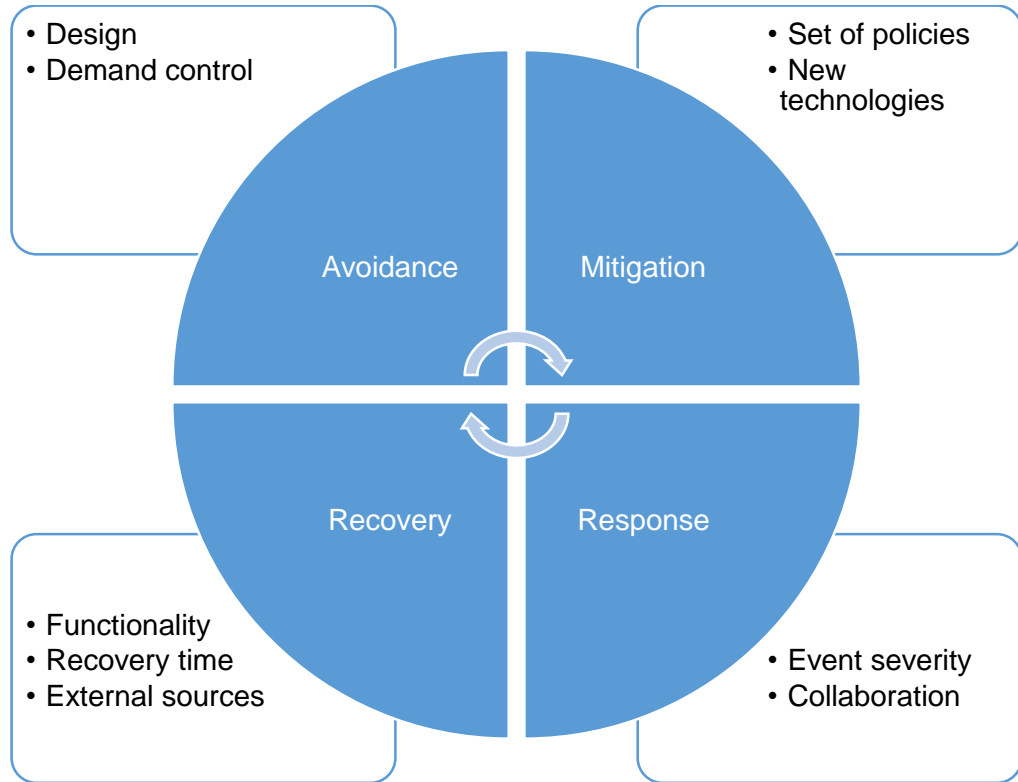


Figure 2.1 Resilience four stages and proposed enhancing procedures (Source: the author).

DfT (2014) defined the transport network resilience as “the ability of the transport network to withstand the impacts of extreme weather, to operate in the face of such weather and to recover promptly from its effects”. Furthermore, Murray-Tuite (2006) suggested that the resilience of a road transport network is a property that indicates the efficiency of the network function under disruptive event, recovery speed (time) and the quantity of external support to retain its original performance. However, as recognized from the previous section, the resilience of a certain system would be highly dependent on both system properties and the nature of the event. Hence, it may be difficult to define the resilience of the transport sector as a whole. However, there are several researchers who have tried to define the resilience of certain parts of the transport infrastructure such as resilience of maritime infrastructure systems (e.g. Mansouri et al., 2010), or a certain mode of

transport such as aviation (Chialastri and Pozzi, 2008; Gomesa et al., 2009). Otherwise, resilience could be related to the disruptive event such as the resilience of public transport networks against attacks (Berche et al., 2009).

2.3 Resilience Dimensions

Bruneau et al. (2003) suggested four resilience dimensions, namely physical, organisational, social and economic. In the transport context, these four dimensions could be interrelated to varying degrees. For example, the physical resilience (refer to the ability of physical infrastructure under disruptive events) could be enhanced due to the high organisational resilience (e.g. the ability of the Highways authorities to take the right decisions in the right time). Moreover, the availability of road transport networks could speed and success of the society resilience (McManus et al., 2008; Bruneau et al., 2003).

According to Kahan et al. (2009), resilience could also be classified into two dimensions; “hard” resilience and “soft” resilience. Hard resilience focusses on organizations and infrastructure and considers their structural, technical, mechanical, and cyber systems’ qualities, capabilities, capacities, and functions. Moreover, the capability and behaviour of individuals, community and society are classified as soft resilience (Kahan et al., 2009). Furthermore, the review of Ta et al. (2008), in the context of freight transport systems, showed that the resilience concept should capture the interaction among organization management, infrastructure and users.

2.3.1 Organisational resilience

According to Bruneau et al. (2003), “*The organizational dimension of resilience refers to the capacity of organizations that manage critical infrastructures and have the responsibility for carrying out critical disaster-related functions to make decisions and take actions that contribute to achieving the properties of resilience*”. Moreover, McManus (2008) defined organizational resilience as “a function of an organisation’s situation awareness, identification and management of keystone vulnerabilities and adaptive capacity in a complex, dynamic and interconnected environment”. Seville et al. (2008) defined organizational resilience as the ability of the

organization to survive and potentially even thrive under disruptive events, and still be able to achieve its core objectives in the face of adversity. A number of researchers (e.g. Gibbs, 2009; McManus, 2008; Bruneau et al., 2003) highlighted the role of management in achieving a good level of resilience in the face of a disruptive event. The organizational dimension of resilience signifies the capacity of organizations to manage critical infrastructures, to take responsibility for carrying out critical disaster-related functions, to make decisions and take actions (Bruneau et al., 2003).

In the transport context, the management of road transport networks has a significant role under business as usual conditions and in the case of a disruptive event. Rogers et al. (2012) suggested that the managerial aspects are as important as the physical aspects for achieving a resilient infrastructure under different scenarios. Furthermore, DfT (2014) emphasised the importance of effective management to restore a transport system after a disruptive event, in addition to the physical resilience that enables the functionality of transport systems. For example, in case of floods, Highways authorities (the Highways Agency and unitary/county councils) have the principal responsibility for managing highway drainage and roadside ditches under the Highways Act 1980 (Defra, 2011) in addition to the key role of developing, negotiating, implementing and monitoring better incident management procedures (Highways Agency, 2008). According to FHWA (2000), incident management is defined as the organized, planned, and coordinated use of human, institutional, mechanical, and technical resources to reduce the duration and impact of incidents, and improve the safety of motorists, crash victims and incident responders. Consequently, the incident management is considered to be response and recovery phases of resilience (DfT, 2014).

2.3.2 Physical resilience

The physical dimension of resilience, also named technical resilience, is defined as “the ability of physical systems to perform to acceptable/desired levels” under disruptive events (Bruneau et al., 2003). In other words, physical resilience focuses on identifying the characteristics of the system that enable it to withstand under disruptive events. A number of researchers (e.g. Murray-

Tuite, 2006) proposed a number of characteristics that could be used to investigate the ability of road transport networks under disruptive events as discussed in detail in the following section.

2.4 Resilience in the Transport Context

In the absence of well-established resilience metrics and standards in the transport field (Henry and Ramirez-Marquez, 2012; Cimellaro et al., 2010; Mansouri et al., 2010; Madni and Jackson, 2009; Gibbs, 2009; Murray-Tuite, 2006), the literature shows that current measurements of physical resilience depend on individual trials to quantify the theoretical concept. It is also noted that resilience is widely used as an overarching umbrella with many related concepts, such as vulnerability and redundancy. Added to this, road transport networks could be affected in a variety of ways by disruptive events at different scales for different parts of the road transport network.

Several quantification approaches can be identified in the physical resilience literature. The first approach is based on identifying resilience characteristics (Bruneau et al., 2003; Murray-Tuite, 2006). These include redundancy, diversity, resourcefulness, efficiency, autonomous components, robustness, collaboration, adaptability, mobility, safety, vulnerability and the ability to recover quickly. Some of these characteristics are related to network configuration such as redundancy and vulnerability; others could be seen as resilience enablers such as collaboration, while efficiency and safety could be considered as outcomes. The dependence of each of these characteristics on others and the complex relationship among them represent a barrier to designing a complete resilience indicator framework (Murray-Tuite, 2006). However, to the best of the authors' knowledge, to date there is no resilience framework utilizing all the above characteristics.

Some studies have discussed the resilience concept in the light of one particular characteristic. Ip and Wang, (2009) proposed a quantitative resilience estimation approach to examine road transport network resilience using only the redundancy characteristic. The resilience of the network for a city is estimated as the weighted average of all reliable independent paths with all other cities in the network. Applying this model to road transport

network examples showed that distributed centres have better resilience than centralised ones. Although, this technique showed some simplicity, it ignores many other important issues such as demand variations and road transport network conditions. Mansouri et al. (2010) developed a risk management-based decision analysis framework for port infrastructure system. However, this study only used the vulnerability of the system and its ability to recovery within an acceptable duration as an indicator of its resilience.

Other researchers have used more than one resilience characteristic. For example, Bruneau et al. (2003) proposed robustness, redundancy, resourcefulness and rapidity (known as “4R” approach) to measure resilience. Murray-Tuite (2006) investigated the effect of four separate characteristics of traffic assignment methodologies, namely adaptability, safety, mobility and recovery, although these were not combined in a resilience framework. Hyder (2010) developed a link vulnerability indicator based on a combination of the above characteristics to identify those road transport links that are least resilient. The characteristics were measured using a number of performance indicators, weighted to reflect the importance of the road link in the network hierarchy. However, some of the characteristics used in Hyder (2010) were not related to the resilience concept, such as environmental efficiency.

The use of a number of performance indicators is another approach that has researched (e.g. Heaslip et al., 2010; Dalziell and McManus, 2004) to quantify the resilience of road transport networks. Dalziell and McManus (2004) suggested using key performance indicators (KPI), derived based on the purpose of the system, to evaluate the vulnerability, adaptive capacity and resilience of the system, in line with the main theme of Bruneau et al (2003). Dalziell and McManus (2004) proposed that the KPI could be considered as a function of the system vulnerability, whereas, the time it takes for the system to recover is a function of the adaptive capacity of the system as visualized in Figure 2.2. Dalziell and McManus (2004) also suggested that the overall resilience of the system could be a function of the area under the curve, which is the total impact on KPIs over the response and recovery period, as shown in Figure 2.2. They (Dalziell and McManus, 2004) did not introduce a case study to show the applicability of their approach, however, it introduced a useful discussion about the resilience, vulnerability and adaptive capacity.

Applying this concept to different physical systems (e.g. water and transport systems) presents considerable conceptual and measurement challenges, as pointed out by Bruneau et al. (2003).

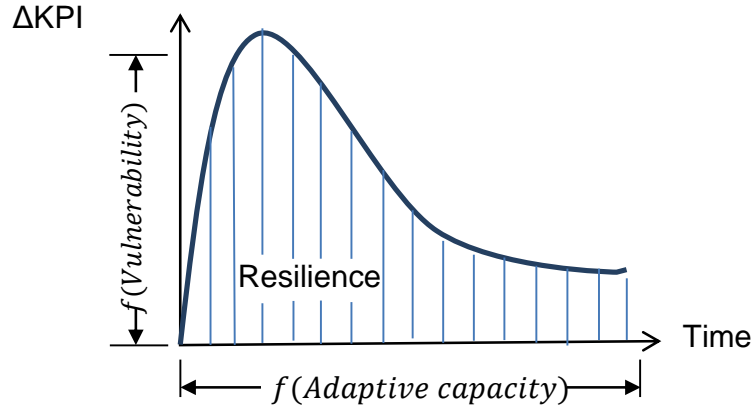


Figure 2.2 Resilience, vulnerability and adaptive capacity of a system (Source: Dalziell and McManus, 2004).

Using a similar approach, Zhang et al. (2009) used the variation of a performance indicator (PI), defined as the ratio of travel speed to the free flow speed (weighted by truck miles travelled) to give a measure of resilience (MOR) as presented below:

$$MOR = \frac{(PI_{before} - PI_{after})(1+t^\alpha)}{PI_{before}} \% \quad (2.1)$$

where t is the total time required to restore the system capacity, and α is a system parameter related to the network size, socioeconomic status, government policy, etc. The study used a value of α equal to 0.5 and did not specify a specific range of α ; however, they referred to the importance of calibrating the system to obtain a more accurate value of α . The lower value of MOR indicates a high level of system resilience under the disruptive event. The technique even allows testing of the effectiveness of different strategies during various scenarios, however including the restoring time in the MOR calculation simply means it is only possible to estimate the MOR after full system restoration. In a real life situation, it could be challenging to identify when a road transport network has fully recovered from a disruptive event,

especially in case of infrastructure damage. However, based on the dynamic nature of resilience, their formulation could be enhanced by calculating *MOR* at different time (t_i) intervals as showed below:

$$MOR_{t_i} = \frac{(PI_{before} - PI_{t_i})(1 + t_i^\alpha)}{PI_{before}} \% \quad (2.2)$$

Consequently, it is possible to compare the effectiveness of a particular strategy based on their impact on recovery time and the improvement of road transport functionality.

Heaslip et al. (2010) used a fuzzy logic approach to develop a sketch level method using a number of performance indicators that were evaluated based on expert advice. The main advantages of this technique are its simplicity and the ability to express a number of attributes in a linguistic way rather than numerical values.

With the purpose of increasing willingness to operationalize the resilience of the road transport network, several researchers started to define resilience as a function of a certain feature related to either the system or event. For example, Li and Murray-Tuite (2008) introduced a measure of resilience given by the ratio of the variation in performance measures before and after applying a certain strategy. They evaluated the effectiveness of the strategies (such as diverting traffic via variable message signs) on congestion using average travel speed, OD travel time, vehicle travel time and maximum queue length as performance measures. However, only considering traffic performance measures may not be enough to fully capture all network characteristics. As a result, there are potential advantages in integrating network structure measures with traffic performance measures. The main advantage of this approach is its ability to give a quick evaluation of the effectiveness of a certain strategy; however, it does not show the impact of the network characteristics. Barker et al. (2013) calculated system resilience as a time-dependent ratio of system recovery over loss. They used a system service function (for example traffic flow) to describe the performance of the network at any time, i.e. before, during and after an external disruptive event. However, they used only one distinctive characteristic of resilience at each stage.

Cox et al. (2011) studied the resilience of the London transport system during and after the 7/7¹ terrorist attack. They considered the reduction in passenger journeys recorded for each of the targeted modes as an indicator of the direct impact of disruptive events. This led to the use of transport mode shifts as a measure of resilience. However, Cox et al. (2011) also referred to the importance of other contributors such as vulnerability and flexibility. The main drawback of the approach by Cox et al. (2011) is in using what could be called “lagging indicators”, as the impact of disruptive events is evaluated based on measures produced after the event.

2.5 Resilience in Governmental and Operational Levels

Following to USA 9/11, London 7/7 and other such terrorist events, a vast number of governmental reports (e.g. DfT, 2014; Cabinet Office, 2011; Hughes and Healy, 2014) reflect the growing interest in the subject of resilience aiming to integrate resilience into a comprehensive risk-management strategy. The UK Cabinet Office (Cabinet Office, 2011) outlined four essential characteristics for resilience, namely resistance reliability, redundancy, and response and recovery, as depicted in Figure 2.3. However, Sircar et al. (2013) considered 7/7 London terrorist attack and 2007 floods in the UK as evidence of inadequacies of the UK Government approach of ‘governing through resilience’ in practice. Sircar et al. (2013) related this to the lack of co-ordination among low-level stakeholder, lack of understanding of critical infrastructure interdependencies and insufficient attention to long-term adaptation. These findings emphasise the importance of considering the organizational resilience (presented in Section 2.3.1) and its attributes (see Section 3.3.1).

¹ Four suicide bombers struck in central London on Thursday 7 July 2005, which targeted the transport system around 08:50 BST (BBC, 2005).

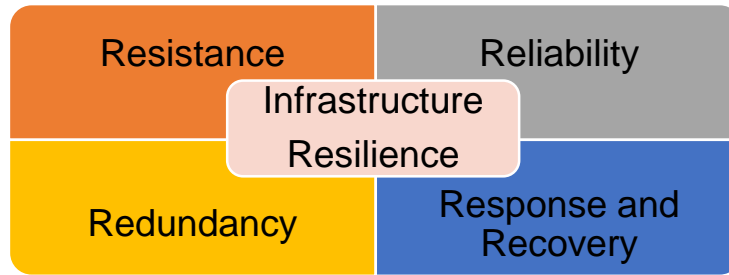


Figure 2.3 Characteristics of infrastructure resilience (Source: Cabinet office, 2011).

A recent investigation (Hughes and Healy, 2014) emphasized the importance of integrated physical and organizational dimensions to evaluate the resilience of transport systems. The report also suggested a number of characteristics under each dimension, e.g. robustness, redundancy and safe to fail for physical resilience and change readiness, leadership and culture, and network to measure organizational resilience.

In the operational level, there are many reports that proposed of a number of indicators to quantify the resilience concept. For example, a study by Hyder (2010) commissioned by Highway Agency used the resilience characteristics defined by Murray-Tuite (2006) to quantify the resilience concept. The report used a number of topological and performance indicators for each characteristics. For example, the redundancy value of a link is estimated as the total number of motorways, A roads, and B roads within a 10 kilometre radius of the link whereas the mobility level is evaluated by maximum volume/capacity, maximum intersection delay and minimum speed (Hyder, 2010).

2.6 General Features of Resilience Indicators

This section briefly reviews the general properties of resilience indicators. Indicators could be generally defined as a measure that quantifies the change in the system elements. In addition, they are used to quantify changes in (and effectiveness of) the system elements. The importance of the indicators in transport context has been discussed within several research projects, e.g. (Litman, 2007; Gudmundsson, 2001). The main common conclusion for most

of these studies is that indicators should have the ability to monitor the milestones towards certain objectives and reflect the impact of a certain policy or technology on the targeted system. Litman (2007) highlighted the role of indicators through planning and management processes. For example, indicators have an effective role in identifying baselines and trends, e.g. the average vehicle speed over a certain period could be used to recognize a congestion period. Decrease in delay per person, or vehicle, within a certain road transport network could be an indicator to measure the impact of a certain scheme such as park and ride or road tolling schemes.

The choice and use of indicators is not a simple process as it needs a good understanding to what is going to be measured, how it can be measured and the assumptions that have been used in monitoring and calculation (Litman, 2007). For instance, the real impacts of LCF strategies, which are applied now, will flourish within 50 years due to the long CO₂ lifecycle in the atmosphere and complexity of the chemical processes in the atmosphere. Hence, a short-term performance indicator, e.g. CO₂ concentration, is not the right measure to evaluate such strategies. In such cases, the intermediate impact could be used as an indicator to assure the effectiveness of the implemented policies or technologies that lead to the main goal. Another challenge in indicator choice is that it should cover all aspects of the concept. Therefore, one single indicator is not adequate to measure system performance (Litman, 2007). Consequently, the definition of all aspects related to a certain concept is an essential stage in the indicator choice stage. For example, the sustainability of a system should not be only measured by an environmental indicator, but social and economic indicators should be also taking into account (Litman, 2007).

In general, the criteria for transport indicators developed by several researchers (e.g. Litman, 2007) could also apply to that of the resilience indicators, for example:

- **Comprehensive:** indicators should reflect the effect of different supply and demand impacts and be clearly defined.
- **Applicable to a real life scale network:** indicators should be developed based on available / measurable data to enable real life applications.

- Intelligibility, easiness to comprehend: indicators are expected to be understood by policy makers, transport professionals, and stakeholders.
- Relevancy: indicators should reflect the change in the process under different conditions.
- Timely: indicators should be able to reflect the dynamic nature of resilience.
- Normalization: indicators should be normalized to allow a standard method of comparison between different characteristics.

To achieve these criteria, a comprehensive literature review has been carried out covering both academic and operational research to find out the appropriate indicators to model resilience characteristics. It had been noted that no single indicator is able to capture all issues related with each resilience characteristic due to the diversity of both impacts and the factors that influence each characteristic. Therefore, a number of methodologies are used to combine more than one attribute into one indicator. Another advantage of using more than one indicator to represent each characteristic is in drawing the attention of policy and decision-makers to specific weaknesses or the potential of a certain policy or technology. However, the main aim is to produce a resilience index of various characteristic indicators that help in drawing an overall picture of road transport network resilience.

2.7 Resilience and Sustainable Transport Systems

The feedback mechanism between economic growth and climate change challenges has led to the creation of a sustainability concept, to identify the equilibrium stage between the growth in demand and resource limitations without affecting future needs. In the context of transport, the characteristics of sustainable transport system have been investigated in many research studies (Boriboonsomsin and Barth, 2009; Richardson, 2005; Richardson, 1999) and outlined in governmental policies (DfT, 2009). Richardson (1999) defined a sustainable transport system as:

“One in which fuel consumption, vehicle emissions, safety, congestion, and social and economic access are of such levels that they can be

sustained into the indefinite future without causing great or irreparable harm to future generations of people throughout the world”.

Fiksel (2006) suggested that the sustainable development in a dynamic environment needs resilience at many levels, including human, technical and management factors. A study by Hyder (2010) commissioned by the Highway Agency showed that the resilience characteristics defined by Murray-Tuite (2006) could maintain one or more goals of “Delivering a Sustainable Transport System” (DaSTS). Table 2.1 links the resilience characteristics with DaSTS goals where every characteristic has the ability to support, or an indirect effect on one or two of DaSTS goals. For example, mobility, defined as the ability of people or goods to move from origin to destination by using an acceptable level of service, has a direct impact on economic competitiveness and growth, and an indirect positive impact on safety and security, equal opportunities, the natural environment and health.

In contrast, Benson and Craig (2014) suggested that resilience concept should be a good replacement to move past the sustainability concept. Benson and Craig (2014) related their point of view to an increasing likelihood of rapid, nonlinear, social and ecological regime changes, which could be treated better with the resilience as it is aiming to coping with variations instead of efforts to sustain the current state.

Table 2.1 Role of resilience measures in supporting achievement of DaSTS goals (Source: Hyder, 2010).

Resilience Measures	Support Economic Competitiveness and Growth	Tackle Climate Change	Improve Quality of Life & Natural Environment & Health	Better Safety, Security	Promote Equality of Opportunities
Redundancy	■				
Diversity	■	■	■		
Environmental efficiency		■	■	■	
Autonomy	■				
Strength	■			■	
Adaptability		■	■		
Collaboration	■		■	■	■
Mobility	■		■	■	■
Safety			■	■	
Recovery	■			■	

Key: ■ Indicates primary impact ■ Indicates secondary impact □ Indicates no impact

2.8 Resilience and Risk Analysis

Risk analysis is the dominate approach to dealing with failure in complex systems. In general, risk analysis has two main components; risk assessment and risk management (Park et al., 2013). Risk assessment includes identification of risk and probabilistic estimate of consequences whereas risk management is the decision-making process. According to Berg (2010), risk management could be implemented to cover both components, risk assessment and risk management, and define as “a systematic approach to setting the best course of action under uncertainty by identifying, assessing, understanding, acting on and communicating risk issues”. Identifying risk and its consequences as the first step in risk analysis could be a challenging process in the context of climate change related events or some manmade events such as terrors attacks or any other emergent disruptive events. For example, prior to 7/7 London attacks it was difficult to carry out a full comprehensive risk analysis for such type of event where there is no information about the location, time or probabilistic estimate of consequences. Consequently, the traditional risk analysis could be inadequate to fully protect road transport network functions and components. According to Park et al. (2013), risk analysis should be combined with resilience analysis to secure a sufficient protection of critical infrastructure systems (e.g. transport networks, water distribution networks) under emergent disruptive events. In line with Park et al. (2013), Stolker (2008) considered the ideal resilience management should include three processes, namely, risk analysis process, the implementation of the risk analysis, and finally testing and maintenance.

2.9 Resilience and Intelligent Transport Systems

According to the Council Directive 2010/40/EU, intelligent transport systems (ITS) are the systems that use information, communication and electronics technologies within transport sector covering static elements such as infrastructure, and dynamic elements such as vehicles and users, in addition to traffic management. This section presents a brief overview of current ITS technologies and also investigates the impact of ITS on the transport system.

2.9.1 ITS Classification

The use of ITS in transport systems could be classified into two main categories, namely real-time travel information and in-vehicle intelligent transport systems. In general, real-time travel information systems (RTTIS) could include real-time traffic information, for example congested roads and speed limits, real-time weather information obtained from roadside sensors or real-time travel information. RTTIS could have several applications for examples, dynamic route guidance system (DRGS) (Boriboonsomsin and Barth, 2009), advanced traveller information systems (ATIS) (Kumar et al., 2005) and advanced traffic management system (ATMS) (Lee et al., 2009), which not only enhance traffic conditions but also deliver great benefits. It could save travel time and cost by avoiding congested links, support pre-trip and en-route decisions regarding the most suitable time and mode, and give a good indicator of network efficiency to decision makers (Lin and Zito, 2005).

In vehicle intelligent transport systems, also known as advanced driver assistance systems (ADAS), include various technologies mostly used to increase safety of the driver and other road users as well as improve the traffic flow performance and decrease fuel consumption and emissions (Arem et al., 2006). Furthermore, these systems could also have an indirect positive impact on network resilience as they can enhance the “multi-faceted capability” of the transport network. For instance, both intelligent speed adaptation (ISA) and night vision system (NVS) have a potential to decrease the number of crashes (Carsten et al., 2008; Hollnagel and Källhammer, 2002), hence increase the network resilience related to man-made incident in avoidance stage. Furthermore, intelligent control systems such as the lane departure warning system (LDWS) (Alkim et al., 2007) and antilock braking system (ABS) (Yuan et al., 2009) to accommodate hazard conditions such as heavy snow or flooding could support the respond stage capability of network resilience under such events. ADAS could be classified into four categories depending on the feedback techniques (Hoc et al., 2009):

- “Information mode devices” which are continuously update the driver awareness, such as speedometer;

- “Mutual control systems” that warn the driver in hazard condition such as collision warning or influence the vehicle system for example resistance in the accelerator pedal;
- Function handing over systems that are being in use according to driver decision such as adaptive cruise control system;
- Fully automated system where the whole driving process is carried out automatically.

The impact of these technologies on transport systems is briefly discussed below.

2.9.2 Impact of ITS

The ultimate goal of ITS is enhancing the efficiency of transport systems and increase safety in addition to decrease the environmental impact of the road transport network (Grant-Muller and Usher, 2014; Carsten et al., 2008; Fitch et al., 2008; Alkim et al., 2007; Abdel-Aty et al., 2006; Dia and Cottman, 2006; Servin et al., 2006; Levinson, 2003). Furthermore, DfT (2005) identified seven main themes where ITS could play a crucial role:

- improving road network management,
- improving road safety,
- better travel and traveller information,
- better public transport,
- supporting the efficiency of road freight industry,
- reducing negative environmental impacts,
- supporting security, crime reduction and emergency.

However, the literature shows that there is no single answer on the magnitude of positive impact or even the adverse effect of ITS. This could be related to the complexity of transport systems and the weaknesses of traffic simulations in congestion modelling (Arem et al., 2006; Levinson, 2003). Another barrier could be the unavailability of ante-assessment of some ITS projects. However, some real life case studies are carried out to investigate the impact of ITS. For example, the use of four lane variable mandatory speed limits at M42 (explained in Section 5.6) has reduced the congestion, improved the journey time reliability, and increased the capacity of the motorway throughout at M42-ATM section, in addition to reducing emissions and incidents (Sultan et al., 2008a). Moreover, a survey conducted by Grant-Muller and Usher (2014)

concluded that ITS systems can provide the technological means to improve the efficiency of vehicles and transport infrastructure, in addition to support behavioural change. It also showed that ITS can reduce the carbon intensity of negotiating distance, if physical travel is unavoidable. ITS could also be utilised to reduce the impact of hazardous conditions caused by adverse weather events, for example, the road weather controlled variable speed limits scheme, where the legal speed limit is changed according to weather and road surface conditions, have been used in three sites in Sweden. The results showed that the fatal and injury accidents rates were decreased by 20% in one site, whereas no difference before and after the introduction of VSL in the other site. (Gunnar and Lindkvist, 2009). In addition, ITS could facilitate the implementation of specific policy measures. As an example, in a controlled access area, such as London charged zones, closed-circuit television (CCTV) and automatic number plates recognition (ANPR) systems are used to identify the vehicles and electronic toll systems (ETS) are then utilised to facilitate the payment of fees and enforcement charges.

Reducing the travel demand is another area where information and communication technology (ICT) as a fundamental part of ITS could have a potential role. As it is well known “Travel is derived demand” (Ortúzar and Willumsen, 2011) so controlling this demand by introducing alternative ways for communication would have a potential impact on demand side. For instance, work from home based schemes, conference meeting, and flexible work hours could decrease the need to travel consequently, affecting traffic performance by reducing the traffic flow especially during peak periods. For example, DfT (2011) suggested that the resilience of infrastructure could be increased by promoting work from home based scheme. Table 2.2 presents a number of ITS along with it potential impacts on travel mode, route choice, travel time, vehicle emissions fuel consumption and Carbon dioxide (CO₂) emission.

ITS can also enlarge the capability of the road transport network to control and minimise the impact of man related incidents or nature related challenges such as flooding and severe weather conditions. For example, real-time travel information system (RTTIS) has a primary impact on route choice and travel

time as depicted from Table 2.2, which could enhance the resilience of road transport network. Furthermore, the use of ITS during the event such as active traffic management including real-time traffic information, high respond vehicle prioritisation, and protecting and prioritising disaster evacuation routes could lead to reduce the demand (Jarašūnienė, 2006).


2.10 Role of Real-time Travel Information on Road Transport Network Resilience

Real-time travel information systems (RTTIS) are one of the main areas in any effective ITS due to its wide range of applications. The use of real-time travel information could achieve a shorter expected travel time in addition to increase travel time reliability due to its influence on the traveller route choice (Gao, 2012). For example, it could be used by individuals such as a dynamic route guidance system (DRGS) (Boriboonsomsin and Barth, 2009) and advanced traveller information system (ATIS) (Kumar et al., 2005) or a network wide impact such as an advanced traffic management system (ATMS) (Lee et al., 2009). Using RTIS could save travel time and cost by avoiding congested links, support pre-trip and en-route decisions regarding most suitable time and mode, and give a good indicator of network efficiency to decision makers (Lin and Zito, 2005). Furthermore, the redundancy indicator of junction 3a in M42 motorway, a part of the ATM section, has improved after the implementation of the scheme as discussed in Chapter 5.

Table 2.2 Positive impacts of ITS applications on traffic performance, fuel consumption, and emissions.

ITS \ Impact	Travel Mode	Route choice	Travel Time	Safe Road	Vehicle, traffic behaviour	Traffic related Emissions rate reduction	Journey time reliability	Reductions in delay	Fuel consumption	CO ₂ emission
RTTIS										
DRGS		Primary	Primary				Secondary	Secondary	Secondary	Secondary
VSM		Secondary	Secondary	Primary	Secondary		Primary	Secondary	Secondary	Secondary
VSL				Primary		Secondary	Primary			
Demand Management										
Road pricing	Primary	Secondary				Secondary		Secondary		
Access control	Primary	Secondary	Primary			Secondary		Secondary	Secondary	Secondary
Bus Priority	Primary		Primary			Secondary	Primary	Primary		
Traffic management										
Junction control		Secondary		Secondary	Secondary	Secondary	Primary			
Network control		Secondary		Primary	Secondary	Secondary	Primary			
Control of lane use				Primary	Primary	Secondary	Primary			

RTTIS=real time travel information system; DRGS = dynamic route guidance system; VSM = variable sign message; VSL = variable speed limits.

Note:  Indicates primary impact  Indicates secondary impact  Indicates no impact
 (Source: the author based on data from: Fits, 2002; Bruzon and Mudge, 2007; DfT, 2005; Park and Lee, 2010).

2.11 Concluding Remarks

This chapter discussed the definition of resilience from different disciplines context in addition to transport literature to provide a clear understanding of the concept. It has also presented resilience dimensions and characteristics. Based on the review presented in this chapter, it could be concluded that there is no common definition of resilience in the literature; each discipline has focused on resilience from one or more perspective.

Furthermore, the chapter critically reviews the up-to-date approaches that are used to quantify the resilience of a road transport network. It shows that the modelling of road transport network resilience is still at an early stage. Few research projects have attempted to model road transport network resilience. It has also been noted that there is a lack of agreement on the operationalization of the resilience concept due to several issues. Firstly, the variation in resilience definitions that leads to different interpretations of the concept. Secondly, the complex relationships among the resilience characteristics in the literature creates many challenges in resilience modelling, such as the selection of the appropriate set of indicators and the double counting effect due to interdependency amongst characteristics.

The resilience concept is defined as the ability of a road transport network to deal with disruptive events that lead to a reduction of roadway capacity or an unexpected increase in demand, and maintain its functionality. Furthermore, resilience could be operationalized by considering the ability of a road transport network to minimize the consequences of a certain disruptive event. To construct a conceptual framework for resilience, it should be noted that the concept of resilience requires a comprehensive understanding, for example:

- Resilience is a dynamic concept and could oscillate under different supply-demand variations during disruptive events. For example, the resilience level of the road transport network under heavy snowfall during afternoon peak may be less than that during periods of lower demand period.

- Resilience involves complex processes of interrelated disruptive events and internal-external factors at operational, management and strategic levels.
- A full representation of resilience requires the identification of network performance, capacities, and the scale and type of consequences of disruptive events.

Consequently, the assessment of road transport network resilience has to take into account the network dynamic nature, the scale of the event and the recovery time needed to return to its optimum performance. Therefore, it is essential to study the disruptive event types and their impact on road transport networks in addition to the role of network structure under demand variation. Furthermore, the assessment of resilience should also consider the role of road management in response to the disruptive events. Therefore, the three elements namely, the disruptive event, organizational resilience and physical resilience will be used to construct the conceptual framework for resilience in the following chapter.

Although, many ITS have been already implemented for many years, there is a lack of evaluation of their effect on road transport network resilience. Therefore, more independent investigations of each ITS technology are welcomed to give a fair assessment of the technology effectiveness and drawbacks. However, the complexity of the transport system and the weaknesses of available traffic simulation are main challenges for achieving accurate assessment. The latest version of OmniTRANS software (Version 6.1.2) which became available in May 2014 has allowed the simulation of real-time travel information as it will be discussed in Chapter 4 and applied to a case studies in Chapter 8.

Chapter 3: Conceptual Framework for Resilience

3.1 Introduction

This chapter describes a conceptual framework for the road transport network resilience considering two dimensions, namely physical and organizational resilience, in addition to disruptive events. Both dimensions are critical to enhance the resilience of a road transport network whereas the level of resilience could be highly affected by the type and scale of disruptive events. According to Meredith (1993), a conceptual framework can offer the core guidelines for decision makers and managers, and can also be used to illustrate the underlying dynamics of resilience (Burnard & Bhamra, 2011). The proposed conceptual framework for resilience has drawn on several topics across the disciplinary boundaries, such as organizational management (e.g. McManus, 2008), disaster literature (e.g. Bruneau et al., 2003) and transport literature (e.g. Murray-Tuite, 2006). Furthermore, government documents (e.g. Cabinet office, 2011; UK Climate, 2013) in addition to operational reports (e.g. Highways Agency, 2009; FHWA, 2000) have also been considered to reflect the experience of different sectors.

In this Chapter, different types of road network disruptive events are first presented along with their consequences in Section 3.2, whereas Section 3.3 explores the main factors that need to be considered in the evaluation of organizational resilience. In addition, the role of road transport network management is investigated in order to explore its effect on the different stages of resilience. A number of physical resilience characteristics are identified that should be implemented in the evaluation of road transport network resilience in Section 3.4.

3.2 Disruptive Events

The road transport network can be exposed to a wide range of disruptive events that vary in their type, scale and consequences. Disruptive events are responsible for around 25% of the congestion experienced on motorways in England (Highways Agency, 2009) and are the largest single cause of journey unreliability (CEDR, 2009). In the USA, the estimated loss due to disruptive events is 1.3 billion vehicle-hours of delay congestion each year, at a cost of almost US\$10 billion (FEMA, 2008).

At the operational level, an incident normally refers to a disruptive event and is defined as any non-recurring event that causes a reduction in roadway capacity (e.g. vehicle accident and highway maintenance) or an unexpected increase in demand due to an event (Highways Agency, 2009). Emergencies such as inclement weather, natural disasters and terrorism incidents could also be included. Furthermore, disruptive events can be classified as manmade or natural events as explained in the following sections.

3.2.1 Manmade Event

A manmade event could be a small accident leading to one lane of a local road being closed or a major accident causing a motorway closure for several hours, which could have cascading effects on the entire network. For example, a five-vehicle crash on the westbound carriageway of M26 in Kent on 16 of April 2014, involving two cars, two lorries and a van (see Figure 3.1(a)), led to the closure of M26 in both directions for around 6 hours. It was then partially opened (i.e. one lane open on the M26 eastbound) whereas the second eastbound lane and westbound lanes between M20 and M25 remained closed for around 12 hours (BBC, 2014). According to the BBC report (2014), two people died in the crash and another seven people, six most seriously injured, had been admitted to hospitals in London. The accident also led to a hundred vehicles being trapped for several hours (see Figure 3.1(b)). According to Clifford and Theobald (2011), the annual cost to the economy of all deaths and injuries caused by road accidents in the UK is still substantial at around £13 billion, with damage-only accidents costing a further £5 billion. These figures do not include the impact of these accidents on the network performance, e.g. the travel time, distance or speed.



(a) M26 five-vehicle crash

(b) Traffic delay on M26

Figure 3.1 Five-vehicle crash on the westbound carriageway of M26 in Kent.

A terrorism attack, e.g. September 11th and London 7/7, is another form of manmade event that could result in widespread consequences for the road transport network (Cox et al., 2011). Road works are another form of disruptive events. However, their impact on road transport networks could vary based on their location, time and duration. For example, several road works that are carried out in London led to significant congestion and major costs on road users and businesses (Arter and Buchanan, 2010). There are two main challenges in assessing this type of disruptive events, namely, the complexity of the phenomena causing them and the individual conditions relevant to each site (Jyrki, 2000). Furthermore, Rogers et al. (2012) highlighted the impact of deterioration of the road transport network due to different factors, funding constraints and demand increase on the functionality of road transport networks.

3.2.2 Natural Events

Natural events, e.g. floods, inclement weather and heavy snowfall periods, could increase due to climate change, causing significant impacts on the road transport network. The impact of such events on the road transport network infrastructure could be represented by a deterioration of the road surface and the functionality of some links, or the availability of certain modes (Pisano and Goodwin, 2004). For example, at the European level, the financial cost of network interruption from extreme weather is estimated to be in excess of

€15 billion annually (FEHRL, 2013) whereas, in USA the estimated repair costs on its network caused by snow and ice at US\$ 62 million per frosty day (Enei et al., 2011). Figure 3.2 provides estimated costs for each transport sector element under different weather related disruptive events per country between 2000 and 2010. Floods, followed by winter conditions cost the UK more than any other weather related disruptive event, whereas storms have a minor effect and heat has nearly no effect. For example, estimated road traffic costs for the 2007 summer floods in the UK was around £191 million, as reported by the Environment Agency (2010). Half of these costs were due to traffic delay because of closure of roads, whereas the other half spent in repairing damage of road infrastructure. According to DfT (2014), floods on 20 of July 2007 caused 2% of the delays for the whole year. Between the six nations included in Figure 3.2, Denmark is the most affected country as it suffers from all the included events to different degrees.

Furthermore, the disaggregated cost, based on the type of stakeholders affected by the extreme weather events, shows that the most affected part is the infrastructure asset and operation (around 50% of the cost) followed by the user time, 20% of the total cost, due to congestion and time losses as indicated in Figure 3.3. (Enei et al., 2011). The costs of vehicle asset and operation are 12% and 7% of the total cost, respectively, as shown in Figure 3.3.

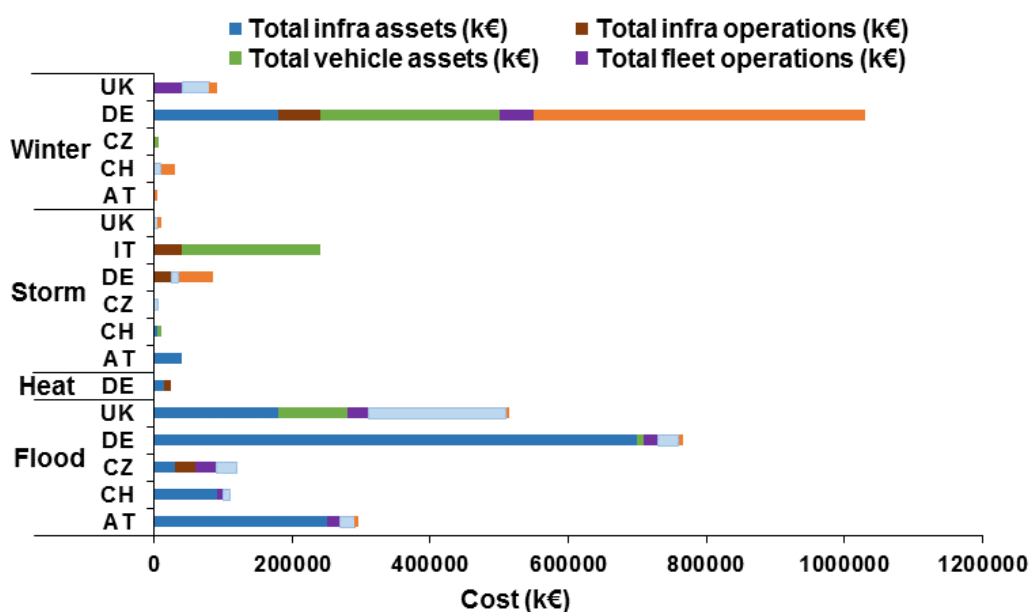


Figure 3.2 Results of the incident cost database (Source: Enei et al., 2011).

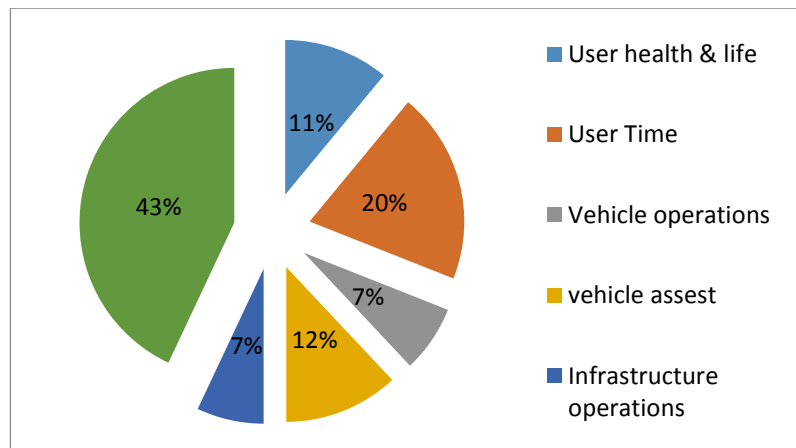


Figure 3.3 Share of extreme weather events costs by stakeholders (Source: Enei et al., 2011).

Moreover, accident rates (accident per vehicle mile) radically rise during inclement weather (Maze et al., 2005; Andreescu and Frost, 1998). A number of investigations (e.g. Knapp et al., 2000; Brown and Baass, 1997) found that accidents during winter storms are less severe compared with those occurring during clear weather conditions. Edwards (1998) concluded that accident severity declines significantly in rain compared with dry weather, whereas severity in fog shows a geographical variation. This is mainly attributed to the decrease in vehicle speeds during adverse weather conditions. Kilpeläinen and Summala (2007) found that drivers followed different compensatory behaviour during adverse weather conditions, including a 6–7 km/h speed decrease. A more detailed study (Morgan and Mannering, 2011) reported that gender and age were among other factors that could have an effect on the accident severity under adverse weather conditions. For example, females and older males have a higher probability of severe injuries when accidents occur on wet or snow/ice surfaces than male drivers under 45 years of age. The probability of severe injuries increases for male drivers under 45 years on dry-surfaces relative to wet and snow/ice road surfaces. The study (Morgan and Mannering, 2011) concluded that drivers perceive and respond to road surface conditions in many different ways. Recent studies (Hooper et al., 2014; Tsapakis et al., 2013) found that the impact of rain and snow on travel speed and time is a function of their

intensity. For example, the increase in the total travel time due to light, moderate and heavy rain is: 0.1–2.1%, 1.5–3.8%, and 4.0–6.0%, respectively (Tsapakis et al., 2013). Furthermore, light snow and heavy snow lead to an increase in travel time of 5.5–7.6%, and 7.4%-11.4%, respectively. Added to this, weather conditions could also affect the demand side, e.g. the variation in movement patterns in the case of a flood because of the evacuation of affected areas (Nicholson and Du, 1997) or a change in mode choice (Maze et al., 2005). For example, the effect of floods on road transport networks could vary hugely from minor effects to a flood-damaged road transport network depending on the flood severity and vulnerability of road transport networks. Suarez et al. (2005) summarized flood effects on road transport networks as follows:

- trip cancellation due to the origin or destination being affected;
- trip cancellation due to the unavailability of links;
- longer travel times due to the use of longer, unaffected, links or because of congestion on the links that are used due to the diversion of traffic.

Table 3.1 summarizes the impacts of weather conditions on the roadway environment and transport system.

Table 3.1 Weather Impacts on Roadway Environments and Transport Systems (Source: Pisano and Goodwin, 2004).

Weather Events	Roadway Environment Impacts	Transport System Impacts
Rain, Snow, Sleet & Flooding	<ul style="list-style-type: none"> • Reduced visibility; • Reduced pavement friction; • Lane obstruction & submersion; • Reduced vehicle stability & maneuverability; • Increased chemical and abrasive use for snow and ice control; • Infrastructure damage. 	<ul style="list-style-type: none"> • Reduced roadway capacity; • Reduced speeds & increased delay; • Increased speed variability; • Increased accident risk; • Road/bridge restrictions & closures; • Loss of communications/power services; • Increased maintenance & operations costs.
High Winds	<ul style="list-style-type: none"> • Reduced visibility due to blowing snow or dust; • Lane obstruction due to windblown debris & drifting snow; • Reduced vehicle stability maneuverability. 	<ul style="list-style-type: none"> • Increased delay; • Reduced traffic speeds; • Road/bridge restrictions & closures.
Fog, Smog, Smoke & Glare	<ul style="list-style-type: none"> • Reduced visibility. 	<ul style="list-style-type: none"> • Reduced speeds & increased delay; • Increased speed variability; • Increased accident risk; • Road/bridge restrictions & closures.
Extreme Temperatures & Lightning	<ul style="list-style-type: none"> • Increased wild fire risk; • Infrastructure damage. 	<ul style="list-style-type: none"> • Traffic control device failure; • Loss of communications & power services; • Increased maintenance & operations costs.

The wide range of disruptive events has a great impact on how to determine the scope of resilience measurements and strategies. For example, floods in central Europe (June 2013) forced thousands of people to move away from their homes in Eilenburg, Germany and Prague, Czech and the closure of the underground, railway and road transport, and schools in many affected areas (BBC, 2013). Under such circumstances, the scope of the resilience framework has to include various interrelated resilience dimensions, namely, physical , organizational, social, and economic (Bruneau et al., 2003). However, the scope of the current research is limited to the physical dimension of resilience. Consequently, the investigation will focus on resilience measurements in the case of disruptive events that affect the road transport supply side, e.g. closing some links or a reduction in traffic flow conditions, without leading to catastrophic impacts.

3.2.3 Disruptive Event Management

Effective management of road transport networks during and after the disruptive event is a very important factor that minimizes the consequences and facilitate the recovery process. However, it might be challenging to rate the level of effectiveness of disruptive event management (CEDR, 2009). In general, disruptive event management includes six stages, namely, detection and verification, motorist information, response, site management, traffic management and clearance (Austroads, 2007). Figure 3.4 summarizes the main processes and methods implemented at each stage.

The duration of each process has an impact on the total delay and the traffic flow during and after the disruptive event, as depicted in Figure 3.5. Consequently, the road management could have a multi-layered role in enhancing the resilience of a road transport network. In order to achieve an effective role of management pre, during and after the disruptive events, organizational resilience is explored in the next section.

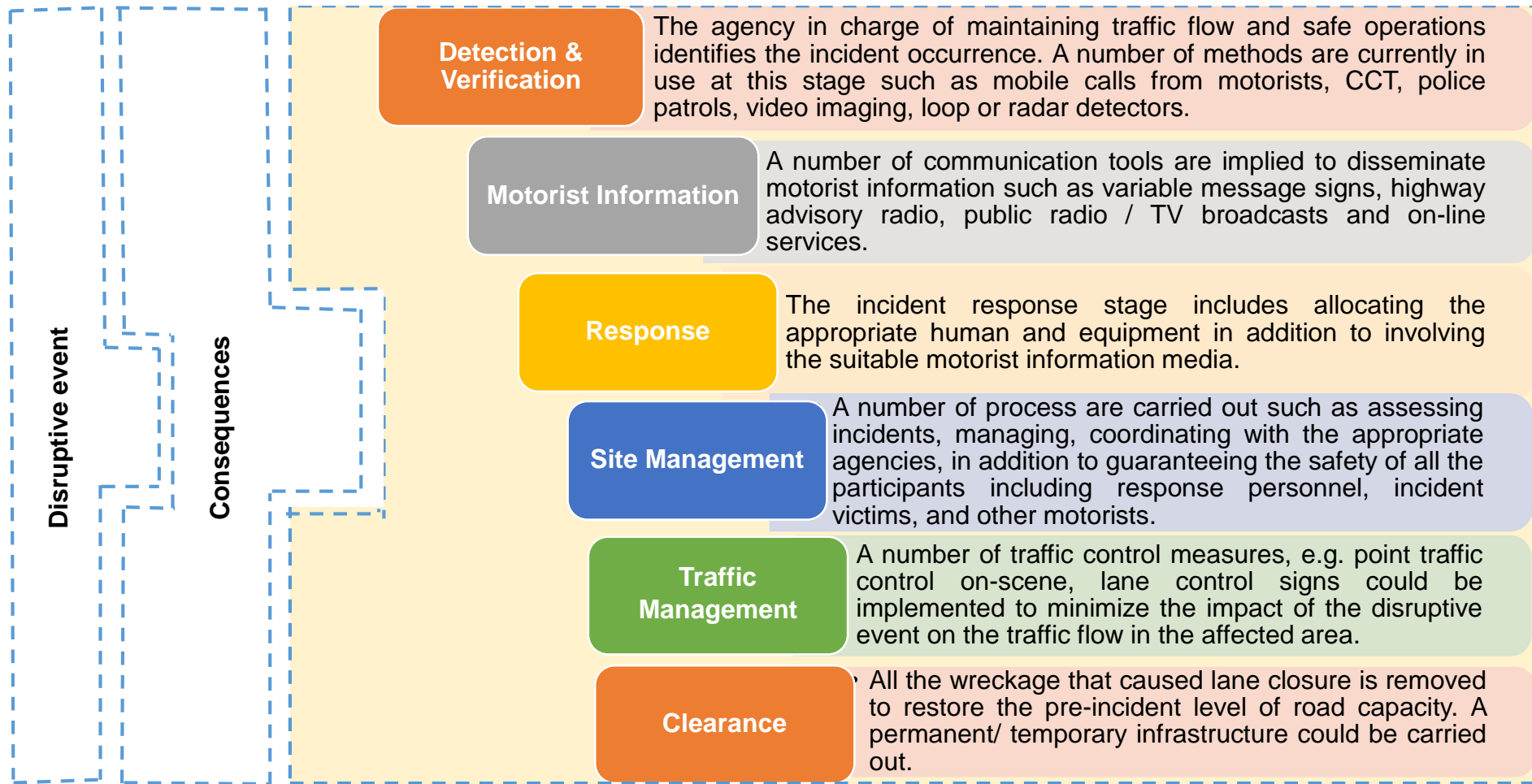


Figure 3.4 Disruptive event management stages and processes (source: the author based on Highway Agency, 2009).

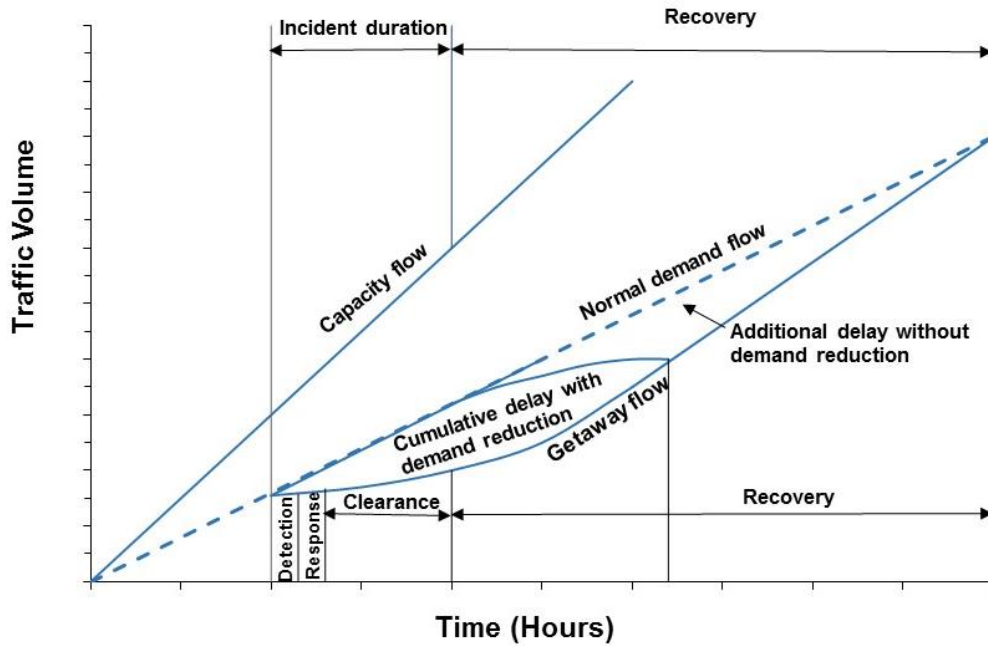


Figure 3.5 Demand reduction and delays due to traffic disruptive events (Source: Cambridge Systematics, 1990).

3.3 Organizational Resilience

The organizational resilience could have a significant role in achieving high resilient road transport networks as discussed in Section 2.3.1. In the following section, the potential attributes of organizational resilience are presented along with illustrative examples from transport context.

3.3.1 Organizational Resilience Attributes

Outlining the attributes that could contribute to organizational resilience could be a challenging issue as there is no unique set of resilience factors that could entirely define organizational resilience potential (Aleksić et al., 2013). Consequently, each organization could adopt a number of resilience factors that promote its organizational resilience under different types of disruptive events. However, a number of researchers (e.g. Wreathall, 2006; McManus, 2008; Aleksić et al., 2012) suggested a set of factors to quantify the role of the management in achieving resilience. In a detailed investigation, McManus (2008) introduced fifteen generic indicators under three main attributes as

presented in Figure 3.6. The first attribute, situation awareness, simply covers (Harwood et al., 1988):

- what characterises identity awareness,
- who is associated with responsibility or automation awareness, and
- when signifies temporal awareness.

For example, DfT report (2011) found that the transport system resilience could be enhanced in many areas within the UK through increased cooperation and coordination, and the smarter use of existing assets. It also highlighted the importance of formal training of employees in some areas such as training for winter service practitioners to avoid inconsistency between authorities and uninformed decisions.

The second attribute, keystone vulnerabilities, indicates the most significant causes of the deterioration of organization performance (Aleksić et al., 2012). Moreover, the adaptive capacity expresses the ability of the organization to change strategy, operations, management systems, governance structure and decision-support capabilities to withstand disruptive events (Starr et al., 2003). The effectiveness of communication and networking among all stakeholders, both internally and externally in day-to-day and disruptive events, have a significant impact on the resilience. For example, Sircar et al. (2013) suggested that the lack of co-ordination among low level of stakeholders in addition to the lack of understanding of critical infrastructure interdependencies and insufficient attention to long-term adaptation were the main reasons of inadequacies of the UK Government approach of 'governing through resilience' in practice.

Moreover, Stephenson et al. (2010) and Lee et al. (2013) introduced a fourth attribute to the ones suggested by McManus (2008), namely resilience ethos. That is measured by commitment to resilience and network perspective indicators. McManus (2008) highlighted the interdependencies among the resilience indicators due to the key relationships between the attributes.

Situation Awareness

- **Roles & Responsibilities:** awareness of roles and responsibilities of staff internally in an organisation and the roles and responsibilities of the organisation to its community of stakeholders.
- **Hazards & Consequences:** awareness of the range of hazard types and their consequences (positive and negative) that the organisation may be exposed to.
- **Connectivity Awareness:** awareness of the links between the organisation and its entire community of stakeholders, internally (staff) and externally (customers, local authorities, consultants, competitors etc.).
- **Insurance:** awareness of the obligations and limitations in relation to business interruption insurance and other insurance packages that the organisation may have or have available.
- **Recovery Priorities:** Awareness of the minimum operations requirements and the priorities involved in meeting those requirements, together with expectations of key stakeholders.

Keystone Vulnerabilities

- **Planning:** the extent to which the organisation has participated in planning activities including risk management, business continuity and emergency management planning.
- **Exercises :** the extent to which the organisation has been involved in external emergency exercises or created exercises internally for staff and stakeholders.
- **Internal Resources:** the capability and capacity of physical, human and process related resources to meet expected minimum operating requirements in a crisis. Includes economic strengths, succession and structural integrity of buildings.
- **External Resources:** the expectations of the organisation for the availability and effectiveness of external resources to assist the organisation in a crisis.
- **Connectivity:** the extent to which the organisation has become involved with other critical organisation to ensure the availability of expertise and resources in the event of a crisis.

Adaptive Capacity

- **Silo Mentality Management:** the degree to which the organisation experiences the negative impacts of silo mentality and the occurrence of strategies in place for mitigating them.
- **Communications & Relationships:** the effectiveness of communication pathways and relationships with all stakeholders, both internally and externally in day-to-day and crisis situations.
- **Strategic Vision :** the extent to which the organisation has developed a strategic vision for the future operations and the degree to which that is successfully articulated through the organisation.
- **Information & Knowledge :** the degree to which information and knowledge is acquired, retained and transferred throughout the organisation and between linked organisations.
- **Leadership & Management:** the degree to which leadership and management encourage flexibility and creativity in the organisation and how successful decision making is in times of crisis.

Figure 3.6 organizational resilience indicators (Source: McManus et al., 2008).

Resilient Organizations (2012) identified 13 indicators to assess the resilience of an organisation under three main principles namely, leadership and culture, networks and change readiness as shown in Figure 3.7.



Figure 3.7 Organisational resilience indicators (Source: Resilient Organisations, 2012).

Furthermore, Aleksić et al. (2013) classified resilience factors into three categories; internal, external resilience and enabling factors based on the literature, as presented in Figure 3.8. Although the authors (Aleksić et al., 2013) applied these factors on small and medium sized enterprises, the factors could still be applied to other types of organizations.

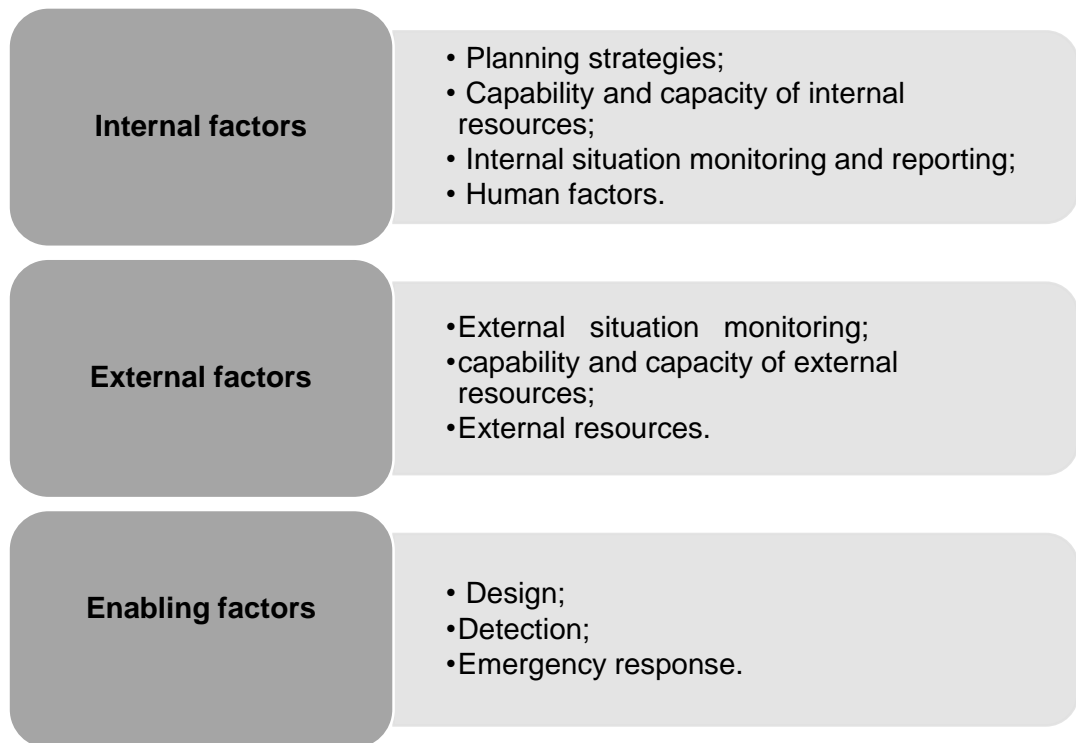


Figure 3.8 Organizational resilience factors (Source: the author based on Aleksić et al., 2013).

Despite using different expressions and classifications shown in the above review, it has been noted that there is a general agreement among researchers on the main factors that could be used to quantify and enhance organizational resilience. For example, most of the researchers include situational awareness, strategic planning, information dissemination, effective partnerships in their proposed framework under different categories.

A recent report (Climate UK, 2013) presented a number of case studies to show different projects that aimed to enhance resilience in real life situations. For example, in January 2001 a storm damaged Slapton Line, a road in South Devon, on the A379, linking the villages of Torcross and Strete had to be closed for 3 months due to the storm, which damaged the road and shingle ridge. Various actions have been implemented to mitigate the future impact of similar storm events, as listed in Table 3.2. In the same table, these actions have been allocated to one or more of the resilience attributes as outline in Figure 3.6. The variation of actions reflecting the role of resilience

concept not only in new ways of allocating land use (i.e. realigning the road further inland) but also in mitigation strategies (i.e. sharing contingency plans with the local community). The report (Climate UK report, 2013) also referred to the danger of losing momentum in scarce of extreme events in line with the suggestion of Sircar et al. (2013) about insufficient attention to long-term adaptation, for example the rare occurrence of storms in recent years in South Devon. However, losing momentum could be avoided when the organization treats the resilience concept as a part of continuous management, adaptation and in new designs (Park et al., 2013). Furthermore, Rogers et al. (2012) suggested that new ways of engineering, managing and delivering resilient local infrastructure need to be developed.

Table 3.2 Outline Slapton Line resilience actions presented in Climate UK 2013 (Source: the author).

Organizational resilience attributes Proposed actions	Change readiness				Networks				Leadership and culture			
	PS	PP	STP	IaC	BS	LN	EP	IR	L	SE	DM	SA
Formation of a community partnership (e.g. local people, businesses, parish councils and local authorities).												
Construct shingle bastions along the beach to protect the road.												
Using a monitoring system, based on the coastguard and tide and weather forecasts, along with a plan to shut the road.												
Established a partnership with Plymouth University.												
Using time-lapse cameras to monitor beach behavior and offer alerts if sections of the beach are missing												
Preparing a contingency plan to deal with varying levels of damage to the road.												
Sharing contingency plans and diversion routes by the local community.												
Potential planning to realign the road further inland if funds are available.												

Note: PS = Planning strategies; PP= Proactive posture; STP= Stress testing plans; IaC= Innovation and creativity; BS= Breaking silos; LN=Leveraging knowledge; EP= Effective partnerships; IR= Internal resources; L= Leadership; SE= Staff engagement; DM= Decision making; SA= Situational awareness.

3.3.2 Measuring Organizational Resilience

It is very important for any organization having a tool to measure its level of organizational resilience, aiming to highlight any deficiency or a need to strengthen some factors. According to Lee et al. (2013), measuring organizational resilience can contribute to two significant organizational requirements:

- demonstrating progress toward becoming more resilient;
- providing leading instead of lagging² indicators of resilience; demonstrating a business case for resilience investments.

A number of investigations have been carried out to introduce a measurable tool for organizational resilience. Most of these investigations are mainly based on the analysis of the individuals' responses (e.g. employees or stakeholders) using an online survey (e.g. Stephenson et al., 2010 ; Lee et al., 2013) or interviews and workshops (McManus , 2008). Introducing such a tool could have a significant impact in enhancing the organizational resilience in two ways. First, it could catalyse the discussion inside the organization around the resilience concept, promoting a clearer understanding of resilience and related concepts such as vulnerabilities and adaptive capacity. Secondly, it could potentially enhance the organisation's ability to identify the most suitable strategies to improve its resiliency level.

For example, McManus (2008) referred to a number of issues that could affect the organizational resilience based on a multiple case-study approach using 10 organizations (6 public business including 2 lifeline organizations³ and 4 private business). McManus (2008) found that nearly all of the studied organisations showed significant problems with knowledge of roles and responsibilities, as one of situational awareness indicators, in day-to-day operations. McManus (2008) referred to a number of issues such as “staff feeling undervalued, not being consulted in areas where they had expertise and disengagement with the organisational vision in addition to increasing

² Leading indicators measure processes, actions and practice that proposed to increase resilience whereas the lagging indicators based on historical data (Lee et al., 2013).

³ Lifeline organizations could include energy, communication, water, and transport sectors.

levels of mistrust of decision makers”. ‘Silo mentality’, is another common low indicator for most of the organisations due to several factors (McManus, 2008) such as poor knowledge of roles and responsibilities of others in the organisation in addition to the lack of understanding and utilising communications pathways. McManus (2008) also highlighted that there are low levels of trust and loyalty from staff and others. It has been noted that some of the above factors could be a cause of one of other factors. For example, “increasing levels of mistrust of decision makers” could be due to “non-transparent governance and decision making structures”. Consequently, the overall estimated resilience of the organization could suffer from double counting effects due to these interdependence among the indicators. McManus (2008) also identified some of these relationships among the indicators and referred to that as an important stage to propose the most effective resilience strategies.

In another study (Stephenson et al., 2010), a web-based survey is developed using the perception of staff members in order to evaluate the resilience of organisations. The study applied McManus (2008) indicators in addition to two further indicators to reflect the resilience ethos attribute. Each indicator is evaluated using three or more questions; then the average is obtained to estimate the score for that indicator. The study (Stephenson et al., 2010) used 68 organizations from across industry sectors. It found that the magnitude of the range of scores for each dimension varied, providing evidence that organisations differ in their strengths and weaknesses. However, the outcome of the tool should be used carefully as it might be influenced by the size of the organization and also participants awareness. Using the same set of indicators, Lee et al. (2013) developed a survey tool that organizations can apply to recognize their strengths and weaknesses and to develop and evaluate the effectiveness of their resilience strategies and investments.

For the transport sector, an American survey (Zhou et al., 2011) emphasised the importance of three elements in disruptive event management procedures, namely; communication, coordination, and cooperation in response to disruptive events. The study found that communication between

incident responders is poor, causing an increase in the incident management timeline in line with the European case studies (CEDR, 2009). The study (CEDR, 2009) also recommended a number of ways that could enhance the effectiveness of the road management under disruptive events, for example, the need to make changes in roles and responsibilities in incident management processes. They also referred to the importance of the use of better information for both: incident responders to ensure an appropriate response and for road users to reduce the impact of the incident.

3.3.3 Impact of organisational resilience

Organizational resilience is essential to identify the potential areas for improvement. However, the main aim of improving organizational resilience is to increase the ability of the highway agencies to avoid or minimize the consequence of the disruptive event through introducing active road transport network management. For example, Table 3.3 presents illustrative case studies with a number of active road traffic management schemes at regional level along with the used tools and technologies. The overall impact of the proposed strategy is also given in Table 3.3. However, for some applications the impacts are not necessarily related to the specific mentioned case study but could be the expected output of the strategy, as the real impacts have not been evaluated up until now. Active road transport network management schemes could introduce different enablers through multi-interdependence phases of resilience: pre-event, during the event and recovery phase. In Table 3.4, the benefits of road traffic management, derived from several operational and research reports (e.g. Austroads, 2007; CEDR, 2009) are allocated to the appropriate resilience stage. In the current research, the role of organizational resilience is taken into account by considering a certain road management and its potential impact under different scenarios.

Table 3.3 Examples of road transport management application at regional level (Source: the author based on Sultan et al., 2008a; Highways Agency, 2008; Gunnar and Lindkvist, 2009).

Strategies	Tactics	Tools and Technology	case studies	Impact*
Active Traffic management	Four Lane Variable Mandatory	AMI; AMS; PTZ cameras; CCTV; MIDAS; SACS; HADECS; VDL	ATM on M42 between J3a and J7	<ul style="list-style-type: none"> • Reduced congestion • Improved journey time reliability • Increased capacity • Reduced emissions • Reduced incidents
Road weather management	Road weather controlled variable speed limits	RWS; RTIC, DMS	Four years field trial in Sweden	Decrease of fatalities and the severity accidents
	Information Dissemination	DMS, HAR, Internet.	HA website HAR	<ul style="list-style-type: none"> • Informed traveller • Network efficiency
Motorway access control	TM	RM	TM at 30 sites	<ul style="list-style-type: none"> • Reliable Journey time; • Traffic speed; • Traffic flow.
	ITM	RM, MJTSCR	ITM at Junction 33 of the M1	<ul style="list-style-type: none"> • Journey time; • Traffic flow.
	Road Pricing	Electronic toll collection	M6 Toll	<ul style="list-style-type: none"> • Relieve congestion
Crash prevention and safety	Accident detection	MIDAS	M25 (j6-j8)	<ul style="list-style-type: none"> • Safe road • Reliable Journey time
	TTM	VPDS	Under trials	Safe roads

Note: AMI= Advanced Motorway Indicator; AMS= Advanced Motorway Signs; PTZ cameras = Pan Tilt and Zoom; CCTV= Closed-circuit television; MIDAS= Motorway Incident Detection and Automatic Signalling; SACS= Semi-Automatic Control System; HADECS= Highways Agency Digital Enforcement Camera System; VDL= Vehicle Detector Loops; ATM= Active Traffic Management; RWS= Road Weather Stations; RTIC= Regional Traffic Information Centre; DMS= Dynamic message signs; HAR= Highway advisory Radio; RM= Ramp Metering; MJTSCR= Motorway Junction's Traffic Signal Controlled Roundabout; VPDS= Vehicle Proximity Detection System.

Table 3.4 Resilience stages and the potential impacts of road traffic management (source: the author).

Resilience phases	Road traffic management impacts
Avoidance	Travel and weather information; Early warning of road transport network closure.
Response and mitigate	Reduction in the duration of traffic incidents; Congestion relief by introducing temporary traffic management measures; Optimal use of road, traffic and travel data; Minimize the impacts by better user information; Reducing the risk of secondary incidents occurring; Reduced mortality.
Recovery	Restoring road conditions, e.g. wreckage removal.

Despite the importance of organizational resilience, the estimation of physical resilience is essential to investigate the impact of network configuration and variation in supply and demand under different scenarios on its functionality. It is also important to rate the level of organizational resilience in respect to the physical resilience achieved under different disruptive events. In other words, physical resilience could offer a number of measures that reflect the level of impact of disruptive events along with the ability to minimize its consequences using managerial and technical tools. As such, a short overview of technical resilience characteristics is given in the rest of this chapter.

3.4 Physical Resilience

The physical resilience of road transport network refers to the ability of the road transport network to function to acceptable/desired levels under disruptive events. The road transport network has four dynamic abilities, namely, the dynamic ability to avoid, withstand, respond and recover from the disruptive event (see Figure 2.1). In this research a number of characteristics are used to quantify the physical resilience of road transport

networks in line with the approach used by McManus, 2008, Muarry-Tuite, 2006 and Bruneau et al., 2003, as presented in Table 3.5.

Table 3.5 Definitions of resilience characteristics (Source: the author).

Resilience Characteristics	Definition	Source
Redundancy	The ability of the road transport network to offer different routes.	Cimellaro et al., 2010; Jenelius, 2010
Mobility	The ability of the road transport network to offer a good level of service to its users.	Kaparias and Bell, 2011; Hyder, 2010; Murray-Tuite, 2006
Vulnerability	The degree to which the system is susceptible or sensitive to threats or hazards that significantly impact on road transport network performance.	Jenelius et al., 2006; Berdica, 2002
Reliability	The probability that traffic can reach a certain destination within an accurately estimated time.	Iida, 1999
Diversity	The availability of different modes serving a certain area.	Litman, 2009
Recovery	The availability of an acceptable level of performance within a short time following the disruptive event and with minimum external help.	Cimellaro et al., 2010

The focus of this research is to assess road transport network physical resilience during disruptive events, as it is assumed that the network will restore its full functionality after the event. For example, in the case of snow or floods, it is expected that the significant effect on road transport networks will be during the event. However, in some cases, there should be some maintenance of road transport networks to overcome the consequences of the disruptive event.

3.4.1 Proposed Characteristics of Physical Resilience

Three of the above characteristics, namely redundancy, vulnerability and mobility are employed here to model road transport network resilience during

disruptive events. Other resilience characteristics are considered to be beyond the scope of this research for the following reasons.

- Diversity requires consideration of different transport modes, including trains, aeroplanes and ferries, however, this research focuses on resilience of road transport networks.
- Reliability could be considered as a pre-event network condition, in line with the approach by Barker et al. (2013).
- Recovery is implicitly evaluated by other characteristics such as mobility, where the mobility 'bounce-back' to the pre-event level indicates a full recovery of road transport networks from the disruptive event.

This wider set of characteristics could be considered as part of future research and as an extension to the method outlined here.

Redundancy, vulnerability and mobility are chosen to reflect different aspects of road transport network resilience. For example, mobility, as defined above, is normally measured by traffic flow speed (Cianfano et al., 2008). However, variations in travel speed may not be the only consequence arising from a disruptive event. For example, the closure of some links would lead to disconnection of some zones creating unsatisfied demand and potentially causing a misleadingly high vehicle speed due to reduced loading on the network. Therefore, other characteristics such as redundancy and vulnerability could be used to fully capture all the consequences of the disruptive event on the network. For example, redundancy is used to investigate the impact of network configuration as will be discussed in detail in Chapter 5. Moreover, vulnerability is defined as the sensitivity of road transport links to be disrupted. However, in reality, all these characteristics interact with each other and it may be difficult to investigate one in isolation i.e. without taking into account the status of other characteristics. For example, the main function of the road transport network is to move people and goods (mobility), which is highly influenced by the road transport network conditions (vulnerability). That is, in turn, affected by the availability of several routes between different OD pairs (redundancy) and the sensitivity of network links to be disrupted (vulnerability).

Each characteristic is measured by choosing one or more indicators to capture the variation in this characteristic under different conditions. In the following sub sections, a brief overview of each characteristic is presented whereas a more detailed investigation of each characteristic and its proposed indicators is presented in Chapter 5 (redundancy), Chapter 6 (vulnerability) and Chapter 7 (mobility).

3.4.1.1 Redundancy in Road Transport Networks

Redundancy could have a significant impact on the resilience of road transport networks as it represents the spare capacity of road transport networks under different scenarios. The link between redundancy and resilience concepts has been discussed in many disciplines. For example, Haimes (2009) suggested that a water distribution system could be resilient against a major storm that would shut down one of the power lines if it has redundancy in its electric power subsystem. Moreover, Yazdani and Jeffrey (2012) considered redundancy along with connectivity as the topological aspects of resilience. Tondini (2002) referred also to the importance of redundancy in ensuring that there is sufficient capacity under local failure conditions. In computer science, Randles et al. (2011) reported that distributed redundancy improves complex system resilience. Anderson et al. (2011) suggested that the redundancy of road transport networks is one of resilience indicators. Furthermore, Lhomme et al. (2012) showed that redundancy indicators could be used to evaluate absorption capacity of the road transport network.

In the current investigation, the redundancy characteristic is quantified based on the entropy concept owing to its ability to measure the system configuration, in addition to being able to model the inherent uncertainties in road transport network. Various system parameters based on different combinations of link flow, relative link spare capacity and relative link speed have been examined, as presented in more detail in Chapter 5.

3.4.1.2 Vulnerability of Road Transport Networks

In this research, vulnerability is defined as the potential negative impact of a disruptive event on the road transport network. Vulnerability is a complex

and dynamic concept (Dalziell and McManus, 2004) as there are spatial-temporal variations that should be considered in the assessment of vulnerability. For example, different elements of road transport networks (e.g. links) may suffer from various consequences under the same disruptive event. As Delor and Hubert (2000) explained, in social science, the assessment of vulnerability has two main components. These are an external side to the consequences of a disruptive event that affect the network component and an internal side which is weakness, meaning the component properties that minimize or maximize the impact of the event on the component functionality. The external side represents the type and scale of the disruptive event.

For the internal side of network, vulnerability assessment could be classified into three types, namely nature, structure and traffic related vulnerability (Husdal, 2005). Nature related vulnerability is concerned with the characteristics of land that is crossed by the road transport network, for example the closeness of a river or an active seismic zone. Structure related vulnerability involves the structure and design of the road transport network, for example, the number of links connected to a node or the availability of several routes connecting the same origin destination pair. Traffic related vulnerability focuses on the traffic conditions and characteristics that describe the variations in traffic flow under different scenarios.

The main aim of including a vulnerability assessment under the resilience framework is to investigate the influence of disruptive events on the links of road transport networks. Barker et al. (2013) used vulnerability as the only resilience indicator during disruptive events, emphasising its importance. However, disruptive events have a wide spectrum in many dimensions, causing impacts with different scales at different parts of road transport networks as explained in detail in section 3.2. Moreover, a simple way of assessing the impact of disruptive events on road transport networks could be by considering the variation of link attributes, for example link capacity and/or link speed. Therefore, the vulnerability assessment here focuses on the development of an indicator based on several link attributes, such as link length, flow, capacity and density jam. Chapter 6 introduces a full discussion

of all the attributes that could have an influence on link importance and the development of a link vulnerability indicator using a combination of fuzzy logic and an exhaustive search optimisation technique.

3.4.1.3 Mobility of Road Transport Networks

Mobility is defined as the ability of road transport networks to provide connections to jobs, education, health service, shopping, etc., at an acceptable level of service (Kaparias et al., 2012; Hyder, 2010). As such, the variation in the level of mobility could be a direct indicator to measure the response of the road transport network to changes in conditions, e.g. deterioration of road capacity due to adverse weather conditions or an increase in demand. For example, a highly resilient road transport network is one that is able to maintain its level of mobility during a disruptive event.

Previous investigations (Zhang et al., 2009; Wang and Jim, 2006; Cianfano et al., 2008) show that no universally agreed indicators to assess road transport network mobility are available. In this investigation, two mobility attributes are proposed to assess the physical connectivity and level of service of road transport networks. A simple technique based on a fuzzy logic approach is then employed to combine the two attributes into a single mobility indicator. The advantage of quantifying two mobility attributes is that it improves the ability of the technique to assess the level of mobility under different types of disruptive events. Chapter 7 presents more details of the technique and its application to a real life case study using a synthetic network based on Delft city.

3.4.2 Proposed Composite resilience index

Each of the above three characteristics can be used to gauge the road transport network resilience and to assess the effectiveness of different management policies or technologies to improve the overall network resilience. However, it is useful to estimate the overall resilience level by a single value. Several ways exist in the literature to obtain a composite index from many indicators using equal or different weights (Saisana and Tarantola, 2002). A composite resilience index was eventually developed based on the aggregation of the three characteristics indicators using two

different approaches, namely equal weighting and principal component analysis methods as presented in Chapter 8.

3.5 Summary and Concluding Remarks

This chapter has presented the development of the conceptual framework for resilience through reviewing three main areas, namely:

- disruptive events and their impact on the road transport network;
- organizational resilience, in order to investigate the role of management in enhancing the resilience of road transport networks;
- the relationship between road transport network attributes and demand variations under disruptive events that have been considered under the physical resilience concept.

Figure 3.9 provides a schematic diagram of the conceptual framework for resilience of road transport networks based on the three chosen components. Road transport networks are increasingly exposed to a wide range of disruptive events including manmade and natural events, which have a great impact on their functionality. Consequently, the current investigation will focus on measuring resilience in case of disruptive events that affect the road transport supply side, (e.g. closure of some links or a reduction in traffic flow conditions), without leading to catastrophic impacts. Catastrophic disruptive events (e.g. 2004 tsunami) are generally expected to demolish the road transport network. In such case, other approaches (e.g. Bruneau et al., 2003) could be more appropriate to assess the resilience of road transport system rather than networks as explained in Section 3.2.2. However, increasing the resiliency of road transport networks during non-catastrophic disruptive events may allow “safe-fail”, implying a reduction of consequences in case of catastrophic disruptive events (Berdica, 2002).

The road management could have a significant effect on the resilience of road transport networks in the avoidance, responding, mitigating and recovery stages. This chapter has emphasised the importance of road transport network management role under business as usual conditions and in the case of a disruptive event by reviewing the role of organizational

resilience and its potential attributes. Communication, coordination and cooperation are found to be essential elements to achieve effective road management scheme during disruptive events.

The role of road transport network attributes, supply side, and demand variations have been outlined through resilience characteristics namely, redundancy, vulnerability and mobility. These three characteristics have been carefully chosen to reflect different aspects of road transport network physical resilience. Each characteristic is defined in a transport context and measured by choosing one or more indicators to capture the variation in the characteristic under different conditions, as presented in Chapters 5, 6 and 7. Moreover, a composite resilience index is introduced from the aggregation of the three characteristics indicators in Chapter 8.

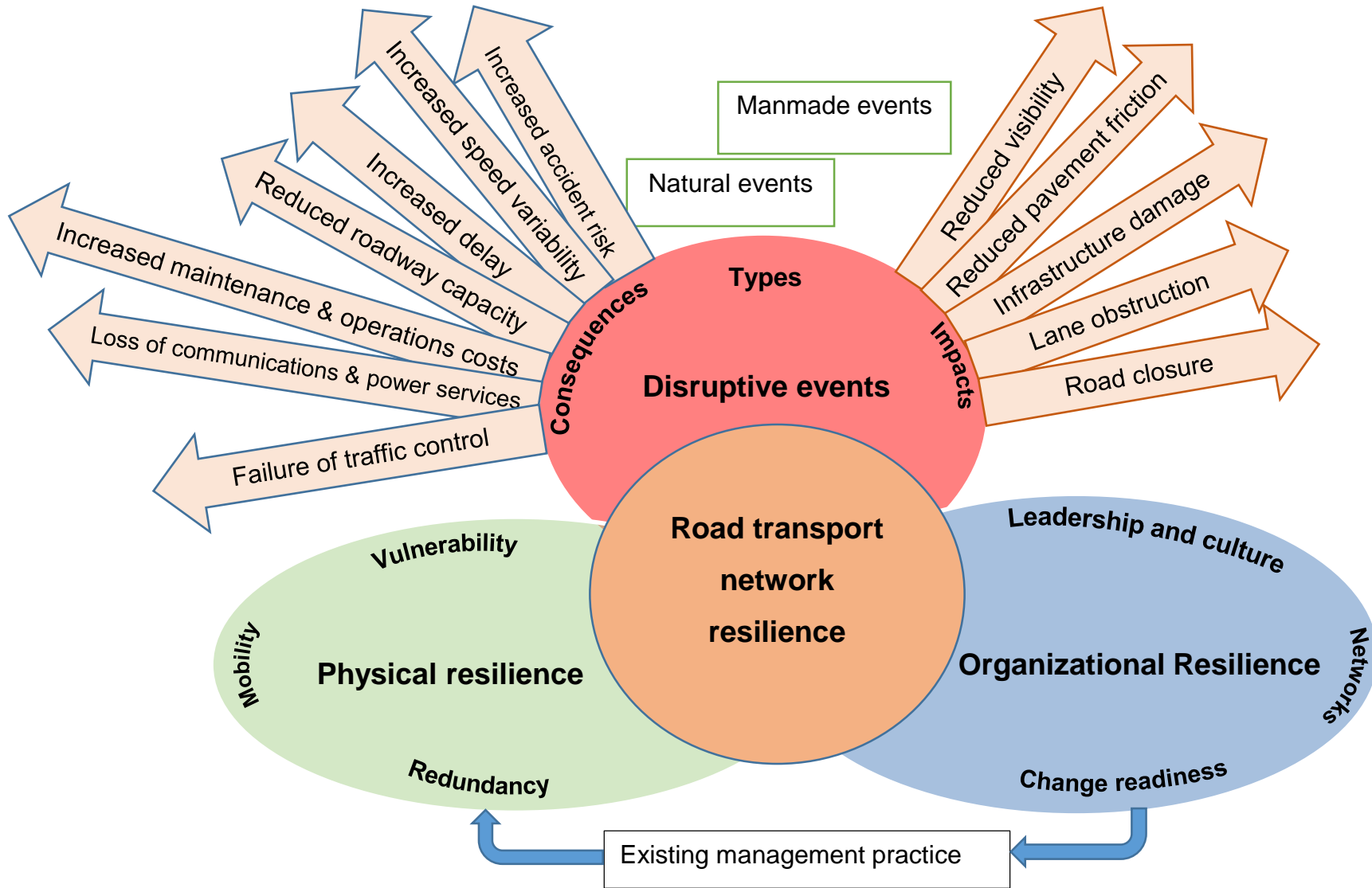


Figure 3.9 Conceptual framework for resilience of road transport networks.

Chapter 4: Road Transport Network Modelling

4.1 Introduction

A traffic data set related to road transport networks under disruptive events along with the available intelligent transport system is not currently available. Consequently, road transport network modelling has been adopted as an alternative technique to generate traffic data under different scenarios. It also introduces a good way to understand traffic flow characteristics and dependence relationships between its parameters. Furthermore, it has been generally used by decision makers and planners to evaluate the effectiveness of various strategies and plans. However, in the current research project, transport models are mainly used as an analytical tool to investigate 'what-if' scenarios. This gives an insight into the interdependent relationships among the road transport network components: a supply side and a demand side including the network wide level of service due to demand variations or capacity decreases due to network wide event such as bad weather.

In general, mathematical models are heavily used in transport modelling where the system is represented by a group of equations based on specific theories (Ortúzar and Willumsen, 2011). The purpose of the model varies according to the context of the problem under investigation. For example, in transport planning, a regression analysis model could be used to predict a number of trips produced from a certain zone (e.g. a city), as a dependant variable, based on a number of independent variables which in this case could be a number of residents, jobs and education. Furthermore, the transport model could also be used as an analytical tool in transport analysis to study the impact of certain measures or introduction of new policy.

This chapter introduces an overview of the main principle of the four steps of road transport network modelling. A general review of the road transport network modelling (Section 4.2) to highlight the main modelling stages. It mainly focuses on the traffic assignment stage (Section 4.3) whilst the other

three stages are presented in Appendix A. Furthermore, an overview of junction modelling is explained. Furthermore, the modelling of real time travel information is introduced in Section 4.4. The road transport network implemented in different case studies is described in Section 4.5. The chapter summary is presented in Section 4.6.

4.2 Structure of Road Transport Network Modelling

A traditional traffic model to envisage traffic flow is recognized as the four step model (Ortuzar and Willumsen, 2011). Figure 4.1 shows a general form of the four step transport model, which can be summarized as follows:

- **Trip generation stage:** it estimates the number of trip generated, and attracted for each zone studied;
- **Trip distribution stage:** in this stage, the direction of the trips is identified;
- **Mode choice:** describes the mode (e.g. cars, public transit or non-motorized) being used in the trips; and
- **Trip assignment:** the route of the trip is forecast in this last stage.

Appendix A gives more details about trip generation, trip distribution and mode choice stages as explained in various road transport modelling sources, for example, Ortuzar and Willumsen (2011) and Garber and Hoel, (2009), in addition to its application in the case study. Traffic assignment stage is discussed in detail in the following section.

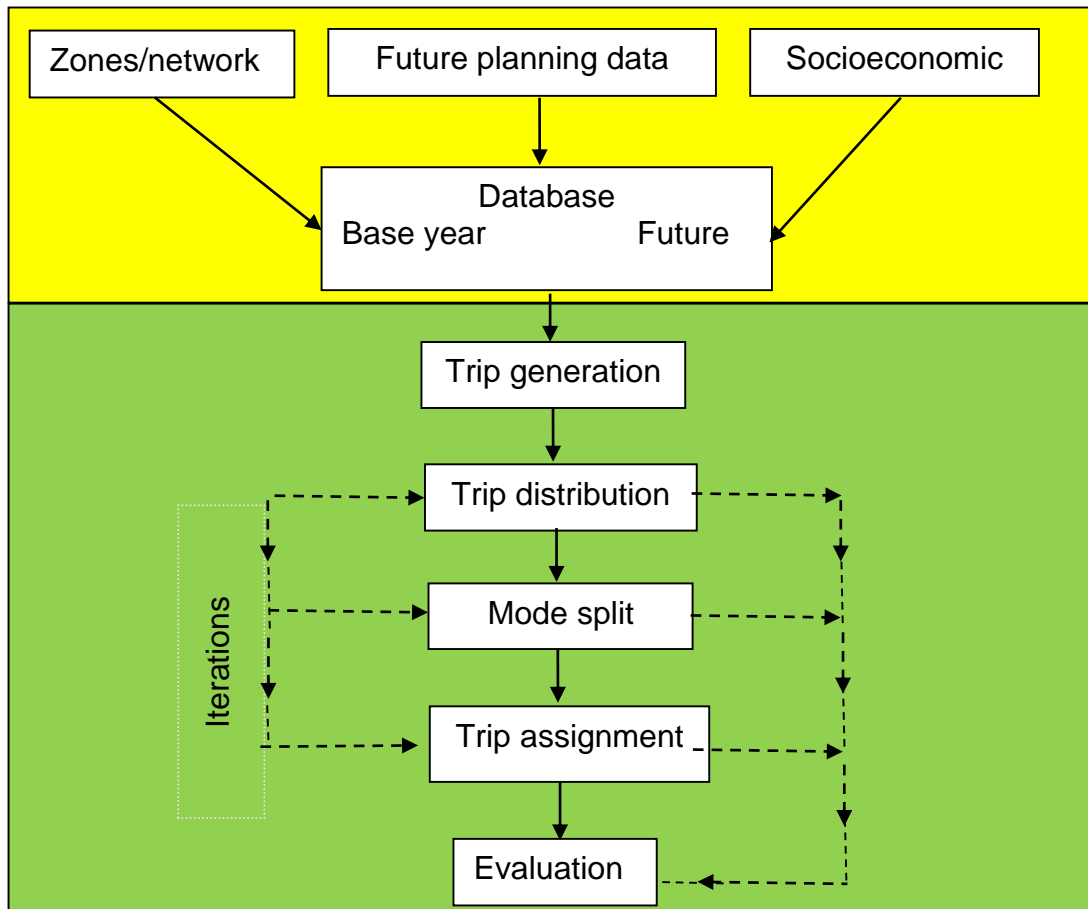


Figure 4.1 Four stage transport model (Source: Ortúzar and Willumsen, 2011).

4.3 Traffic Assignment

The traffic (trip) assignment model aims at allocating trips generated for different modes to the corresponding road transport network. The traffic assignment model is categorised into three main types, namely microscopic, mesoscopic, and macroscopic (Hoogendoorn and Bovy, 2001). Appendix B presents a brief summary on each type and its mathematical formulation. Several assignment model packages that used widely by planners and decision makers are developed based on any of these three categories. Table 4.1 introduces some of these packages along with their characteristics and main features and capabilities. Ratrouf and Rahman (2009) conducted a comparative analysis of currently used microscopic and macroscopic traffic

simulation software including the ones shown in Table 4.1. However, OmniTrans software has been used in the current research due to its ability to take into account the variation in demand over time and the response of traffic to dynamic conditions within the transport network. Furthermore, it is possible to investigate the impact of ITS such as real time travel information systems using dynamic traffic assignment available in OmniTRANS software (Version 6.1.2) as it will be explained in Section 4.4. Moreover, it is user-friendly and widely used by practitioners and researchers.

Table 4.1 Examples of Models and Their Main Features and Capabilities
(Source: Ratrouf and Rahman, 2009)

Name	Characteristic	Main Features/Capabilities
OmniTrans	Macroscopic	Urban areas, motorways.
CORFLO	Macroscopic	Urban areas, motorways.
KRONOS	Macroscopic	Motorways lane changing, merging, diverging, and weaving, the simultaneous development of queues and propagation of congestion on both the motorways and its ramps.
SATURN	Microscopic	Individual junctions, traffic assignment.
VISSIM	Microscopic	Urban areas, motorways, ramp metering, pedestrians, transit operations, 3-D animation.
INTEGRATION	Mesoscopic	Urban areas, motorways, traffic assignment, intelligent transport system, toll plaza, vehicle emissions.

In traffic assignment stage, the transport system can be divided into two main categories: the supply side, which is represented by the road transport network and the demand side represented by the number of trips for all OD pairs and modes. The road transport network includes links' characteristics and associated costs. The costs refer to the generalised cost that could be a function of different attributes such as travel time and distance, free flow speed, capacity and a speed flow relationship (Ortúzar and Willumsen, 2011). Typically, for each mode, e.g. car, truck, etc, there is a separate assignment, since the network for each of these modes is different in terms of link capacity

and free flow speed. In the current investigation, the focus of the assignment of road traffic is only on cars. However, other modes may be included in the modelling.

The assignment of trips into the road transport network depends on the equilibrium concept between demand and supply. For instance, in the road transport network, the equilibrium state is obtained when the user finds the best route, either the shortest or the cheapest route, for their OD pair and is no longer looking for a different route.

In general, the traffic assignment stage has two steps. The first stage is the route generation model, which is used to determine the routes to which the traffic demand is assigned. Secondly, the network loading model (NDL), which describes the way in which the traffic is propagated through the network (Dijkhuis, 2012). In the following sub sections, full details of the route choice and network loading models used in each stage are explained and related to OmniTRANS software.

4.3.1 Route Generation Model

The first step in the assignment process is building the shortest route paths between each origin-destination (OD) pair and storing them in a specific data structure called a “tree”. According to Ortúzar and Willumsen (2011), two algorithms are used for finding the shortest paths, namely Moore (1957) and Dijkstra (1959) techniques. For larger networks, Dijkstra’s algorithm is more efficient than Moore’s but more difficult to program (Ortuzar and Willumsen, 2011). In OmniTRANS software used in the current research, Dijkstra’s algorithm is used. The core modelling elements of the shortest paths comprise the definition of the shortest path according to the generalised cost formulation, the effect of congestion (capacity restraint), and drivers’ uncertainty represented by Burrell spread parameter in OmniTRANS software (Version 6.026 manual, 2014).

The shortest path is determined based on the minimum generalised cost estimated from the travel time and distance in addition to other costs such as tolls or parking. Link cost functions can be estimated in different ways: using

the fundamental diagram (i.e. hydrodynamic theory) and queuing theory. The basic assumption of the traffic flow modelling was developed by Greenshields (1935) and becomes known as the “fundamental equation” that defines a relation between traffic speed, density and flow (i.e. $flow = density/speed$). A brief introduction on the fundamental equation is presented in Appendix B. However, in this research, the widely used BPR link performance function (Bureau of Public Road, 1964) is implemented to calculate the link travel time in case of static assignment where the link travel time is expressed as a function of the flow/capacity ratio of that link as presented in Eq. (4.1) below. In case of dynamic traffic assignment (DTA), METANET model (Messmer and Papageorgiou, 1990) using fluid mechanics principle to calculate the speed, density and flow of each link segment (Dijkhuis, 2012) as explained in details in Section 4.3.2.2.

In case of static assignment, a stochastic 'randomising' term (ε) could be added to the generalised cost (Burrell, 1968) to reflect the uncertainty associated with the traveller behaviour under a certain scenario. Consequently, the general formulation for the generalised cost (GC) is:

$$GC = aTD + b(T_0(1 + \alpha(\frac{f_m^i}{C_m})^\beta) + c C_1 + dC_2 + \varepsilon \quad (4.1)$$

where TD is the OD travel distance, $(T_0(1 + \alpha(\frac{f_m^i}{C_m})^\beta)$ is the BPR travel time function, C_1 and C_2 are two optional additional fixed link costs (tolls, parking charges etc). a , b , c and d are coefficients for travel distance, travel time, C_1 and C_2 , respectively applied throughout the network, T_0 is the free-flow travel time, f_m^i is the link flow during time interval i using a travel mode m ., C_m is the link capacity using a travel mode m , and α and β are two function coefficients.

The two BPR function coefficients, α and β , are normally set at 0.15 and 4.0, respectively (Sheffi, 1984); however, some operational research found that these values could vary depending on the road type. For example, the value of α could be equal to 0.15 to 0.5, e.g. congestion will occur if the link volume is close to its saturation capacity. However α may be assigned a value more than 1, e.g. significant delays will occur before full capacity is reached for

urban area roads. Normally, the parameter β in Eq. (4.1) is set at 4.0 from previous experience (OmniTRANS 6.026 manual, 2014). For the Delft road transport network case study, two groups of α and β are tested to investigate their significance on the results. It was found that the variations of α and β have no major impact on the results.

4.3.2 The Network Loading Model

The network loading model deals with how the trips are loaded to the shortest paths in the network. Two types of traffic assignments, static and dynamic traffic assignments, in addition to junction model are implemented in OmniTRANS software to allocate the estimated travel demand (the number of trips between each OD pair) on the road transport network in order to obtain the spatial distribution of the traffic volume. A brief coverage of the static and dynamic traffic assignment models is presented below and full details are available in other sources, for example OmniTRANS on-line help (OmniTRANS, 2014) and Dijkhuis (2012).

4.3.2.1 Static Traffic Assignment

Static traffic assignment is normally used to investigate the impact of long and medium changes in socioeconomic developments or road transport network infrastructures. In general, there are two approaches to assign the estimated travel demand on the road transport network in order to obtain the spatial distribution of the traffic volume to the network, capacity independent and capacity restrained approaches. Five methods for a static assignment are available in OmniTRANS software. For capacity independent approach, all or nothing (AON) assignment is implemented, whereas, two methods, namely Frank-Wolfe (FW) algorithm and the method of successive averages (MSA), are used to obtain the user equilibrium (the capacity restrained approach). Furthermore, incremental assignment and a system optimum are also available in OmniTRANS software. A brief discussion of each method is presented below.

Capacity Independent Approach

In the capacity independent approach, known as all or nothing (AON) assignment, the traffic is assigned to the network using the shortest paths determined using a fixed generalized cost without considering the link capacity limitation. Therefore, this method does not account for the congestion effects assuming all drivers have the same route choice criteria and receive the same level of service in terms of travel time and distance. These assumptions likely only hold true where the networks are sparse and uncongested because of the lack of alternative routes and their variety in cost (Sheffi, 1984). However, the main advantage of this method is its use as a basic building block for other types of assignment techniques, e.g. incremental, volume averaging and equilibrium assignments.

Capacity Restrained Approach

In contrast, in the capacity restrained approach, also known as congested assignment, the shortest paths are determined by the generalized cost influenced by the link flow and capacity through the travel time. This is done by an iterative process where trips are loaded onto the network and link travel times are adjusted according to the assignment volume and capacity using a travel time function (Ortuzar and Willumsen, 2011). These models typically endeavour to estimate the equilibrium conditions.

Under this approach, there are three methods for loading trips onto the network, namely incremental, user equilibrium and system equilibrium assignments. In an incremental assignment, the OD matrix is assigned in steps where in each step a fraction of OD matrix is loaded to the shortest paths using all-or-nothing method and the link travel time is calculated. The re-calculated link travel time is used in the following step to find a new shortest path for an O-D pair. Simplicity and practicality are the main advantage of this method, however the fact that an assigned step flow remains in the following step, e.g. short link with small capacity, could lead to unrealistic results. Further details may be found in many references (for example, Garber and Hoel, 2009; Ortúzar and Willumsen, 2011).

In the current research, the user equilibrium assignment (UE) is implemented to obtain the spatial distribution of the traffic volume. It is based on Wardrop's first principle, where no individual trip maker can reduce his/her path cost by switching routes. This principle is also known as the user optimum (Wardrop, 1952). The suitability of the UE method based on two issues (Scott et al., 2006). Firstly, the ability of the method of taking into the account the link functionality level by allocated the user into the best routes in terms of their travel time, e.g. the users can not improve their travel time by changing their routes. Secondly, using the user equilibrium assignment allows the impact of link removal on both link's user and non-users because of rerouting of link's user.

To obtain the user equilibrium, the Frank-Wolfe (FW) algorithm and the method of successive averages (MSA) are also available in OmniTRANS as mentioned earlier. According to Muijlwijk (2012), in practice MSA is the most utilized technique by OmniTRANS users whereas the FW algorithm is a widely used technique in general.

Furthermore, the user equilibrium could be divided into deterministic and stochastic user equilibrium based on the considered generalized cost. The deterministic user equilibrium as defined earlier in this section is based on Wardrop's first principle where the impact of the uncertainties is neglected assuming that the users have a perfect knowledge about the network conditions. However, in the stochastic user equilibrium, equilibrium is achieved when no traveller believes that his/her travel time can be improved by changing routes (Sheffi, 1985). Consequently, the perceived travel costs have to be equal on all used routes rather than the 'real' cost.

4.3.2.2 Dynamic Traffic Assignment

Dynamic traffic assignment (DTA) is used to study the short term variation in the traffic flow due to a disruptive event or traffic management measures. Up to OmniTRANS 6.026 version (used in Chapters 5, 6 and 7), DTA was based only on the dynamic network loading (DNL) with two components, namely the macroscopic dynamic assignment model (MaDAM) along with the junction model. MaDAM model is developed based on METANET model (Messmer and Papageorgiou, 1990) using fluid mechanics principle to calculate the

speed, density and flow of each link segment (Dijkhuis, 2012). Furthermore, DTA uses turning movements (proportions) calculated at each node in the network that was created by the static assignment carried out prior to the MaDAM model to express travellers' behaviour (i.e. route choice). The main drawback of this approach is that modelling route choice in such a way leads to fixed routes during dynamic simulation period despite the variations in road transport network conditions. However, the traffic data obtained from the simulation were based on static assignment as opposed to 'real-world' observations. This approach cannot capture the full effects of unexpected link closure or demand increase, as it does not take into account the impact of imperfect information, traveller behaviour under different conditions, etc. To obtain more realistic results, two issues should be considered; traveller behaviour (e.g. the proportion of travellers who will change their route due to congestion or link closure) and the availability of an en-route choice model implemented within the dynamic traffic assignment model. However, the main aim of the analysis reported in Chapters 5, 6 and 7 is to investigate the ability of the resilience characteristics indicators to reflect the changes of traffic conditions. The results obtained and reported, therefore, assume that all drivers have good knowledge on road transport network condition and the availability of alternative routes. As the modelled period used in this research is the morning peak, it would be quite reasonable to assume that a high proportion of the road users are regular commuters/travellers and nearly all the users have a high level of knowledge about route availability and traffic conditions. Alternatively, in practice a variable message sign or in-vehicle intelligent transport system may update travellers' knowledge of the link closure and alternative routes.

However, to investigate the impact of real-time travel information on the resilience characteristics and the composite resilience index (Chapter 8) the very recent version of OmniTRANS software (Version 6.1.2) (available from May 2014) is implemented. OmniTRANS software (Version 6.1.2) is able to take into account the impact of road transport network conditions on travellers' behaviour by implementing a route choice model within the DTA framework, called StreamLine. StreamLine framework has a number of blocks such as route generation, route choice behaviour, a dynamic network loading model

(including a propagation model and junction model), in addition to traffic management controls. Figure 4.2 presents the main steps in StreamLine framework implemented in OmniTRANS software (Version 6.1.2). A full discussion about the mathematical formulations and model parameters of StreamLine framework could be found in Dijkhuis (2012).

Route Generation

In the route generation block, there are three main processes. Firstly, a shortest path between each OD pair is determined using Dijkstra algorithm similar to the way discussed in Section 4.4.1. A Monte Carlo simulation (repeated random sampling) is, then, carried out to generate a number of alternatives routes for each OD pair. Finally, routes are filtered based on the overlapping and cost between the alternative routes and initial route, leading to exclusion of the alternative routes from the route set (Dijkhuis, 2012).

Route Costs

The demand fraction allocation to a specific route is based on the route cost. In OmniTRANS software (Version 6.1.2), the route costs can be determined using either a reactive or predictive approach.

In the reactive approach, the travel times based on the current situation on the network are calculated by the average speeds obtained from MaDAM on the links at that moment in time. This method is a static approach as it is calculated from a single moment within the simulation. It is mainly used in the first iteration of the simulation owing to the non-availability of data from a previous iteration. Therefore, the results are generally not realistic.

Alternatively, the predictive route costs based on the traffic that is already on the network predicts what the travel time of a route will be. Two methods are built in StreamLine approach to calculate predictive route costs: a method based on cumulative vehicles and the other based on average link speeds. The predictive route costs are far more accurate than the reactive approach but it is more time-intensive.

MaDAM model

As mentioned earlier in Section 4.4.2.2, the macroscopic traffic propagation model in StreamLine is called MaDAM. It is a deterministic macroscopic

modelling tool for traffic flow simulation in road transport networks. It can deal with several traffic conditions, for example free, dense and congested flow conditions. MaDAM divides a link to several segments of equal lengths, where each segment has information on traffic variables including speed, density and flow.

MaDAM estimates the average speed on a link by modifying the existing link speed using relaxation, convection and anticipation terms, that are realistic for motorway traffic. The relaxation term describes how the vehicles adapt their speed according to the fundamental diagram (speed-density diagram), where the density of the link segment at that time is the input of the fundamental diagram. The convection term describes how vehicles change their speed owing to departure and arrival of vehicles. In this term, the difference between the average current segment speed and the previous link segment speed is multiplied by a constant, including the time step size divided by the link length. The anticipation term describes to which extent car drivers anticipate on concentration conditions downstream the road. The mathematical formulation of these three terms are detailed in Dijkhuis (2012).

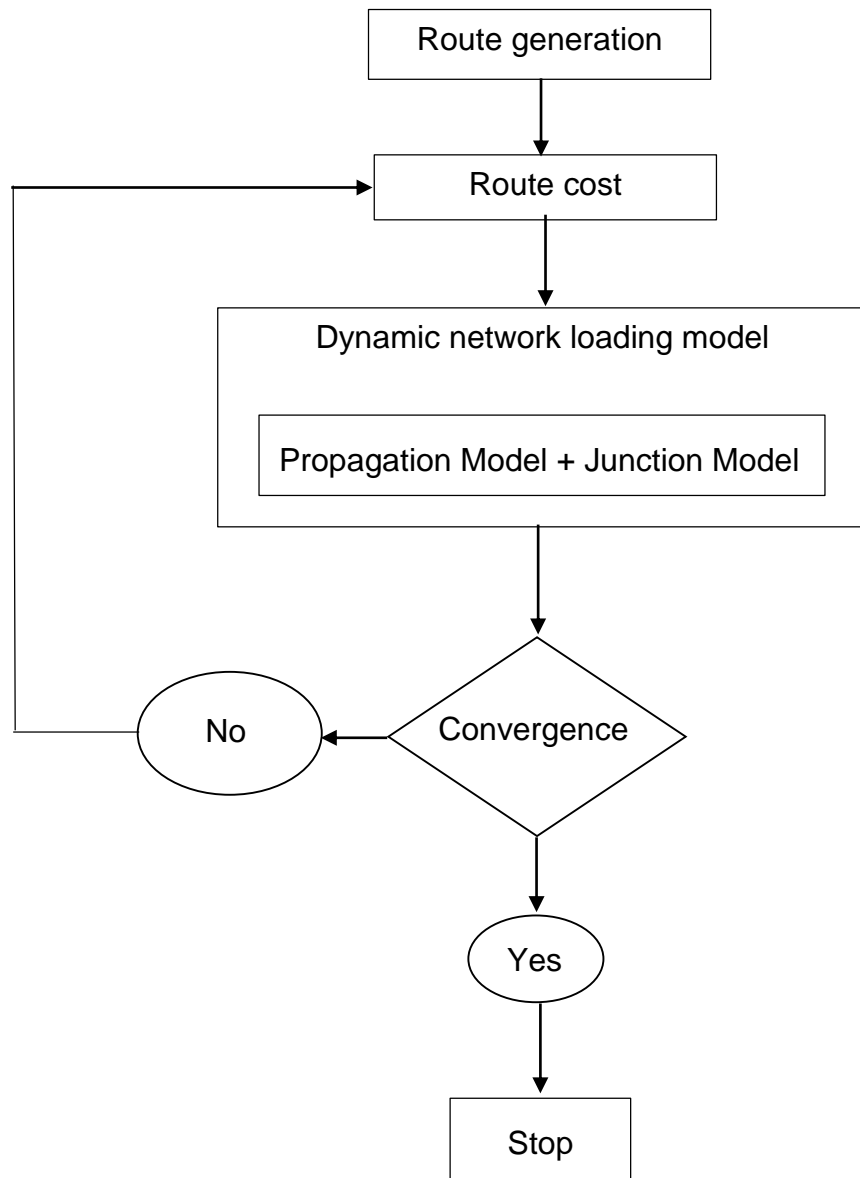


Figure 4.2 Overview of StreamLine model.

4.3.2.3 Junction Modelling

It is very important to consider the impact of junctions in the road transport network modelling to obtain realistic traffic flow as a significant part of travel time delay is experienced at junctions especially in urban areas. For example, Figure 4.3 shows the total zone travel time for the synthetic Delft city road transport network during the morning peak, calculated by summing up all the travel time per zone, with and without considering the junction modelling. The total travel time per zone increases due including the junction modelling as depicted from Figure 4.3.

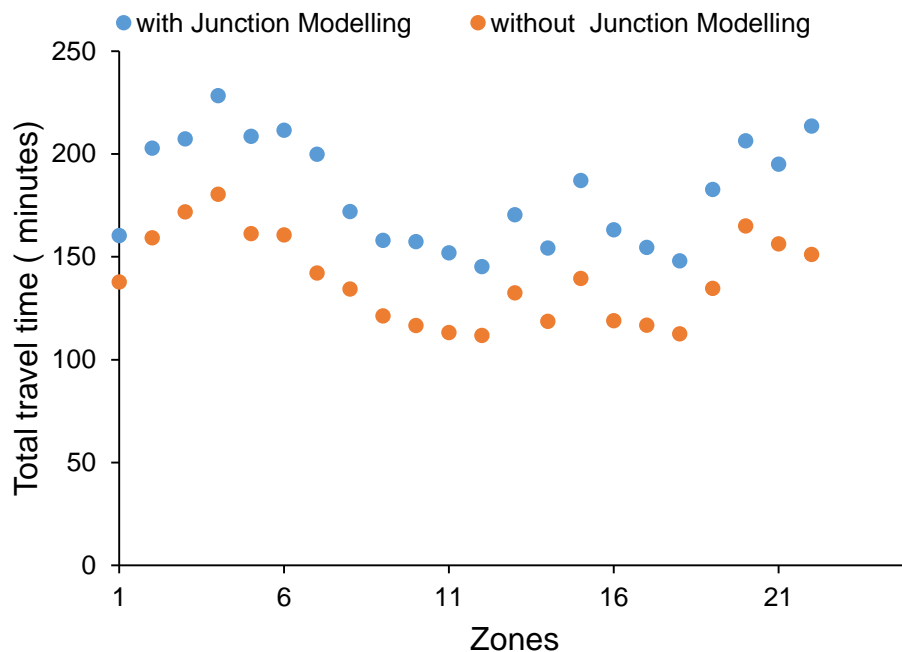


Figure 4.3 Zone total travel time with and without junction modelling.

In OmniTRANS software, the junction model calculates the average delay per vehicle for each turning movement based on a number of parameters taking into account the junction layout, turning flow and optionally signal settings. The calculated turning delays are then applied to the route choice and blocking-back processes of the assignment model in an iterative process.

A number of mathematical formulations based on several investigations (e.g. Brilon, 1995; Akçelik, 1988) are implemented in OmniTRANS software to

calculate the average delay per vehicle for each turning movement based on junction types. OmniTRANS software includes a number of junction types namely:

- Uncontrolled junctions (no signs and/or signals);
- Signalised junctions and roundabouts;
- Sign-controlled junctions (two-way stop, all-way stop and give-way/yield).

Full details on the mathematical formulations for each junction type can be found in OmniTRANS junction modelling on line help (OmniTRANS, 2014).

4.4 Modelling of Real-Time Travel Information in OmniTRANS

The new version of OmniTRANS software (Version 6.1.2) which became available in May 2014 includes a route choice model in the dynamic traffic assignment (DTA) framework. To simulate the influence of real-time travel information a number of route choice stages are included where travellers choose their routes during the simulation period, assuming dynamic user equilibrium is achieved at every route choice stage. This simply means that at every route choice stage, travellers can reduce their travel cost by switching routes assuming that they have real-time travel information enabling them to make a better route selection.

Furthermore, variable sign message (VSM) is also available to consider the influence of real-time travel information on en-route choice. There are two types of VSM; static and dynamic messages that are used to modify the demand fraction of each route (the percentage of the demand of an origin-destination pair that is assigned to a route). In static VSM, a fixed route factor is used to influence the demand fraction of each route during a certain period of time to modify the demand distribution over the available routes. The paired combinatorial logit (PCL) model is applied to influence the demand distribution among the available routes in the dynamic VSM. PCL assigns traffic among alternative routes based on the cross-elasticity between pairs of route

alternatives. In the current simulation, only pre-trip route choice is used; i.e. the route choice is kept fixed during the route choice stage.

The percentage of travellers who may consider changing their route (based on real-time travel information) should be identified in the simulation as it could influence the impact of operating the information system. According to Gao and Wang (2010), several factors could affect traveller responses to the real-time travel information including the level of confidence in the information (i.e. credibility of the information system), traveller experience (i.e. the traveller has full knowledge about route conditions or is new to the route) and his/her route choice criteria. In a group of scenarios in the Delft road transport network case study presented in Chapter 8, the impact of traveller behaviour when real-time travel information is available on the three resilience characteristics has been investigated. In other scenarios, it has been assumed that all travellers consider real-time travel information in selecting their routes.

4.5 Delft City Road Transport Network Overview

A synthetic Delft city road transport network will be used to validate and examine the indicators developed in the following chapters. The synthetic Delft road transport network is supplied with the OmniTRANS software (version 6.022). The network is based on Delft city, but has been simplified and modified so it deviates from the real network for the city somewhat. However, the research is mainly focused on the development of the methodology so in principle it could be applied with any road transport network.

Delft is a city and municipality in the province of South Holland in the Netherlands. The synthetic road transport network of Delft city consists of 25 zones. Zones 1 to 7 are considered as external zones, where there is no socioeconomic data available therefore an external trip matrix is used to represent the generated and attracted trips from/ to these zones. For zones 8 to 23, the socioeconomic data available from the OmniTRANS software tutorial example was used to estimate the network traffic flow using the four-step transport model. The road transport network consists of 1142 links; 483 links are two way and 176 are one way including connectors and different road

types as shown in Figure 4.4. The socioeconomic data available (e.g. residents, number of jobs) were used to estimate the morning peak demand.

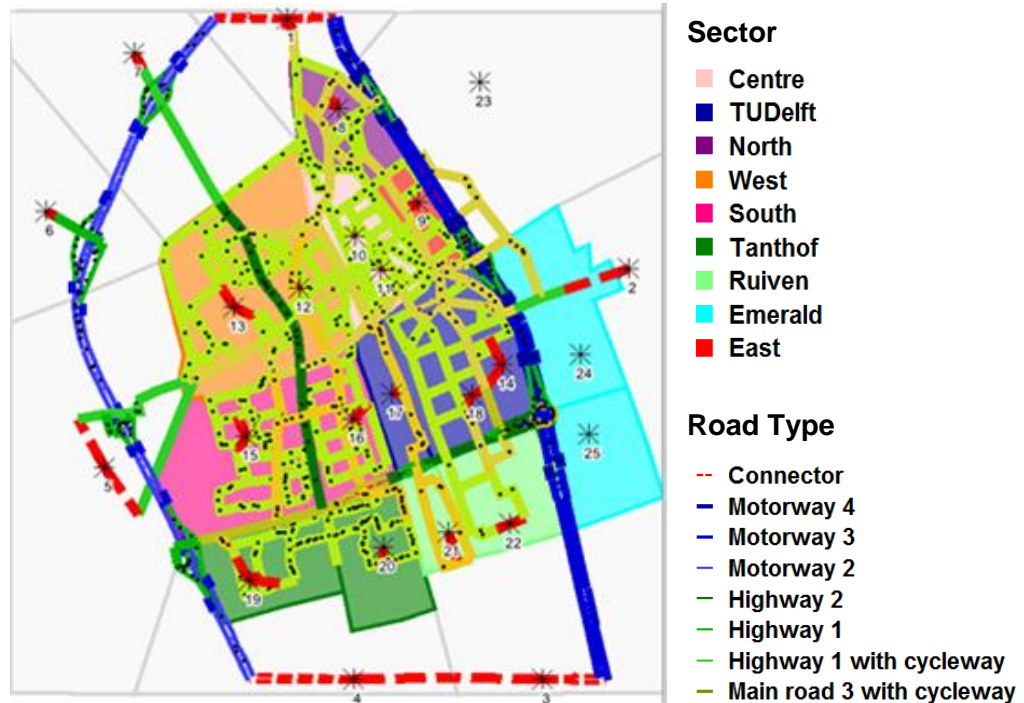


Figure 4.4 The synthetic road transport network of Delft city.

4.6 Summary

This chapter has presented a brief idea about the main principle of the road transport network modelling. The current project will be mainly using the road transport network modelling software such as OmniTRANS as a tool to generate data under different scenarios. Consequently, the presentation was mainly focused on OmniTRANS software and the details of the synthetic Delft city road transport network case study was given. Furthermore, the traffic assignment models, static and dynamic assignments including the new DTA framework (StreamLine) are presented in some detail to explore their role and limitation in the current research. To obtain more realistic results, junction modelling is included in all the scenarios as it could have a significant effect on travel time as explained in Section 4.4.2.3.

It is also to be noted that the main objective of the current investigation is to develop generic methodology for the estimation of road transport network resilience. Thus, intensive calibration studies of the modelling of a road transport network are beyond the scope of this project but for future development.

Chapter 5: Redundancy of Road Transport Networks

5.1 Introduction

As explained in Chapter 3, redundancy is one of the main characteristics of road transport network resilience. Downer (2009) argued that redundancy in technical systems should be understood as a 'design paradigm' as redundancy not only allows designers to design for high reliability, but it also permits them to quantitatively demonstrate reliability. According to Downer (2009), in engineering literature redundancy could be used as an indicator for reliability because it offers 'a powerful and convincing rubric' with which engineers could mathematically establish reliability levels much higher than they could derive from lab testing. Furthermore, Javanbarg and Takada (2007) highlighted the importance in assessing the redundancy of water networks from three perspectives. Firstly, it is very important to consider the redundancy in the network design stage to obtain the optimum network layout. Secondly, the insufficiency of redundancy could have a significant impact on the road transport network level of service, in addition to catastrophic consequences in the case of rapid evacuation (Immers et al., 2004). The third advantage according to Javanbarg and Takada (2007) is that the consideration of redundancy could help in finding the best-recommended mitigation plans against different kind of disruptive events.

The main aim of this chapter is to propose a redundancy indicator that is able to account for the topology characteristics of road transport networks and the dynamic nature of traffic flow, while maintaining the advantages of easy implementation. The proposed indicator is developed based on the entropy concept. The chapter initially presents a general review of the interpretation of redundancy in different disciplines. The development of the proposed redundancy indicator is then described along with a discussion of the entropy concept and its use in transport applications. Two case studies are given in order to investigate the implementation of the proposed redundancy indicator and to test its variations under different scenarios. The methodology also

explores the need to develop an aggregated redundancy indicator in order to evaluate the redundancy of the overall network under different conditions.

5.2 Survey of Redundancy Measures

The concept of redundancy is well established in technological fields such as engineering, computer science, and system design (Streeter, 1992). According to Streeter (1992), the redundancy characteristic of a system refers to its ability to self-organize, e.g. a process whereby internal structure and functions readjust along with changing circumstances. In engineering systems however, the redundancy of a system could be defined as the extent of degradation the system can suffer without losing some specified elements of its functionality (Kanno and Ben-Haim, 2011). Meanwhile, in the transport context it is defined as the availability of several paths for each set of origin destination (OD) pairs in the road transport network. Moreover, Immers et al. (2004) used the redundancy concept to refer to the degree of spare capacity in the network. Meanwhile, Javanbarg and Takada (2007) suggested that the redundancy of the water distribution system does not only imply the availability of several paths but also includes the excess capacity, known in the literature as the spare capacity of the network. Furthermore, (Snelder et al., 2012) suggested two types of redundancy: active and passive redundancy. According to Snelder et al. (2012), alternative routes could be considered as 'active redundancy' that could be preserved under regular conditions by various measures such as road pricing or speed adjustments. For example, the M42 active traffic management (ATM) project increases the capacity and reduces the variability of journey times by allowing the use of the hard shoulder between J3a and J7 together with variable mandatory speed limits during periods of peak demand (Sultan et al., 2008a). Passive redundancy could be used to represent back-up options that are only used in case of disruptive events. As a specific example, the use of fast train services, ferries, coaches to travel across Europe as a result of airline disruptions during the 2010 Eyjafjallajökull Volcano, from 14 to 20 April, (eTN, 2010). Furthermore, Immers et al. (2004) explained that redundancy could be a multi-level concept as follows:

- Strategic level: coordination between activity patterns such as avoiding major road works during peak period or organized events.
- Tactical level: coordination amongst multimodal transport services and networks, similar to passive redundancy explained above. This is also known as 'distributed redundancy' where different systems could deliver the same outcomes (Randles et al., 2011).
- Operational level: to manage the supply-demand relationships in the road transport network by applying different intelligent transport systems (ITS). For example using variable message signs to advise travellers on alternative routes in the case of link closure due to an accident.

Despite the importance of redundancy at both strategic and tactical levels, the current research focuses on proposing an indicator to quantify the operational redundancy of road transport networks (i.e. active redundancy) that could feed into both levels. It has been noted that there is a lack of research into the redundancy concept in the case of road transport networks compared with other networks, such as water distribution networks and power networks. For example there are several indicators (Yazdani and Jeffrey, 2012; Javanbarg and Takada, 2007; Awumah et al., 1991; Hoshiya et al., 2004) that have been developed to investigate the redundancy in the water distribution network using the entropy concept.

In the road transport network, the redundancy concept could be evaluated by considering the static conditions of the network such as road density. Jenelius (2009) pointed out that a higher road density to some extent guarantees a higher availability of alternative paths. However, road density only reflects the impact of the supply side without considering the effect of changes in demand and traffic conditions. Furthermore, road density only considers the fully operational link status e.g. by adding the link length to the whole network length or subtracting link length when the link is fully closed. Hyder (2010) estimated the redundancy value of a link as the total number of motorways, A roads, and B roads within a 10 kilometre radius of the link. However, both approaches (i.e. Hyder, 2010; Jenelius, 2009) introduced static, purely topological indicators. They do not indicate the impact of different traffic

conditions (e.g. the road density or the number of adjacent routes despite the traffic flow conditions of the alternatives) in estimating the redundancy of the link.

Graph theory has also been used to quantify the redundancy of networks by using a number of indicators, such as a clustering coefficient and the number of independent routes (Boccaletti et al., 2006). The clustering coefficient, also known as transitivity, is a measure of redundancy as it represents the overall probability for the network to have interconnected adjacent nodes (Rodrigue et al., 2009), which could be measured by different indicators (Boccaletti et al., 2006). The clustering coefficient is a significant characteristic of road transport network redundancy; however, it only considers the directly neighbouring nodes or links and neglects possible capacity limitations, which may restrict redundancy (Erath et al., 2009b). Similarly, the number of independent routes is not an ideal measure of network redundancy as it is purely a topological measure and is based on an arbitrary threshold (Corson, 2010).

Jenelius (2010) introduced a “redundancy importance” concept as a new way to study the role of the link in network redundancy. The author quantified the importance of redundancy in two ways. Firstly, the importance of flow based redundancy was calculated as the weighted sum of the difference in flow arising from the closure of all links in the network. Secondly, an impact based redundancy importance measure was computed as the weighted sum of the difference in the impact measure arising from the closure of all links in the network.

The above discussion highlights the lack of redundancy research in the transport context compared with the case for water distribution networks and power grids. Furthermore, the redundancy indicator developed should be able to account for the topological characteristics of road transport networks as well as the dynamic nature of traffic flow.

5.3 A Redundancy Model

Based on the previous discussion, the quantification of redundancy requires both traffic flow variations and network topology to be taken into account. In

this research, the level of redundancy has been investigated at the 'node to node' level rather than 'zone to zone'. By doing so, it is possible to identify critical nodes that have a lower value of the redundancy indicator and their impact on the road transport network redundancy overall.

There are many uncertainties associated with road transport networks under different operational conditions. These include the uncertainties related to the supply side (such as link flow under different operational conditions) in addition to uncertain demand. To deal with these uncertainties, the concept of information entropy is adopted as one way of measuring uncertainty in the road transport network. In the following section a brief introduction to the entropy concept is given, followed by an outline of its use in modelling systems.

5.3.1 The Entropy Concept

The concept of entropy was initially proposed by Shannon (1948) to investigate the performance of communication channels and measure the uncertainties. The generic form of the entropy is presented as follows:

$$H(x) = \sum_{i=1}^n p_i \ln(1/p_i) \quad (5.1)$$

where: $H(x)$ is an entropic measure of a system x , n is the total number of the system elements under consideration and p_i represents a system parameter that could be used to identify a certain characteristic of element i . According to Swanson et al. (1997), the entropy measure suggested by Shannon (1948) is a good measure to quantify the existing number of degrees of freedom of a system. In general, the relative link flow is used as a system parameter (Javanbarg and Takada, 2007). For example, if a node (J) has a number of adjacent links (l), then p_i could be the relative flow of link (i), e.g. flow f_i of link i divided by the total flow of node J , i.e. $p_i = f_i / \sum_{k=1}^l f_k$.

According to Wilson (1970) there are two main streams in the use of the entropy concept; namely a measure of some property of a system and a model building tool to maximise the available information. For example, the entropy concept is used widely in water distribution networks (Hoshiya et al., 2002), power grids (Koc et al., 2013) and computer networks (Randles et al., 2011).

In transport literature, the entropy concept is widely accepted as a subjective measure to develop a trip distribution model using entropy-maximising methods (Wilson, 1970). For example, Sun et al. (2011) proposed an entropy based optimization approach to estimate the demand for transfers between the transport modes available in an intermodal transport terminal. Miao et al. (2011) developed an assessment model of capacity reliability for road network from the perspective of route entropy. Allesina et al. (2010) introduced a new quantitative measurement of complexity for a supply network using eight indicators based on the entropy concept.

5.3.2 Junction Redundancy Indicator

Eq. (5.1) above is used here to develop a proposed redundancy indicator for nodes in the road transport network. Two redundancy indicators are developed for each node; an outflow redundancy indicator ($RI1_{out}$) and an inflow redundancy indicator ($RI1_{in}$). $RI1_{out}$ is estimated based on the outbound links whereas $RI1_{in}$ is calculated based on the inbound links of a node, as given in Eqs. (5.2) and (5.3) respectively, below.

$$RI1_{out}(o) = \left(\sum_{b=1}^k \frac{f_{bm}^i}{\sum_{z=1}^k f_{zm}^i} \ln \frac{\sum_{z=1}^k f_{zm}^i}{f_{bm}^i} \right) / \ln(k) \quad (5.2)$$

$$RI1_{in}(o) = \left(\sum_{a=1}^n \frac{f_{am}^i}{\sum_{z=1}^n f_{zm}^i} \ln \frac{\sum_{z=1}^n f_{zm}^i}{f_{am}^i} \right) / \ln(n) \quad (5.3)$$

where: f_{bm}^i is the outbound flow of link b during time interval i using a travel mode m , k is the total number of outbound links attached to node o , f_{am}^i is the inbound flow of link a during time interval i using a travel mode m and n is the total number of inbound links attached to node o (see Figure 5.1). The travel mode m indicates different highway or public transport networks; however, in this research, the focus is on the highway network. The redundancy indicators in Eqs. (5.2) and (5.3) are normalized by $\ln(k)$ or $\ln(n)$ respectively, so as to have a range between 0 and 1 (Nagata and Yamamoto, 2004; Corson, 2010), provided that each link considered should have a traffic flow greater than 0 ($f_{bm}^i > 0$ and $f_{am}^i > 0$), i.e. links with zero traffic flow are not considered. The value of $RI1_{in}(o)$ or $RI1_{out}(o)$ is equal to 0 when either all traffic flow from or

to node (o) is assigned to one link, whilst the maximum value of node redundancy indicator is 1, when the traffic flow is equally distributed over the attached links as proved below.

Assuming a node o having k links where the inbound traffic flow of link i is f_i and the total inbound flow at the node is F , the inflow redundancy indicator $RI1_{in}(o)$ using Eq. (5.3) is:

$$RI1_{in}(o) = \left(\frac{f_1}{F} \ln \left(\frac{F}{f_1} \right) + \frac{f_2}{F} \ln \left(\frac{F}{f_2} \right) + \dots + \frac{f_n}{F} \ln \left(\frac{F}{f_n} \right) \right) / \ln(n)$$

As $0 < f_i/F \leq 1$, therefore $RI1_{in}(o) \geq 0$. When $\frac{f_i}{F} = 1$, other links are not assigned any traffic flow and $RI1_{in}(o) = 0$. Meanwhile, the maximum value of entropy is achieved when the flow over the attached links is equally distributed. In such case, the inbound traffic flow of each link is:

$$f_1 = f_2 = \dots = f_n = \frac{F}{n}$$

Substituting the inbound traffic flow of each link in the above formula produces the inflow redundancy indicator $RI1_{in}$ as follows:

$$RI1_{in}(o) = \left(\frac{1}{n} \ln(n) + \frac{1}{n} \ln(n) + \dots + \frac{1}{n} \ln(n) \right) / \ln(n)$$

$$RI1_{in}(o) = n \left(\frac{1}{n} \ln(n) \right) / \ln(n)$$

$$RI1_{in}(o) = 1$$

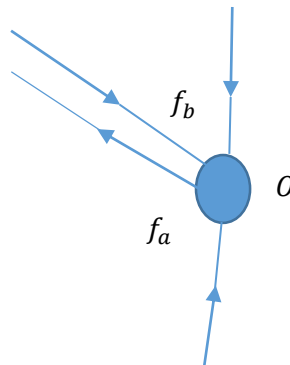


Figure 5.1 Example illustrating the outbound and inbound flow of node o .

The redundancy indicator $RI1(o)$ of a node (o) is eventually controlled by either $RI1_{in}(o)$ or $RI1_{out}(o)$. To identify the more influential redundancy indicator i.e. $RI1_{in}(o)$ or $RI1_{out}(o)$, the junction delay and junction volume capacity ratio are calculated for each direction (i.e. inbound and outbound) and correlated against the respective values of $RI1_{in}(o)$ or $RI1_{out}(o)$. The indicator most strongly correlated with these two junction levels of service identifies the junction redundancy level, as presented in section 5.5 below. The junction delay, $JD_{in}^i(o)$, for inbound links is calculated by the following equation:

$$JD_{in}^i(o) = \sum_{a=1}^k (t_{am}^i - T_{am}^i) f_{am}^i / \sum_{z=1}^k f_{zm}^i \quad (5.4)$$

where: t_{am}^i is the actual travel time for inbound link a during time interval i using travel mode m . k is the total number of inbound links and T_{am}^i is the free flow travel time of inbound link a during time interval i using travel mode m . The junction volume capacity ratio, $JVCR_{in}^i(o)$, is calculated as:

$$JVCR_{in}^i(o) = \sum_a \frac{f_{am}^i}{C_{am}} f_{am}^i / \sum_{z=1}^k f_{zm}^i \quad (5.5)$$

where: C_{am} is the design capacity of link a with mode m . Similarly, the two Eqs. (5.4) and (5.5) can also be adjusted to obtain junction delay and the volume capacity ratio for the outbound links.

5.3.3 Illustrative Examples: the Redundancy Indicator for Simple Transport Network Junctions

In this section, simple numerical examples are presented to examine the validity of the proposed $RI1_{in}$ and $RI1_{out}$ in reflecting the topological properties of the node (e.g. number of attached links) in addition to traffic flow variation. Figure 5.2(a) shows node J with five links (2 inbound and 3 outbound links) whilst the traffic flow for each link is also shown in Figure 5.2. Eqs. (5.2) and (5.3) have been used to calculate $RI1_{out}(J)$ and $RI1_{in}(J)$ as 0.96 and 0.89 respectively, reflecting the impact of the increase in the number of outbound links. However, if the number of inbound links is the same but the flow distributions are different, e.g. node (O) in Figure 5.2(b), $RI1_{in}(O)$

increases to 0.94 due to the change in load distribution (i.e. change from 900/400 to 830/470), whereas $RI1_{out}(0)$ significantly decreases to 0.78 (see Table 5.2) due to the reduction of outbound links. This illustrates how the entropy concept reflects the effect of load distribution on the redundancy level in addition to the influence of the number of attached links in each direction. A higher value of $H(x)$ presented in Eq. (5.1) could be obtained for the same total flow by the uniform distribution of the flow over the incident links, as concluded by Shannon (1948). For example, if the outbound flow of node Z shown in Figure 5.2(c) are equally distributed over the two outbound links, $RI1_{out}$ will be 1, higher than a value for $RI1_{in}$ of 0.90 in the case of a 580/270 flow distribution. Doubling the flow on each link (with the same flow distribution between links) gives the same redundancy indicator. For example $RI1_{in}$ for node Q (see Figure 5.2(d)) has the same value of 0.90 when the link flow increases to 1160 and 540 from 580 and 270, as that shown for node Z in Figure 5.2(c).

This shortcoming of $RI1_{out}$ and $RI1_{in}$ (defined by Eqs. (5.2) and (5.3)) highlights the need to introduce traffic flow variation compared with the link capacity in the definition of the redundancy indicator. In this respect, the redundancy indicator will then incorporate the link spare capacity in line with Immers et al. (2004). The next section introduces alternative redundancy indicators to include the impact of link traffic conditions in the calculation of the redundancy of attached nodes.

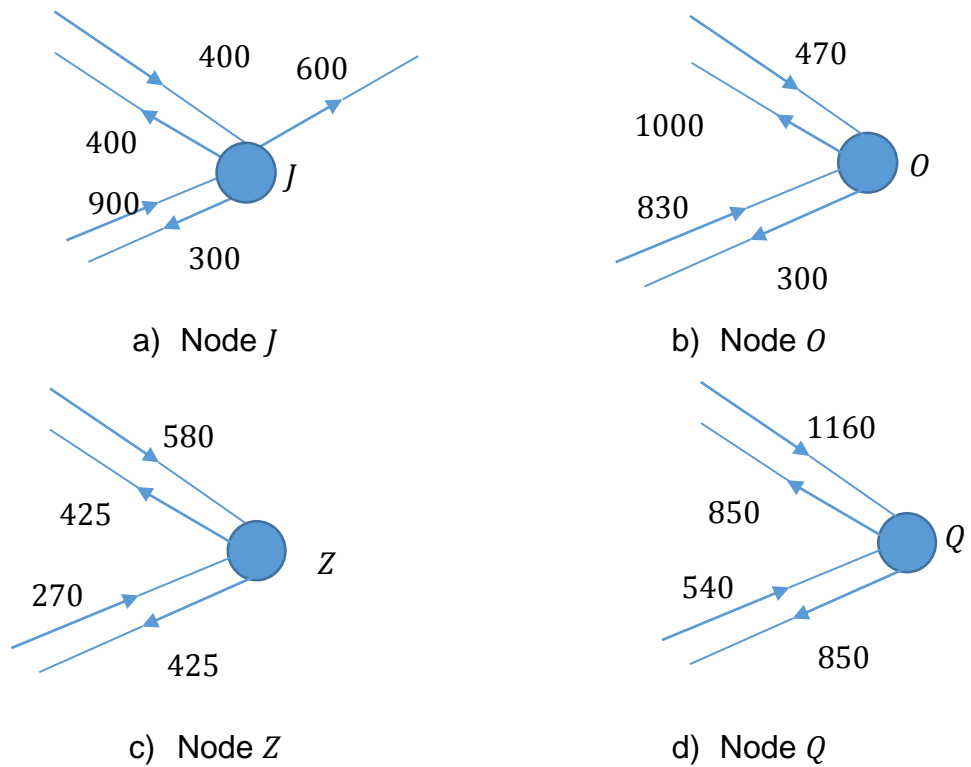


Figure 5.2 Examples illustrating different traffic flow (vehicles/hour) and topology properties.

5.3.4 Impact of Link Spare Capacity and Travel Speed on Junction Redundancy

To reflect the impact of increases/decreases in flow on node redundancy, the relative link spare capacity, ρ_{am}^i is introduced. For an inbound link a , ρ_{am}^i is represented by the percentage of the link spare capacity with respect to the node total spare capacity, as given by Eq. (5.6).

$$\rho_{am}^i = \frac{c_{am} - f_{am}^i}{\sum_{a=1}^n c_{am} - f_{am}^i} \quad (5.6)$$

In addition to the impact of link spare capacity, link average travel speed should also be integrated to reflect the impact of the level of service on the redundancy indicator. As each link has its own free flow speed, the influence of link flow speed on junction redundancy is incorporated here using the relative link speed, RLS and calculated by the following equation:

$$RLS(a) = \frac{v_{am}}{V_{am}} \quad (5.7)$$

where: v_{am} is the average travel speed of link a and V_{am} is the free flow travel speed of link a .

A number of redundancy indicators are proposed here based on different logical combinations of relative link spare capacity, ρ_{am}^i and relative link speed (RLS). The main aim is to identify the best system parameters that can be used to develop a junction redundancy indicator, reflecting the junction topology and traffic flow conditions. Five additional redundancy indicators are therefore introduced as given in Table 5.1. In $RI2_{in}$ and $RI6_{in}$ the relative link spare capacity ρ_{am}^i is used as the system parameter; however, in $RI6_{in}$, the calculated entropy for each link is weighted by the relative link speed, RLS_a , to account for the dynamic flow variation. In contrast the effect of the relative link speed, RLS_a , is included in the system parameter of $RI3_{in}$. The system parameter p_i used in $RI3_{in}$ is therefore given by the multiplication of the relative link speed RLS_a by the relative link spare capacity, ρ_{am}^i . Otherwise, the system parameter used in $RI5_{in}$ is the relative link speed RLS_a multiplied by the relative link capacity with respect to the total junction capacity $\frac{C_{am}}{\sum_{a=1}^n C_{am}}$. In the final redundancy indicator considered, $RI4_{in}$, the relative link spare capacity $(C_{am} - f_{am}^i)$ to link capacity C_{am} has been employed as the system parameter. However, the calculated entropy for each link has been weighted by the relative link speed RLS_a in a similar way to $RI6_{in}$.

Table 5.1 System parameters used in the six redundancy indicators considered.

	System parameter	Redundancy indicator formulation	System parameter explanation
$RI1_{in}$	$p_i = \frac{f_{am}^i}{\sum_{z=1}^n f_{zm}^i}$	$RI1_{in}(o) = \left(\sum_{a=1}^n \frac{f_{am}^i}{\sum_{z=1}^n f_{zm}^i} \ln \frac{\sum_{z=1}^n f_{zm}^i}{f_{am}^i} \right) / \ln(n)$	Link flow f_{am}^i with respect to the total junction flow $\sum_{z=1}^n f_{zm}^i$
$RI2_{in}$	$p_i = \rho_{am}^i$	$RI2_{in}(o) = \left(\sum_{a=1}^n \rho_{am}^i \ln (1/\rho_{am}^i) \right) / \ln(n)$	Relative link spare capacity ρ_{am}^i
$RI3_{in}$	$p_i = RLS_a \rho_{am}^i$	$RI3_{in}(o) = \left(\sum_{a=1}^n (RLS_a \rho_{am}^i) \ln (1/(RLS_a \rho_{am}^i)) \right) / \ln(n)$	Relative link speed RLS_a multiplied by relative link spare capacity ρ_{am}^i
$RI4_{in}$	$p_i = \frac{C_{am} - f_{am}^i}{C_{am}}$	$RI4_{in}(o) = \left(\sum_{a=1}^n RLS_a \left(\frac{C_{am} - f_{am}^i}{C_{am}} \right) \ln \left(\frac{C_{am}}{C_{am} - f_{am}^i} \right) \right) / \ln(n)$	Relative spare capacity ($C_{am} - f_{am}^i$) to link capacity C_{am} . However, the calculated entropy for each link is weighted by the relative link speed RLS_a
$RI5_{in}$	$p_i = RLS_a \frac{C_{am}}{\sum_{a=1}^n C_{am}}$	$RI5_{in}(o) = \left(\sum_{a=1}^n (RLS_a \frac{C_{am}}{\sum_{a=1}^n C_{am}}) \ln \left(\frac{\sum_{a=1}^n C_{am}}{RLS_a C_{am}} \right) \right) / \ln(n)$	Relative link speed RLS_a multiplied by relative link capacity with respect to the total junction capacity $\frac{C_{am}}{\sum_{a=1}^n C_{am}}$
$RI6_{in}$	$p_i = \rho_{am}^i$	$RI6_{in}(o) = \left(\sum_{a=1}^n RLS_a (\rho_{am}^i) \ln(1/\rho_{am}^i) \right) / \ln(n)$	Relative link spare capacity ρ_{am}^i . However, the calculated entropy for each link is weighted by the relative link speed RLS_a

Tables 5.2 and 5.3 show the flow of links and the values of $RI1_{in}$, $RI1_{out}$, $RI2_{in}$ and $RI2_{out}$ for the four nodes presented in Figure 5.2 and two different road capacities of 1200 and 2200 vehicles per hour (vehicles/hour), respectively. Other redundancy indicators are not presented in Tables 5.2 and 5.3 as their calculation requires the relative link speed value RLS . The values of each link capacity, C_{am} , could vary based on the road type and speed limit. For example, C_{am} could be equal to 1200, 1500, or 1800 vehicles/hour in case of urban links whereas 2200 or 2400 vehicles/hour is more appropriate for a motorway link type. In this numerical example, C_{am} is taken equal to 1200 (Table 5.2) and 2200 (Table 5.3) vehicles/hour to investigate the impact of link capacity on the redundancy indicators. Taking the impact of spare capacity into account leads to a decrease in the redundancy indicator when the flow increases; however, its importance is highlighted when the flow doubles but has the same distribution (see Table 5.2).

For example in Table 5.2, nodes Z and Q have the same number of links but double the flow, consequently $RI2_{in}(Q)$ is decreased compared with $RI2_{in}(Z)$, whereas $RI1_{in}(Q)$ is equal to $RI1_{in}(Z)$. Furthermore, the outbound flow for both nodes, Z and Q are equally distributed over the two outbound links, leading to the same $RI1_{out}$ and $RI2_{out}$ for the two nodes Z and Q . This reflects the ability of $RI2_{in}$ to consider the impact of flow increases, other than in the case of equally distributed flow. To investigate the impact of flow distribution on node redundancy, node (O) has an inbound flow distribution different to that of the outbound flow. This leads to different inbound and outbound redundancy indicators. It has been found that the increase in a link flow compared with the other adjacent links leads to a decrease in the redundancy indicators even though the total flow remains the same. To investigate the impact of the number of links adjacent to the node, node (J) has been introduced with 2 inbound links, meanwhile the number of outbound links are 3. Consequently both indicators, $RI1_{out}$ and $RI2_{out}$ are higher than the inbound redundancy indicators $RI1_{in}$ and $RI2_{in}$, respectively, reflecting the ability of both indicators to represent the topological aspects of nodes.

Comparing Tables 5.2 and 5.3, the increase in link capacity (from 1200 to 2200 vehicles/hour) leads to an increase in $RI2_{in}$ and $RI2_{out}$ of different

percentages, whereas $RI1_{in}$ and $RI1_{out}$ are the same for each node. For example, $RI2_{in}$ and $RI2_{out}$ of nodes (J), (O), (Z) and (Q) increase due to capacity increases and as other properties such as flow distribution and total flow remain the same.

Table 5.2 Redundancy indicators for nodes shown in Figure 5.2 using $c_{am}=1200$ vehicles/hour.

Node	Inbound links flow	$RI1_{in}$	$RI2_{in}$	Outbound links flow	$RI1_{out}$	$RI2_{out}$
J	900/400	0.89	0.85	600/400/300	0.96	0.99
O	830/470	0.94	0.92	1000/300	0.78	0.68
Z	580/270	0.90	0.97	425/425	1.0	1.0
Q	1160/540	0.90	0.32	850/850	1.0	1.0

Table 5.3 Redundancy indicators for nodes shown in Figure 5.2 using $c_{am}=2200$ vehicles/hour.

Node	Inbound links flow	$RI1_{in}$	$RI2_{in}$	Outbound links flow	$RI1_{out}$	$RI2_{out}$
J	900/400	0.89	0.98	600/400/300	0.96	1.0
O	830/470	0.94	0.99	1000/300	0.78	0.96
Z	580/270	0.90	0.99	425/425	1.0	1.0
Q	1160/540	0.90	0.96	850/850	1.0	1.0

The suitability of the redundancy indicators presented in Table 5.1 is further applied on two case studies, namely a synthetic road transport network of Delft city and Junction 3a of the M42 motorway near Birmingham, as explained in sections 5.5 and 5.6, respectively, of the chapter.

5.4 Network Redundancy Indicator

Despite the importance of the node redundancy based indicator in identifying nodes with low redundancy, there is still a need, however, for an aggregated redundancy indicator in order to evaluate the redundancy of the whole network

under different conditions. An aggregated indicator could be used to assess the effectiveness of different policies or technologies on the improvement of overall network redundancy.

The redundancy indicators, $RI_{in}(o)$ and $RI_{out}(o)$, for all the nodes in the road transport network are calculated first. A network redundancy indicator (NRI_{in}) is developed by summing a weighted RI_{in} for all the nodes in the network as given in Eqs. (5.8) and (5.9) below. The weight considered in the equations below is the node flow with respect to the total network flow.

$$NRI_{in} = \sum_{o=1}^N \frac{f_{om}^i}{\sum_{o=1}^N f_{om}^i} RI_{in}(o) \quad (5.8)$$

$$NRI_{out} = \sum_{o=1}^N \frac{f_{om}^i}{\sum_{o=1}^N f_{om}^i} RI_{out}(o) \quad (5.9)$$

where f_{om}^i is the total flow of node o during the time interval i using a travel mode m and N is the total number of nodes in the road transport network.

5.5 Case Study 1: Delft Road Transport Network

A synthetic road transport network of Delft city is used to illustrate the redundancy of road network under different scenarios using the proposed methodology. The Delft road transport network consists of 25 zones, two of which are under development (24 & 25) and 1142 links. 483 links are bi-directional and 176 are one-way including connectors and different road types. The Delft road transport network demonstrates a realistic network size, in addition to the availability of socioeconomic data of Delft in OmniTRANS software (Version 6.024). A full description of the Delft city road transport network is given in Chapter 4.

5.5.1 Redundancy Indicators of Various Nodes in Delft Road Transport Network

In the case study undertaken here the OmniTRANS modelling software (Version 6.024) has been employed to obtain the spatial distribution of the traffic volume using the user equilibrium assignment (UE). UE is based on

Wardrop's first principle whereby no individual trip maker can reduce his/her path cost by switching routes. This principle is also known as the user optimum (Wardrop, 1952). The mathematical formulation of UE is explained in detail in (Ortúzar and Willumsen, 2011). Junction modelling available in OmniTRANS software is also integrated with UE model to enhance the network simulation.

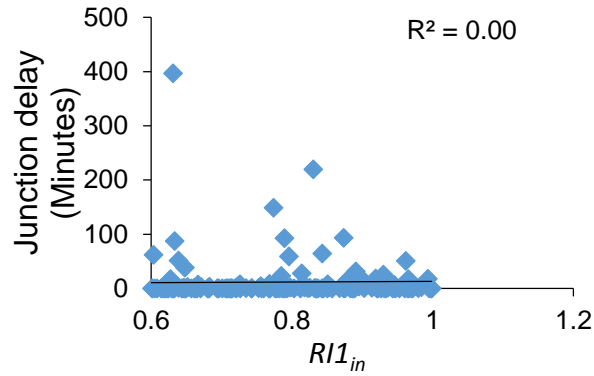
The output from OmniTRANS (version 6.024) includes traffic flow in various links connected to each network node. A computer programme has been developed using MATLAB (R2011a) to calculate RI_{out} and RI_{in} for each node using the different equations presented in Table 5.1.

The proposed indicators are calculated under the same network and traffic conditions to test the ability of the indicator to reflect the redundancy concept. The aim of using different performance parameters is to find out the most suitable one to develop the redundancy indicator. Each proposed indicator is calculated for each junction using MATLAB code and compared with the junction delay in adjacent links. For example, the inbound redundancy indicator of a junction is compared with the junction delay for inbound links, whereas the outbound redundancy indicator of this node is compared with the junction delay of outbound links. Furthermore, in the case of a strong correlation between a redundancy indicator and junction delay or volume capacity ratio, each redundancy indicator is classified according to the junction type and investigated further. The following analysis focuses on RI_{in} only, given there was no correlation between any RI_{out} and either the junction delay or volume capacity ratio.

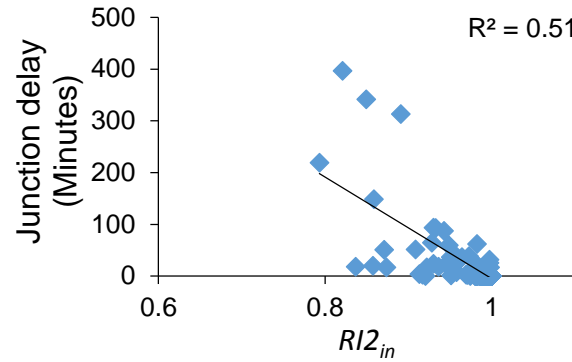
Figure 5.3 shows the correlation between the proposed redundancy indicators and junction delay. Figure 5.3(a) shows the redundancy indicator ($RI1_{in}$) developed based on relative link flow with junction delay. The analysis shows no correlation between $RI1_{in}$ and junction delay as depicted by Figure 5.3(a) and indicated by the coefficient of determination $R^2 = 0.0$. Figure 5.3(b) indicates a stronger correlation between the redundancy indicator ($RI2_{in}$) and the relative spare capacity and total junction delay ($R^2 = 0.51$). A further improvement in the correlation between the redundancy indicator $RI3_{in}$ developed from the relative link speed and junction delay is shown in Figure

5.3(c), where $R^2 = 0.6$. The redundancy indicator $RI4_{in}$ has a very low correlation ($R^2 = 0.12$), with junction delay as presented in Figure 5.3(d). In a similar way, the correlation of $RI5_{in}$ and $RI6_{in}$ with junction delay is presented in Figures 5.3(e) and 5.3(f). $RI5_{in}$ demonstrated a very weak correlation but $RI6_{in}$ exhibits a strong correlation with junction delay.

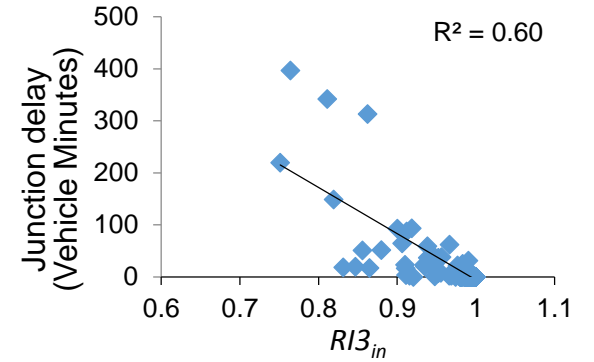
In addition, the correlation between the junction volume capacity ratio (Eq. 5.5), and the redundancy indicators are presented in Figure 5.4. It was found that $RI4_{in}$ is strongly correlated with the junction volume capacity ratio ($R^2 = 0.9$ as shown in Figure 5.4(d)), indicating the unsuitability of $RI4_{in}$ to model junction redundancy, as redundancy should be inversely proportional to the junction volume capacity. $RI6_{in}$, $RI3_{in}$, and $RI2_{in}$ exhibit moderate correlation with the junction volume capacity ratio (0.58, 0.50 and 0.47, respectively), as depicted from Figure 5.4. In contrast, both $RI1_{in}$ and $RI5_{in}$ show a very weak correlation with the junction volume capacity ratio as shown in Figures 5.4(a) and 5.4(e). The above analysis led to the exclusion of $RI1_{in}$, $RI4_{in}$ and $RI5_{in}$ as redundancy indicators from any further analysis.



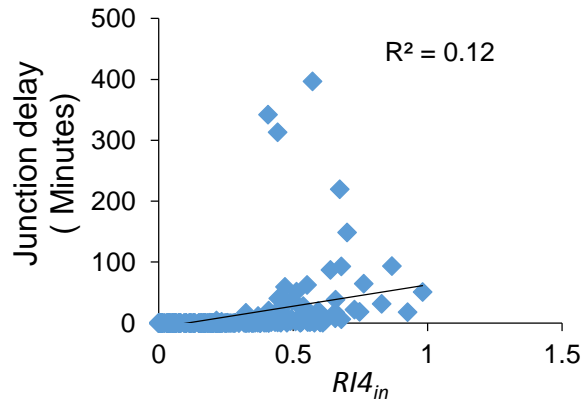
(a) $RI1_{in}$ and junction delay



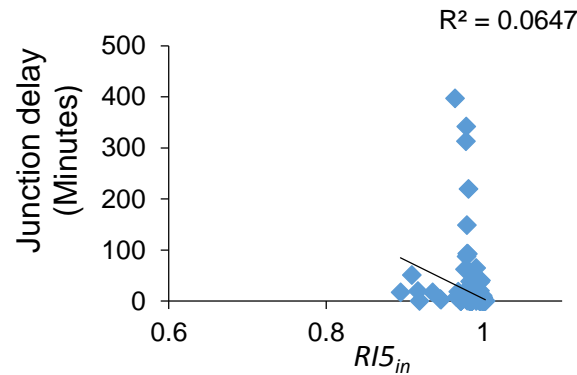
(b) $RI2_{in}$ and junction delay



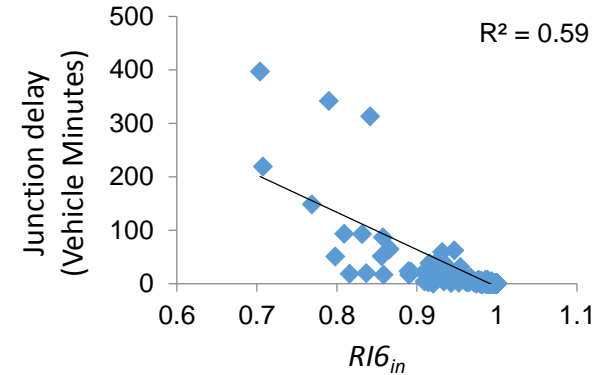
(c) $RI3_{in}$ and junction delay



(d) $RI4_{in}$ and junction delay

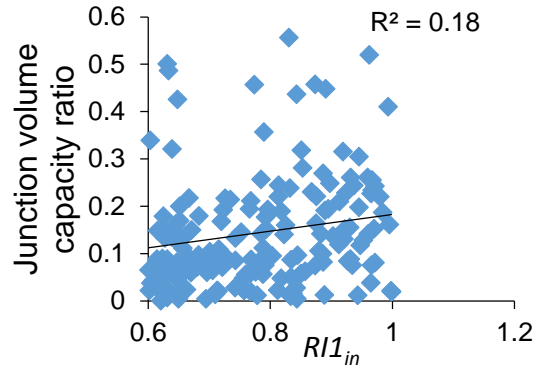


(e) $RI5_{in}$ and junction delay

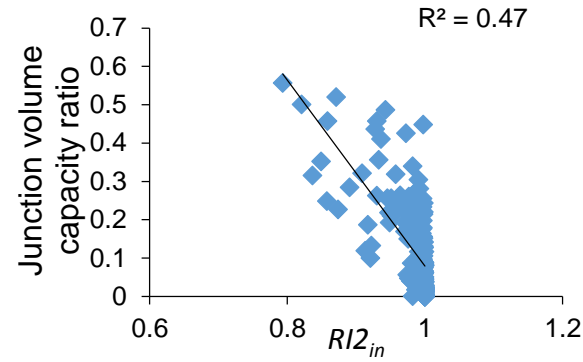


(f) $RI6_{in}$ and junction delay

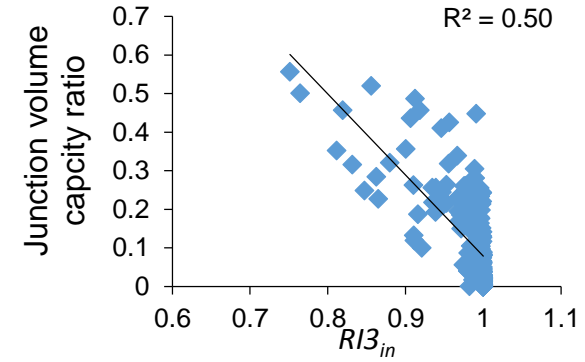
Figure 5.3 Correlation between different redundancy indicators and junction delay.



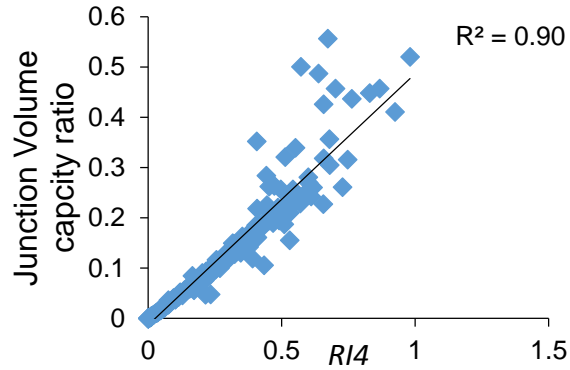
(a) $RI1_{in}$ and Junction volume capacity ratio



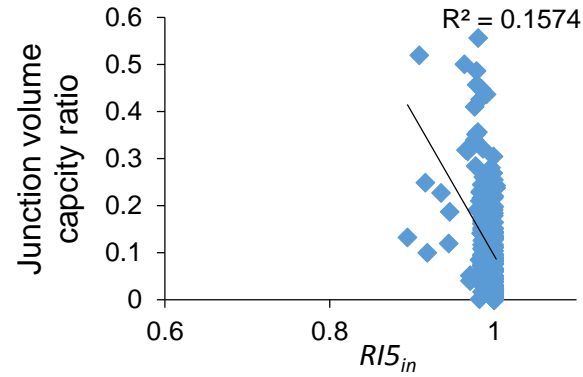
(b) $RI2_{in}$ and Junction volume capacity ratio



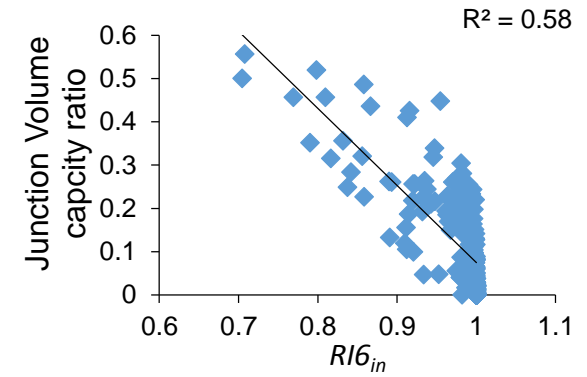
(c) $RI3_{in}$ and Junction volume capacity ratio



(d) $RI4_{in}$ and Junction volume capacity ratio



(e) $RI5_{in}$ and junction volume capacity ratio



(f) $RI6_{in}$ and junction volume capacity ratio

Figure 5.4 Correlation between different redundancy indicators and Junction volume capacity ratio.

Table 5.4 gives a summary of R^2 values of the remaining three redundancy indicators for different junction types. In general, it suggests that $RI3_{in}$ and $RI6_{in}$ are the most suitable redundancy indicators as they can reflect junction delay and volume capacity ratio for different junction types, as indicated by the high value of R^2 . Furthermore, the analysis of $RI2_{in}$ based on junction type shows that there is variation from one junction type to another. For example, the highest R^2 , 0.76, between $RI2_{in}$ and total junction delay is for an equal priority junction type, followed by the roundabout junction type (see Table 5.4). The lowest value of R^2 (=0.24) between $RI2_{in}$ and total junction delay is for a giveaway junction type, as depicted in Table 5.4. Similarly, the correlation between $RI2_{in}$ and junction volume capacity ratio varies according to the junction type.

R^2 for $RI3_{in}$ with junction delay for all junction types is higher than those for $RI2_{in}$, except for the roundabout junction type (which decreases by 4%). The highest increase occurs for the giveaway junction type, where R^2 increases by 64% (see Table 5.4). Regarding the correlation between $RI3_{in}$ and junction volume capacity ratio, two junction types (i.e. equal priority and giveaway junction types), show some improvement over $RI2_{in}$ (see Table 5.4). For the other two types (i.e. signalized junction and roundabout), the R^2 value between $RI3_{in}$ and the junction volume capacity ratio has declined compared to that between $RI2_{in}$ and junction volume capacity ratio. Table 5.4 also confirms the high correlation of $RI6_{in}$ with junction delay and junction volume capacity ratio for different junction types. Overall, Table 5.4 indicates that the suitability of each redundancy indicator relies on the junction type. However, $RI2_{in}$ has generally a lower correlation with junction delay and the junction volume capacity ratio for different junction types than either $RI3_{in}$ or $RI6_{in}$. As a result, $RI3_{in}$ and $RI6_{in}$ are examined further below.

Table 5.4 Summary of R^2 of various redundancy indicators with junction delay (JD) and volume capacity ratio (v/c).

Redundancy index	All junction type		Junction Type							
			Equal priority		Give way junction		Signalized junction		Roundabout junction	
	JD	v/c	JD	v/c	JD	v/c	JD	v/c	JD	v/c
$RI2_{in}$	0.51	0.47	0.76	0.44	0.24	0.25	0.48	0.72	0.75	0.81
$RI3_{in}$	0.60	0.50	0.80	0.60	0.67	0.49	0.49	0.40	0.72	0.52
$RI6_{in}$	0.59	0.58	0.81	0.60	0.65	0.61	0.51	0.50	0.73	0.4

Note: R^2 = coefficient of determination.

In the following, both $RI3_{in}$ and $RI6_{in}$ are calculated for a small number of junctions from the synthetic Delft road network to show their validity. $RI3_{in}$ and $RI6_{in}$ have been selected as they exhibited a reasonably consistent performance for various junction types. Table 5.5 shows four selected junctions from the synthetic Delft road network with the flow, average speed, free flow speed and capacity of their inbound links along with the calculated values of $RI3_{in}$ and $RI6_{in}$. The calculated values of both redundancy indicators show the impact of spare capacity and speed variations. For example, node 5001 is connected with two inbound links with a very low traffic flow compared with their link capacity (i.e. junction volume capacity ratio = 0.07) and average speed equal to free flow speed (junction delay = 0) exhibits a maximum value of $RI3_{in}$ (=1) and $RI6_{in}$ (=1). Node 6856 has 3 inbound links with a slightly high traffic flow compared with link capacity (=0.64) in one link, causing a reduction in its average speed (junction delay = 23.53 min and volume capacity ratio = 0.26), and therefore, $RI3_{in}$ = 0.91 and $RI6_{in}$ = 0.88. Furthermore, node 6983 connected with inbound links has a higher junction delay time and volume capacity ratio than node 6856, consequently, its $RI3_{in}$ and $RI6_{in}$ are lower than node 6858 redundancy indicators as presented in Table 5. Furthermore, to compare the effect of the variation in junction delay and the volume capacity ratio on the redundancy indicators, node 7094 was chosen as it has a higher junction delay and lower volume capacity ratio than node 6983. The calculated values of $RI3_{in}$ and $RI6_{in}$ for junction 7094 are 0.81 and 0.79 respectively. These are higher than the calculated redundancy indicators for junction 6983, indicating that both indicators experienced more sensitivity to the increase in junction volume capacity ratio than the increase in junction delay.

Table 5.5 $RI3_{in}$ and $RI6_{in}$ values for selected nodes in road transport network of Delft city.

Node number	Inbound links				Junction delay (min)	Junction volume capacity ratio	$RI3_{in}$	$RI6_{in}$
	Link flow (vehicles/hour)	Link capacity (vehicles/hour)	Link speed (km/hr)	Link free flow speed (km/hr)				
5001	198	1800	50	50	0	0.07	1	1
	41.04	1800	50	50				
6856	773	1200	29.86	35	23.53	0.26	0.91	0.88
	142	1200	35	35				
	32	1200	35	35				
6983	293	2200	70	70	219.33	0.56	0.75	0.67
	1844	2200	55.4	70				
	1538	2200	61.8	70				
7094	1483	1800	35.7	50	341.72	0.35	0.81	0.79
	225	1500	39.98	40				
	88	2800	50	50				

5.5.2 Impact of Demand Variations on Redundancy Indicators of Delft Road Transport Network

The impact of variations in demand on $RI3_{in}$ and $RI6_{in}$ in addition to the network redundancy indicator (NRI) for the Delft road transport network was investigated using different departure rates during the morning peak. $RI3_{in}$ and $RI6_{in}$ were calculated from the equations presented in Table 5.1, whereas Eq. (5.8) is implemented to calculate the network redundancy indicators $NRI3_{in}$ and $NRI6_{in}$.

Figure 5.5 shows the variations of $NRI3_{in}$ and $NRI6_{in}$ under uniformly distributed departure rate, whilst Figure 5.6 plots the variations of $NRI3_{in}$ and $NRI6_{in}$ under different departure rates. Figure 5.5 shows that as the load rate stays constant, $NRI3_{in}$ and $NRI6_{in}$ are also constant; however, $NRI3_{in}$ is larger than $NRI6_{in}$. Otherwise, the redundancy level measured by $NRI3_{in}$ and $NRI6_{in}$ follows an opposite trend to the departure rate as depicted in Figure 5.6, i.e. decreases with the departure rate increase. Similarly, both network indicators, $NRI3_{in}$ and $NRI6_{in}$ follow an opposite trend to the total delay (Vehicle hour) as shown in Figure 5.7. This leads to the conclusion that the proposed network indicators $NRI3_{in}$ and $NRI6_{in}$ are able to reflect the impact of demand variation under the same network condition.

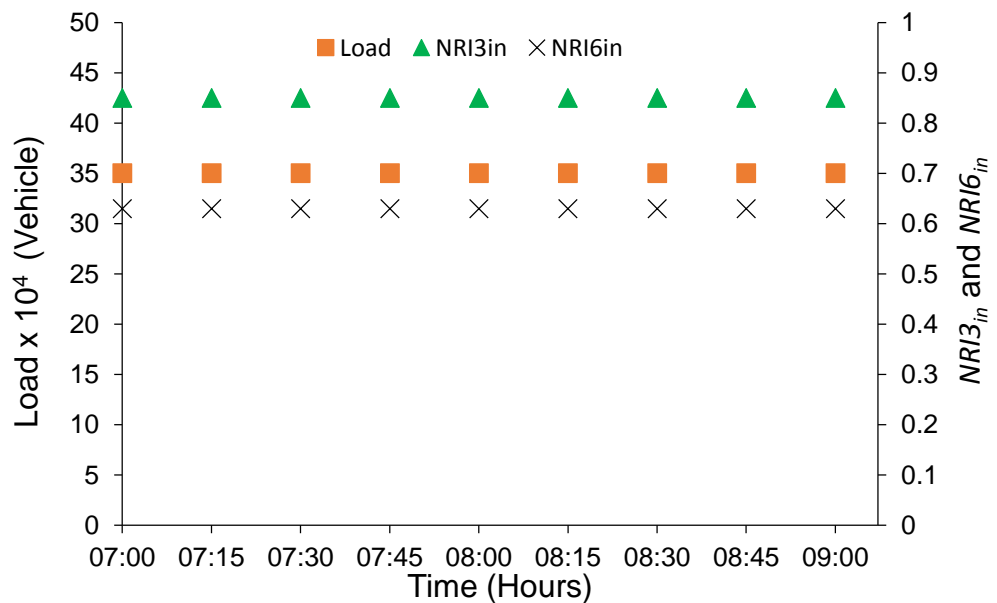


Figure 5.5 $NRI3_{in}$ and $NRI6_{in}$ under uniform distributed departure rates.

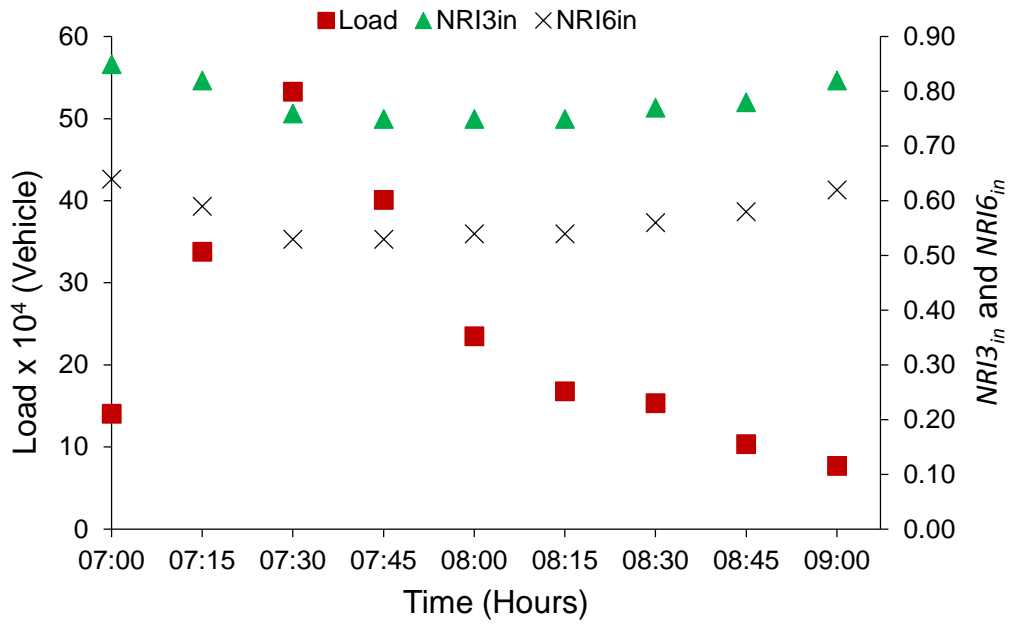


Figure 5.6 NRI_s and network load under different departure rates.

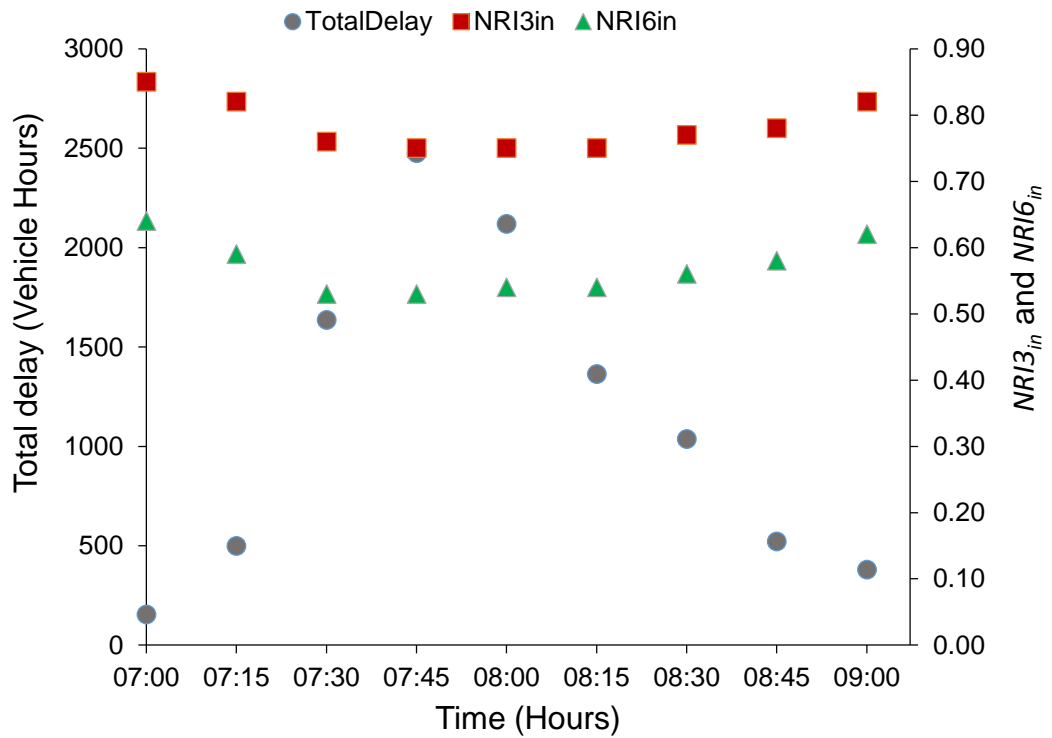


Figure 5.7 NRI_{3in} and NRI_{6in} and total delay under different departure rates.

5.5.3 Impact of Supply Variations on Redundancy Indicators of Delft Road Transport Network

In this analysis, the ability of $NRI3_{in}$ and $NRI6_{in}$ to capture the impact of reductions in network capacity under the same variations of demand is examined. Overall network capacity could be reduced in real life conditions due to the effect of network wide events such as heavy rain or snowfall. This group of scenarios was undertaken using a reduced capacity of 2, 4 and 10% in order to model the impact of a weather related event. Figure 5.8 shows the variations in the network redundancy indicator, $NRI3$, for the variations in supply (as stated above) and the same variation in departure rate shown in Figure 5.6. $NRI3$ shows variations during the modelling period (7:00-9:00) in the case of reduced capacity compared with full network capacity as depicted in Figure 5.8. In general, the largest reduction of network redundancy level occurs at 10% capacity reduction (see the difference between $NRI3_{in}$ calculated for full capacity and $NRI3_{in}$ for 10% capacity reduction) under different departure rates. Figure 5.9 presents the total delay for the full network condition in addition to the reduced capacity scenarios. Figures 5.8 and 5.9 indicate that the network redundancy for different network conditions follows an opposite trend as the total delay for the same network conditions. For example at 7:30am, $NRI3_{in}$ and the total delay for the network at: a) full capacity, b) 2% and c) 4% reduction are almost the same. When the network capacity reduction increased to d) 10%, more delay is experienced by the network and $NRI3_{in}$ is lower than the previous cases.

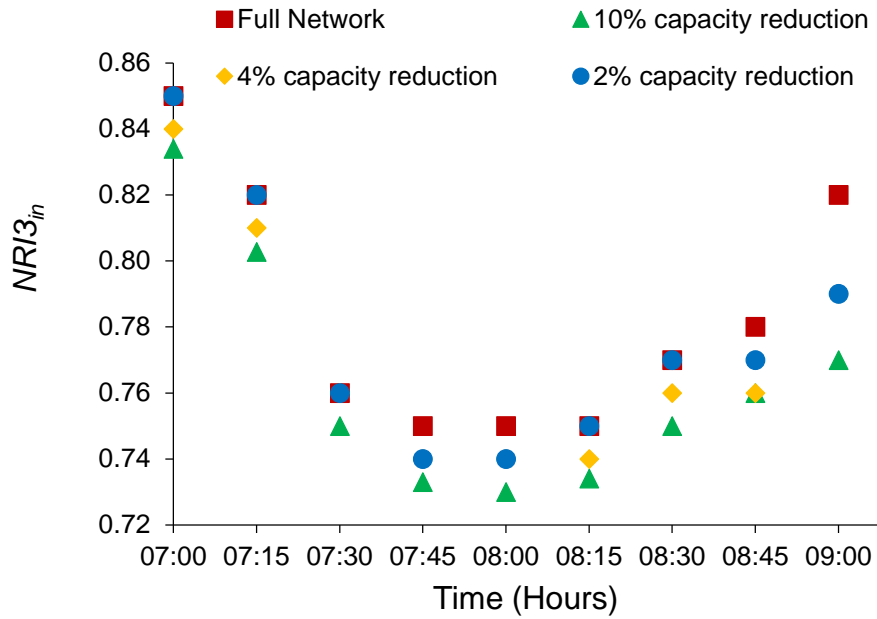


Figure 5.8 $NR/3_{in}$ under different departure rates and network capacity.

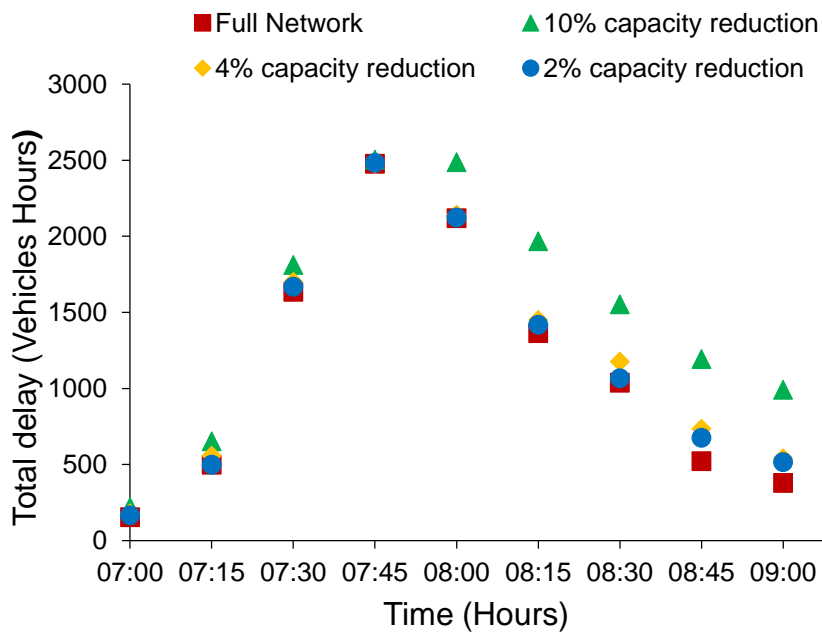


Figure 5.9 Total delay under different capacity reduction.

5.6 Case Study 2: Junction 3a in M42

Junction 3a in M42 motorway shown in Figure 5.10 was also employed to investigate the applicability of the proposed redundancy indicators to reflect real life conditions. The choice of Junction 3a in M42 is due to the fact that the

junction was a part of Active Traffic Management (ATM) scheme by the Highways Agency in 2006, therefore it is possible to study the variation of redundancy under different conditions. The scheme has enhanced the performance of M42 between J3a and J7 by the temporary usage of the hard shoulder to increase the route capacity from 3 lanes (3L) to 4 lanes (4L), jointly with the use of variable mandatory speed limits (VMSL) during periods of peak demand (Sultan et al., 2008b). In this study, four time periods were chosen to check the scheme effectiveness i.e. from October 2002 to April 2003 (NO-VMSL), from January 2006 to April 2006 (3L-VMSL), from October 2006 to April 2007 (4L-VMSL), and from January 2007 to April 2007 (4L-VMSL), as indicated in Table 5.6. According to Sultan et al. (2008a), the period October 2006 to April 2007 could be a suitable period to represent the influence of the full scheme, 4 lanes jointly with variable mandatory speed limits (4L-VMSL). Furthermore, the period October 2002 to April 2003 represent the pre-scheme period (NO-VMSL). Furthermore, the periods January 2006 to April 2006 and January 2007 to April 2007 could be implemented to compare between 3L-VMSL and 4L-VMSL, respectively.



Figure 5.10 Junction 3a in M42 motorway near Birmingham (© Crown Copyright and database rights 2014; an Ordnance Survey/EDINA-supplied service).

Table 5.6 Time periods considered for scheme effectiveness.

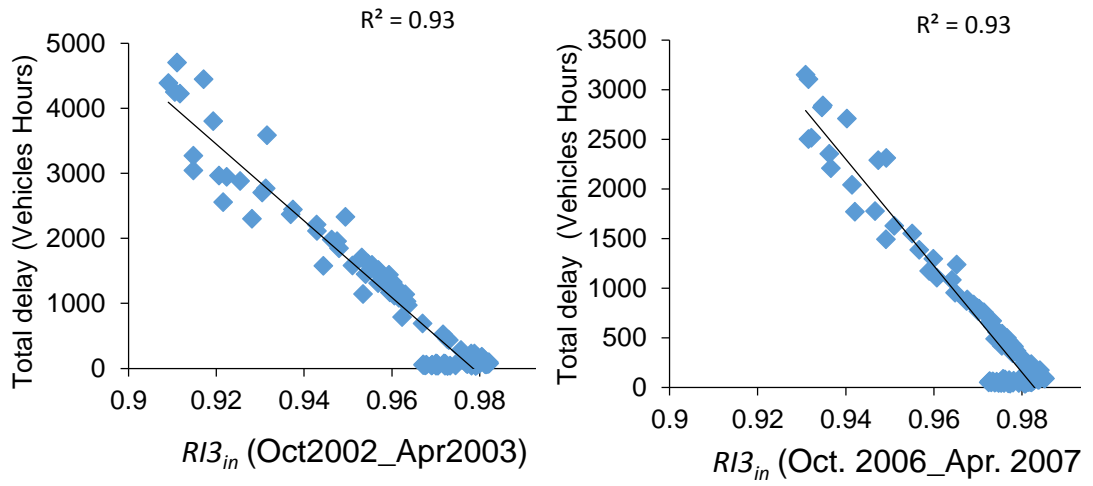
Comparison Task	Time period
NO-VSML against 4L-VMSL	October 2002 to April 2003 October 2006 to April 2007
3L-VMSL against 4L-VMSL	January 2006 to April 2006 January 2007 to April 2007

5.6.1 Redundancy Indicator of Junction 3a in M42.

The traffic flow parameters (i.e. link flow, speed, capacity and free flow speed), on the attached links of J3a were used to calculate $RI3_{in}$ and junction delay. Data for the analysis had been collected from the journey time database (JTDB) which is part of the Highways Agency Traffic Information System (HATRIS) (Highways Agency, 2013).

The database included journey time, speed and traffic count data for the motorway and all-purpose trunk road network in England. Data were provided at 15-minute intervals. For each time period, Sundays and Saturdays were excluded from the analysis to examine varied traffic flow profiles during the weekdays.

Figure 5.11 shows the correlation between $RI3_{in}$ and delay of J3a for two periods of time, October 2002 to April 2003 in Figure 5.11(a) and October 2006 to April 2007 in Figure 5.11(b). Both $RI3_{in}$ and delay were calculated as the average for the total period considered at 15 minute intervals. $RI3_{in}$ for J3a showed very strong correlation with the junction delay for both time periods as depicted from Figure 5.11, confirming the results from the Delft case study.



(a) $RI3_{in}$ and total delay

(b) $RI3_{in}$ and total delay

(Oct 2002 to Apr 2003, No-VMSL)

(Oct 2006 to Apr 2007, 4L-VMSL)

Figure 5.11 $RI3_{in}$ and total delay.

Furthermore, Figure 5.12 shows the variation of $RI3_{in}$ for the two time periods, October 2002 to April 2003 (pre ATM activation) and October 2006-April 2007(after the activation of ATM scheme). Comparing $RI3_{in}$ for the time period October 2002 to April 2003 with October 2006 to April 2007 shows that the scheme results in a general improvement in the redundancy indicator $RI3_{in}$ as depicted from Figure 5.12. The amount of improvement varies throughout the day, for example at 6:30am (off-peak) both values are very similar, meanwhile there are noticeable improvements between 7:45am to 11:00 pm with different rates.

Figure 5.13 shows the impact of capacity increase by considering the period between January to April 2006 (3L-VMSL) and the period between January to April 2007 (4L-VMSL). A little improvement in $RI3_{in}$ due to the use of the hard shoulder, especially the morning peak is observed. However, the ATM scheme has attracted more traffic flow (as shown in Figure 5.14) for both periods that could negatively affected the improvement of $RI3_{in}$.

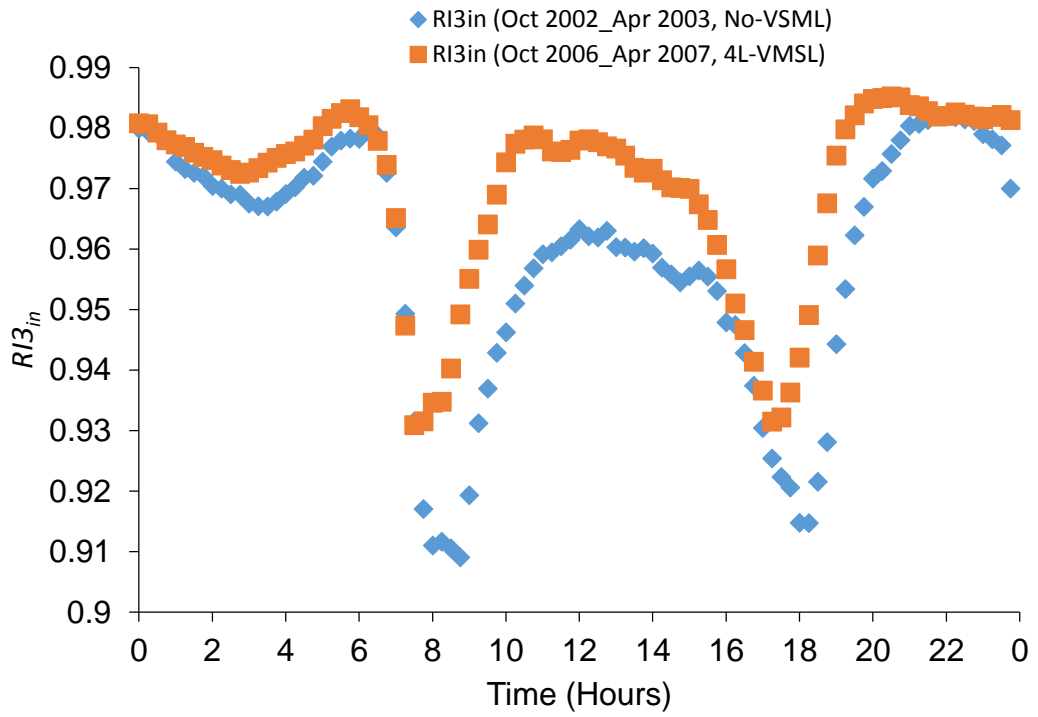


Figure 5.12 $RI3_{in}$ for the time periods October 2002 to April 2003 and October 2006 to April 2007.

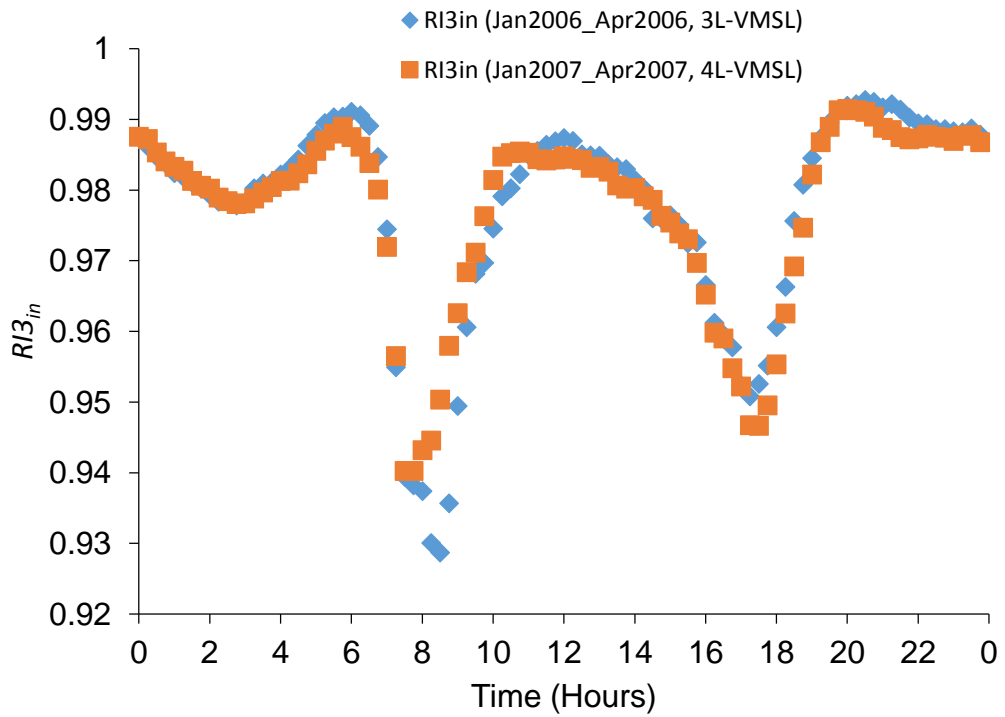


Figure 5.13 $RI3_{in}$ for the time periods January to April 2006 and January to April 2007.

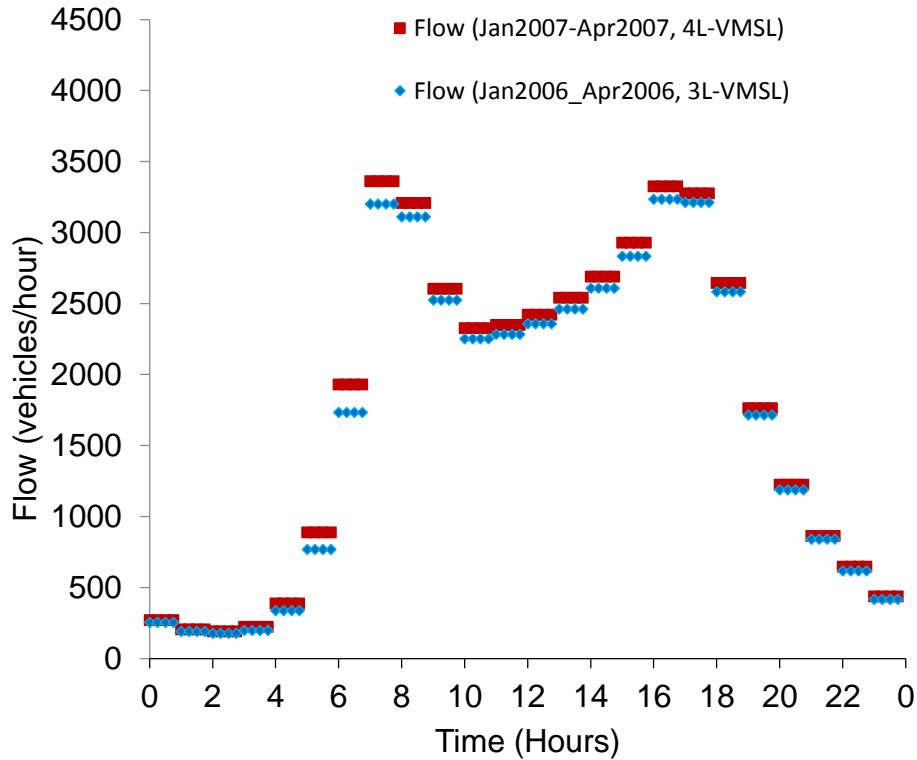


Figure 5.14 Variation of traffic flow for the time periods January to April 2006 and January to April 2007.

5.7 Conclusions

The main aim of this chapter was to introduce a redundancy indicator for various nodes in road transport networks that is able to cover both static and dynamic aspects of redundancy. The static aspect of redundancy refers to the existence of alternative paths to a certain node whereas the dynamic aspect covers the issues related to the availability of spare capacity under different network loading and level of service such as the relative average speed. The proposed technique is based on the entropy concept owing to its ability to measure the configuration of a road transport network in addition to being able to model the uncertainties inherent in road transport network. In contrast with previous investigations on redundancy in water systems based on one system characteristic, a number of redundancy indicators were developed from combinations of link characteristics to enhance their correlations with the junction delay and the volume capacity ratio.

For each proposed redundancy indicator, two values are calculated (i.e. outbound redundancy and inbound redundancy indicators) to quantify the

redundancy level of each node in the network. It was found that none of the outbound redundancy indicators correlated well with the junction delay or junction volume capacity ratio. Consequently, the analysis focused on the inbound redundancy indicators, as they were able to reflect the variations in topology of the nodes (e.g. number of incident links) and the variation in link speed. However, further research is recommended to investigate the impact of the outbound links on the junction redundancy indicator. A network redundancy indicator is also developed by aggregating a weighted redundancy indicator for all the nodes.

Two case studies based on a synthetic road transport network of Delft city and Junction 3a in M42 motorway near Birmingham are considered to test the ability of the redundancy indicators to reflect various network conditions and demand variation. Each proposed redundancy indicator was assessed against the junction delay and volume capacity ratio and consequently two redundancy indicators based on combined relative link speed and relative link spare capacity were chosen. Furthermore, the suitability of each redundancy indicator relies on the junction type based on analysis of various junction types in the synthetic road transport network of Delft city. The two chosen redundancy indicators responded well to the variation in demand under the same network conditions as well as supply variation, for example network capacity reduction.

The proposed redundancy indicators could be a potential tool to identify the design alternatives in addition to the best control and management policies under disruptive events or for daily operation of the road transport network. Furthermore, they will be integrated with other resilience characteristics developed in the following two chapters to define the composite resilience index of the road transport networks as presented in Chapter 7.

Chapter 6: Vulnerability of Road Transport Networks

6.1 Introduction

Chapter 3 emphasised the importance of the vulnerability assessment within the resilience framework to capture the influence of disruptive events on the vulnerability of road transport networks. Barker et al. (2013) employed the vulnerability as the only resilience indicator during disruptive events. This chapter, therefore, presents a method to quantify the vulnerability of road transport networks. The main advantage of the proposed method is the ability to take into account link attributes such as link flow, free flow speed and capacity in estimating a link vulnerability indicator. A new method based on fuzzification and an exhaustive search optimisation technique is employed to combine a set of defined attributes with different weights into a single vulnerability indicator. The proposed methodology can be extended in principle to include further attributes to reflect a wider set of vulnerability related issues.

This chapter begins with a critical review of vulnerability assessment methods and indicators. In Section 6.3, a set of vulnerability attributes are then proposed to capture as many features as possible of the impact of link closures in reality. A single link vulnerability indicator based on the proposed attributes is developed from fuzzy logic approach and an exhaustive search optimisation technique. An aggregated vulnerability indicator is also introduced to evaluate the vulnerability of the overall network under different conditions. In Section 6.4, the vulnerability of the synthetic road transport network of Delft city is calculated under different scenarios using the proposed methodology.

6.2 Vulnerability Assessment Methods and Indicators

According to (Gaillard, 2010) the concept of vulnerability was first introduced in the disaster literature as early as the 1970s and spread quickly in the 1980s to other disciplines. However, vulnerability does not have a widely accepted definition based on the context (Jenelius et al., 2006). For example in the context of transport research, vulnerability is normally used to express the “susceptibility” or “sensitivity” of the transport network to threats or hazards (Berdica, 2002) that can lead to significant effects on road transport network performance. Jenelius et al. (2006) related the concept of vulnerability to risk theory. Consequently, they defined vulnerability using two components of risk assessment i.e. the probability of a disruptive event and its consequences - in similar vein to risk evaluation. However, the probability of certain events could be very low in some geographic areas or not identified, which limits the potential of this approach. In contrast, (Taylor and D’Este, 2007) and (Maltinti et al., 2011) suggested that the concept of vulnerability is more strongly related to the consequence of link failure, regardless of the probability of failure and the event itself.

A number of different vulnerability assessment methods and indicators are available in the literature, e.g. Jenelius, 2009; Berdica, 2002; Rashed and Weeks, 2003; Taylor and Susilawati, 2012; Susilawati, 2012, arising from different interpretations of the concept of vulnerability and the scope of analysis. In general there are two main methods; use of a network wide screen (Jenelius et al., 2006) and techniques based on pre-selection of potentially vulnerable links according to a set of criteria (Knoop et al., 2012). The network wide screen approach gives a full analysis of the transport network by investigating the impact of the closure of each link on the overall network performance, measured by the total travel time. However, the high computational time of this approach is considered to be something of a disadvantage. To address this issue, Murray-Tuite and Mahmassani (2004) introduced a bi-level approach based on game theory in order to identify the most critical links in the road transport network. They defined a vulnerability link indicator to measure the importance of a particular link to the connectivity of an origin-destination (OD) pair, and then aggregated over all OD pairs to

obtain a link indicator. They did not demonstrate the application of the technique with an authentic road transport network however. Meanwhile Knoop et al. (2012) reviewed the link vulnerability attributes proposed by Tampère et al. (2007) and found that different criteria identified different links as the most vulnerable. Their conclusion was that attributes should be seen as a complementary set rather than singularly.

Different approaches in the literature could also be classified according to the indicators used to assess vulnerability. For example Taylor and D'Este (2007) and Chen et al. (2012) used accessibility and network efficiency indicators as metrics of vulnerability to identify the wider socioeconomic consequences of link closure. Meanwhile Scott et al. (2006) employed transport network performance indicators to identify the most "critical" or "important" link in the road transport network. Overall, the use and applicability of each approach appears to be heavily dependent on the scope of the research.

Most of the previous research on vulnerability measures and methodologies has focused on assessing the impact of link closure for a particular origin-destination or at link level, but has not referred to the link characteristics that lead to vulnerability. This chapter extends the work of Tampère et al. (2007) by introducing a new link vulnerability indicator developed based on link vulnerability attributes. The vulnerability indicator could be used to measure the impact of disruptive events (e.g. manmade events such as accidents or natural events such as adverse weather conditions) on road transport network functionality. The network vulnerability indicator is then calculated using two different aggregations: an aggregated vulnerability indicator based on physical characteristics and an aggregated vulnerability indicator based on operational characteristics.

6.3 Modelling the Vulnerability of the Road Transport Network

According to Srinivasan (2002), a vulnerability assessment may include deterministic factors (such as network capacity), quantitative time-varying factors (such as traffic flow and speed), some qualitative measures (for example event type and expected consequences), plus some random factors.

There is therefore a need to develop an indicator in such a way that it can take into account various attributes of vulnerability. In the vulnerability model described in this chapter, a number of vulnerability attributes are selected from the literature (e.g. Srinivasan, 2002; Tampère et al., 2007) and combined with relative weights to assess the vulnerability of the road transport network. The calculated vulnerability indicator value is then compared with the generalized travel cost to test the ability of the method to identify the most critical links in a case study (see Section 6.4). Section 6.3.1 below presents the vulnerability attributes adopted to develop the indicator, whilst Section 6.3.2 introduces the fuzzification and exhaustive search optimisation techniques used to develop the link vulnerability indicator.

6.3.1 Vulnerability Attributes

Ideally, the set of vulnerability attributes should be as complete as possible, capturing as many features as possible of the impact of link closures in reality. It should also be as orthogonal as possible, capturing different aspects with a minimum degree of duplication. According to Srinivasan (2002), several types of attributes may have a significant effect on link vulnerability and these could be classified into four main categories, namely network characteristics, traffic flow, threats and neighbourhood attributes. Network attributes could include characteristics such as road types and physical configuration, whilst traffic attributes could cover link capacity, flow and speed. Attributes concerning 'threats' may include event types and their expected consequences, with neighbourhood attributes capturing the influence of adjacent subsystems such as land use and population. Whilst the traffic and network related attributes are the focus in the current research, the methodology developed here allows the addition of further attributes to cover each of the four categories.

A number of vulnerability attributes (VAs) were therefore selected from the literature in order to estimate a vulnerability indicator for each link of the network. The first three attributes (VA_1 , VA_2 and VA_3) adopted here from Tampère et al. (2007) and Knoop et al. (2012), are dependent on link capacity, flow, length, free flow and traffic congestion density. VA_1 reflects the link traffic flow in relation to link capacity and is estimated by:

$$VA_1 = f_{am}^i / (1 - f_{am}^i / C_{am}) \quad (6.1)$$

where f_{am}^i is the flow on link a during period time i for a travel mode m , C_{am} is the capacity of link a for a travel mode m . As the flow f_{am}^i increases with respect to capacity C_{am} , the number of vehicles experiencing higher levels of delay will increase.

The second attribute VA_2 identifies the direct impact of link flow with respect to link capacity as defined below.

$$VA_2 = f_{am}^i / C_{am} \quad (6.2)$$

The main difference between VA_1 and VA_2 is that the calculated value of VA_1 from Eq. (6.1) is scaled with respect to the highest and lowest VA_1 values for all links in the road transport network considered (see Eq. (6.7) below). This normalisation is not applied in the calculation of VA_2 . Therefore, VA_1 measures the relationship between f_{am} and C_{am} for each link with respect to the whole network. VA_2 , however, is intended to reflect local values of f_{am} and C_{am} for each link.

VA_3 represents the inverse of the time needed for the tail of the queue to reach the upstream junction and is estimated by:

$$VA_3 = f_{am}^i (n_a kj_{am} - f_{am}^i / V_{am}) / l_a \quad (6.3)$$

where n_a is the number of lanes of link a that have been used by travel mode m , kj_{am} reflects congestion density for link a , V_{am} is the free flow speed of link a for a travel mode m , and l_a is the length of link a .

All the above attributes were derived based on accident scenarios (see Tampère et al., 2007; Knoop et al., 2012). A number of other attributes were therefore also added to capture the significance of network characteristics (such as link capacity and length) on vulnerability. As a result, two further attributes, VA_4 and VA_5 have been formulated and included in the vulnerability indicator.

The fourth attribute, VA_4 , is calculated from the capacity of link a relative to the maximum capacity of all network links in order to reflect relative link importance, as presented in Eq. (6.4).

$$VA_4 = \frac{C_{am}}{C_{max}} \quad (6.4)$$

where C_{max} is the maximum capacity of all network links.

The fifth attribute, VA_5 , simply uses the link length as a physical property representing the level of importance of the link, as given in Eq. (6.5).

$$VA_5 = l_a \quad (6.5)$$

Finally, the number of shortest paths that use the link is also considered due to the importance of this feature in link vulnerability analysis (Srinivasan, 2002), leading to the definition of attribute VA_6 . This sixth attribute is calculated by Eq. (6.6) below reflecting the number of times the link is a component of the shortest path between different OD pairs.

$$VA_6 = \sum_{ij} s_{ij} \quad (6.6)$$

where s_{ij} is given a value of one if link a is a component of the shortest path between origin i and destination j and a value of zero otherwise. Expert opinion may also be used to allocate a higher weight to the value of VA_6 for a particular link if the link is part of a strategic route.

6.3.2 Link Vulnerability Indicator

To develop a single measure for vulnerability based on more than one attribute, three approaches have been proposed in the literature (Srinivasan, 2002). The first approach is based on experts' opinions in ranking or weighting each attribute and then combining these attributes using a simple linear regression model. This model can be calibrated using observed or reported vulnerability ratings for various levels of the contributing factors. In the second approach, a continuous vulnerability indicator is represented by a function that includes all the proposed attributes. The relative weights are derived

according to the best fit between the model prediction and actual ratings. The vulnerability indicator is then compared against a set of ordered thresholds that are estimated from empirical models. For example, if the vulnerability indicator is below the first threshold then the vulnerability rate will be 1 or if it falls in the range between the first and second thresholds then the vulnerability rate will be 2. However, the determining these thresholds in an accurate way is a significant challenge and much further research would be needed in order to establish the threshold values. The third approach is based on operational experience whereby experts choose a set of weights for some attributes (such as spare capacity and flow) in order to evaluate vulnerability if a particular scheme is implemented. The main advantages of this approach compared with the previous two methods are simplicity and flexibility (Srinivasan, 2002); however, it may be difficult to obtain the necessary data in practice.

In the current research therefore, a new method based on fuzzification and an exhaustive search optimisation technique is employed to combine the various attributes (defined above) into a vulnerability indicator. Fuzzification is the process of converting a crisp quantity to a fuzzy one (Ross, 2010). It is adopted here to accommodate the complexity and uncertainty in traffic behaviour alongside randomised elements in both traffic data and the simulation process. Each attribute is evaluated according to four assessment levels represented by four fuzzy membership functions. An exhaustive search technique is then employed to identify the optimal weight contribution of each fuzzified attribute. This is determined by the level of weights at which the correlation between the vulnerability indicator (obtained from the weighted attributes) and the given total travel cost is the strongest. Travel cost could be estimated based on different factors such as travel time, distance or toll. In this research travel time is used as an estimate of travel cost, however, the method is flexible and could accommodate other cost measures. The full details of the technique are presented in the following sub sections.

6.3.2.1 Data Normalization

A normalization process is firstly applied so that a standard method can then be used to allocate a membership grade value for each of the link attributes

in the fuzzification process. Each calculated VA for each link is therefore normalized using the following equation:

$$(VA_{x,a})_n = \frac{VA_{x,a} - VA_{x,min}}{VA_{x,max} - VA_{x,min}} \quad (6.7)$$

where $(VA_{x,a})_n$ and $VA_{x,a}$ are the normalized and non-normalized values of the vulnerability attribute x of link a . $VA_{x,max}$ and $VA_{x,min}$ are the maximum and minimum values of the vulnerability attribute set following normalization respectively. The normalisation process maps the value of each attribute into a closed interval [0, 1]. However given that the two vulnerability attributes, VA_2 and VA_4 , are already scaled between [0, 1], these are not subject to the normalisation procedure using Eq. (6.7).

6.3.2.2 Fuzzy Membership of Vulnerability Attributes

Four assessment levels are proposed to evaluate each VA, where each level is defined by a fuzzy function having membership grades varying from 0 to 1. Various membership functions have been proposed in the literature (Ross, 2010). However, triangular and trapezoid membership functions were adopted to fuzzify the four normalized vulnerability attributes. The rationale was twofold: these functions are by far the most common forms encountered in practice and are relatively simply in terms of calculating membership grades (Torlak et al., 2011; Ross, 2010). Other membership functions such as a Gaussian distribution may also be used. However, previous research (e.g. Shepard, 2005) has indicated that real world systems are relatively insensitive to the shape of the membership function. The membership grade value μ of each normalised attribute $(VA_{x,a})_n$ for link a is obtained from the following fuzzy triangular and trapezoidal functions:

$$\begin{aligned}
 \mu_{low} &= \begin{cases} 1 & 0 \leq (VA_{x,a})_n \leq 0.25 \\ \frac{0.5 - (VA_{x,a})_n}{0.5 - 0.25} & 0.25 < (VA_{x,a})_n < 0.5 \\ 0 & (VA_{x,a})_n \geq 0.5 \end{cases} \\
 \mu_{Medium} &= \begin{cases} 0 & (VA_{x,a})_n \leq 0.25 \\ \frac{(VA_{x,a})_n - 0.25}{0.5 - 0.25} & 0.25 < (VA_{x,a})_n \leq 0.5 \\ \frac{0.75 - (VA_{x,a})_n}{0.75 - 0.50} & 0.5 < (VA_{x,a})_n < 0.75 \\ 0 & (VA_{x,a})_n \geq 0.75 \end{cases} \\
 \mu_{high} &= \begin{cases} 0 & (VA_{x,a})_n \leq 0.5 \\ \frac{(VA_{x,a})_n - 0.5}{0.75 - 0.5} & 0.5 < (VA_{x,a})_n \leq 0.75 \\ \frac{1 - (VA_{x,a})_n}{1.0 - 0.75} & 0.75 < (VA_{x,a})_n \leq 1.0 \end{cases} \\
 \mu_{very\ high} &= \begin{cases} 0 & (VA_{x,a})_n \leq 0.75 \\ \frac{(VA_{x,a})_n - 0.75}{1 - 0.75} & 0.75 < (VA_{x,a})_n \leq 1.0 \\ 1 & (VA_{x,a})_n > 1.0 \end{cases}
 \end{aligned}$$

The membership grade function outlined above can be adjusted or re-scaled to reflect real life conditions and expert opinion. However, a single membership grade function is assumed for each of the attributes in this chapter.

Membership grades for link a represented by a fuzzy relationship $R(a)$ for different VA for link a in the network are calculated based on the equations above and are shown below:

$$R(a) = \begin{bmatrix} \mu(VA_1)_{low} & \mu(VA_1)_{medium} & \mu(VA_1)_{high} & \mu(VA_1)_{very\ high} \\ \mu(VA_2)_{low} & \mu(VA_2)_{medium} & \mu(VA_2)_{high} & \mu(VA_2)_{very\ high} \\ \mu(VA_3)_{low} & \mu(VA_3)_{medium} & \mu(VA_3)_{high} & \mu(VA_3)_{very\ high} \\ \mu(VA_4)_{low} & \mu(VA_4)_{medium} & \mu(VA_4)_{high} & \mu(VA_4)_{very\ high} \\ \mu(VA_5)_{low} & \mu(VA_5)_{medium} & \mu(VA_5)_{high} & \mu(VA_5)_{very\ high} \\ \mu(VA_6)_{low} & \mu(VA_6)_{medium} & \mu(VA_6)_{high} & \mu(VA_6)_{very\ high} \end{bmatrix}$$

Each row of the matrix above represents attribute membership grades, whilst the columns show the memberships grades for the four attributes for a particular assessment level.

To obtain a single vulnerability indicator $VI(a)$ for link a , based on VAs , the above matrix is modified by two vectors. First, a weighting vector w_i is introduced to reflect the importance of each VA in the vulnerability assessment as expressed in Eq. (6.8) below.

$$VI(a) = R(a)w_i$$

$$VI(a) = \sum_{i=1}^6 w_i VA_i(a) \quad (6.8)$$

An optimization technique is used to identify the relative weight for each VA as described in Section 6.3.2.3. The outcome of this step is a fuzzy vector containing the membership values for each link at each assessment level. There are then two possible approaches to calculate a single value for $VI(a)$ from the fuzzy vector. The first considers the maximum membership grade value whilst the second approach involves multiplying the fuzzy vector by a standardising vector to take into account the effect of each assessment level (Ross, 2010). In this research, the second method is used as it allows for the accumulating effect of each assessment level on the calculated $VI(a)$. The standardising vector (s) shown in Eq. (6.9) is therefore proposed in order to obtain a single value, adjusted from 0 to 1.

$$s = [0.25 \ 0.5 \ 0.75 \ 1] \quad (6.9)$$

The values of the standardising vector (s) are equal to those for VA_x when $\mu(VA_x) = 1$ for low, medium, high and very high, as obtained from the membership grade function previously defined.

6.3.2.3 Attribute Weight Identification

The weight vector w_i for each attribute could be proposed by traffic experts and policy makers. It could also vary according to the modelled scenario. However in the current research, the weight value for each attribute is estimated by comparing the vulnerability indicator, $VI(a)$, for link a against the relative travel time per trip, $RTTpT(a)$, with the closure of link a – a similar approach to that used by Knoop et al. (2012). The relative travel time per trip, $RTTpT(a)$, is defined as the difference between the total network travel time

during link closure and the total network travel time under normal conditions, with respect to the total network travel time under normal conditions.

A linear regression analysis between $VI(a)$ and $RTTpT(a)$ for the road transport network is then calculated and the weight vector is obtained when the coefficient of determination R^2 is maximised: i.e. maximise R^2 for the linear regression between $VI(a)$ and $RTTpT(a)$ subject to the following constraint:

$$\sum_i w_i = 1$$

In the above formulation w_i is implicitly included in $VI(a)$ and is the only design variable. An exhaustive search is employed to find the weight vector w_i for each attribute, where each weight W_i is increased from 0.0 to 1.0 with an increment of 0.01. For each weight combination, the vulnerability indicator, $VI(a)$, is calculated using Eq. (6.8). A linear regression analysis is performed between $VI(a)$ for each weight combination and $RTTpT(a)$, with the coefficient of determination R^2 estimated by:

$$R^2 = 1 - \frac{SS_{resid}}{SS_{total}}$$

where SS_{resid} is the sum of the squared residuals from the regression and SS_{total} is the sum of the squared differences from the mean of the $RTTpT(a)$.

The above approach is repeated for various combinations of W_i considering the weight constraint and re-calculating R^2 for each combination. The weight combination achieving the highest R^2 is then selected as the optimum weight set for the attributes. The flow chart in Figure 6.1 illustrates the procedure for obtaining the optimum weight combination for the attributes based on the strongest correlation between $VI(a)$ and $RTTpT(a)$. A constrained linear least squares approach could also be used to find the weights that achieving the best fit between $VI(a)$ and $RTTpT(a)$. However, no particular advantage would be anticipated through this alternative method as the exhaustive search optimisation was a straightforward and low resource task with the search space limited between [0, 1].

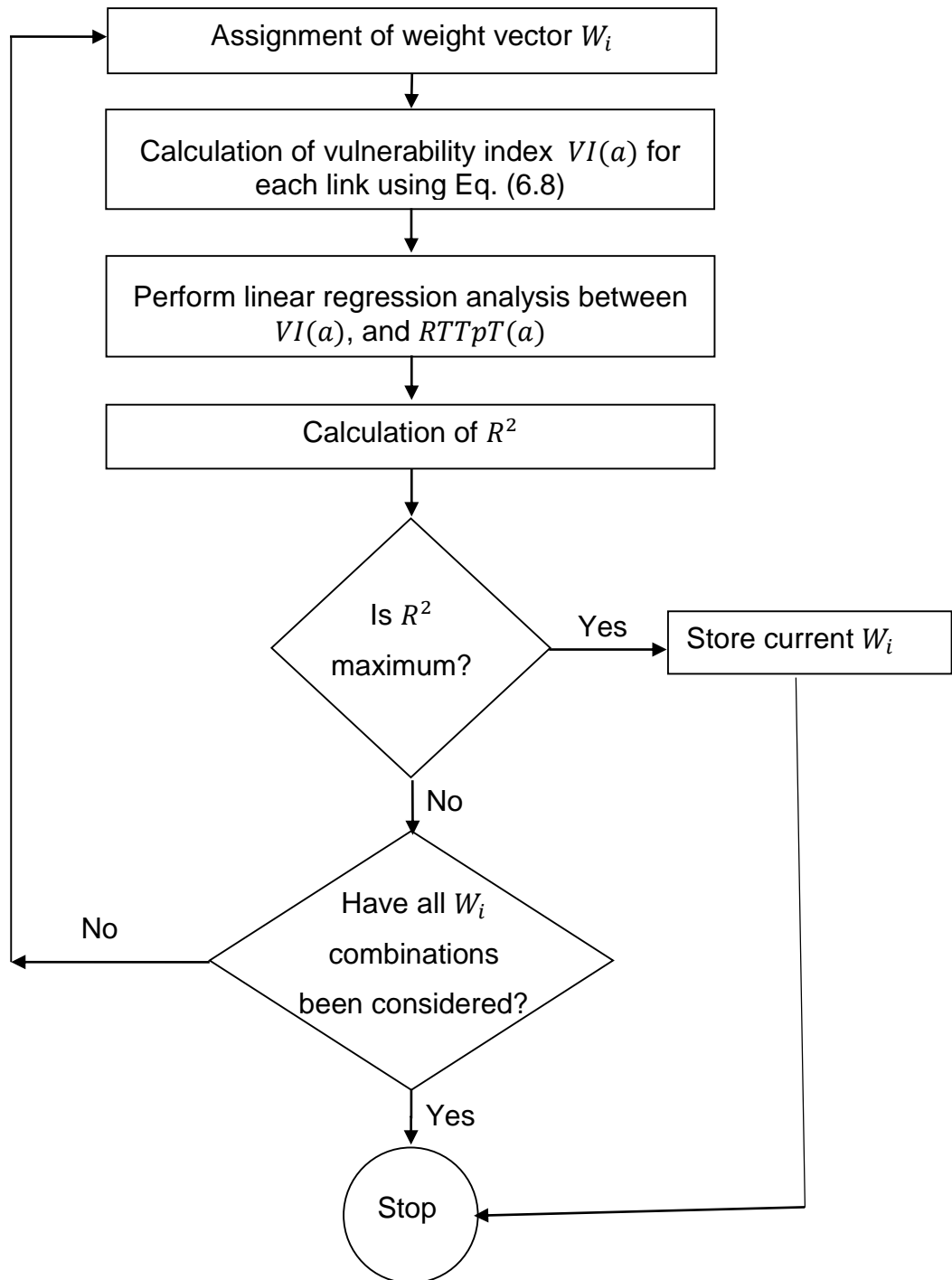


Figure 6.1 A flow chart for the optimum weight combination for the four attributes.

6.3.3 Network Vulnerability Indicator

Based on the steps described above a vulnerability indicator for each link can then be calculated. Despite the importance of this link based indicator in identifying the most critical links, there is still a need however for an aggregated vulnerability indicator in order to evaluate the vulnerability of the overall network under different conditions. Two aggregated vulnerability indicators are proposed i.e. a physically based aggregated vulnerability indicator and an operational based aggregated vulnerability indicator. The physical based aggregated vulnerability indicator (VI_{PH}) is calculated using the length and number of lanes of each link as follows:

$$NVI_{PH} = \frac{\sum_a^e VI_a l_a n_a}{\sum_a^e l_a n_a} \quad (6.10)$$

where e is the number of links in the road transport network, n_a is the number of lanes in link a and l_a is the length of link a . The operational based aggregated vulnerability indicator (NVI_{OP}) is calculated based on link capacity as follows:

$$NVI_{OP} = \frac{\sum_a^e VI_a f_{am}^i}{\sum_a^e f_{am}^i} \quad (6.11)$$

where f_{am}^i is the flow of link a during time interval i using a travel mode m .

6.4 Case Study

The synthetic road transport network of Delft city presented in Chapter 4 is used to illustrate the vulnerability of road transport network under different scenarios using the proposed methodology.

In the case study undertaken here, the user equilibrium assignment (UE) was chosen to obtain the spatial distribution of the traffic volume as discussed in Chapter 4. The suitability of the UE method for identifying the most vulnerable link is based on two issues (Scott et al., 2006). Firstly, the ability of the method to take into account the level of link functionality by allocating the user to the best route in terms of travel time, i.e. users cannot improve their travel time by

changing their route. Secondly, the use of user equilibrium assignment allows the impact of removing the link to be calculated for both the link user and non-users (due to rerouting the link user).

However, traffic data obtained from simulation based on a static UE assignment without any junction modelling (as opposed to 'real-world' observations) cannot capture the full effects of unexpected link closures, as this process is not able to capture queuing, imperfect information, etc. As a result, the optimum attribute weights arising from the highest R^2 criteria may be different from the weights that may arise from the best fit against observed data. However, real world measurements may also vary, for example according to individual traveller behaviour and this is not covered in the scope of the model presented in this research. In order to examine the effect of queuing on the travel time, junction modelling was undertaken using the OmniTRANS software ((Version 6.024) for a case involving the closure of a small number of links. Junction modelling with OmniTRANS generates outputs including queue lengths alongside a number of performance measures for the junction as a whole. The results indicated that travel time increased slightly and by a maximum of 1%.

For the case study as a whole, three different scenarios were considered. The first calculated VAs for each link in the network and estimated VI for each link. In the second scenario, the impact of demand variations on VI_{PH} and VI_{OP} were investigated using different departure rates during the morning peak. The impact of network capacity reduction under the same demand variations were then studied in the third scenario.

6.4.1 Results and Discussion

6.4.1.1 Group One Scenarios

All VAs were calculated for each link in the network based on the steps described in Section 6.3, using a static assignment model for the morning peak. 1068 simulations (equivalent to the number of links in the network) were carried out to check the impact of each individual link closure on the network travel time. In each case, only one link was blocked, i.e. to represent a link closure due to a road accident or roadwork.

As the used OmniTRANS version in this chapter (Version 6.024) does not allow “en-route” route-choice modelling, closure of the link is implemented at the start of simulation, resulting in a subsequent new equilibrium state. This implies that drivers would need to be aware of the link closure and of alternative routes. To overcome this shortcoming, a deterministic user-equilibrium (UE) assignment was used for the base condition scenario, assuming drivers have previous experience and knowledge of their shortest paths. A stochastic 'randomising' term (ε) was also added to the generalised cost in order to reflect the uncertainty associated with traveller behaviour under a link closure scenario. However, the use of this stochastic 'randomising' term (ε) leads to instability in link flow even with large number of iterations (up to 1000). Consequently, the stochastic 'randomising' term (ε) was abandoned and a deterministic UE assignment used for all scenarios instead. This implies that the perceived travel times are very accurate and therefore all vehicles on each link would experience the same travel time. In this case, the simulation results may underestimate the impact of each link closure in the new equilibrium state. To obtain more realistic impact results two issues should be considered; traveller behaviour (e.g. the proportion of travellers who will change their route with a link closure) and the availability of an en-route choice model implemented within the traffic assignment software. However, the main aim of the analysis reported here was to investigate the ability of the attributes to reflect link importance under different conditions. The results obtained and reported therefore assume that all drivers have good knowledge about the link closure and the availability of alternative routes. As the modelled period is the morning peak it would be quite reasonable to assume that a high proportion of the road users are regular commuters/travellers and nearly all the users have a high level of knowledge about route availability and traffic conditions. Alternatively, in practice a variable message sign or in-vehicle intelligent transport system may update travellers' knowledge of the link closure and alternative routes.

Figure 6.2 introduces the variation in VAs for each link for the base condition, i.e. no link closure. It should be noted that each VAs highlighted a different set of critical links (in terms of highest values) in line with the findings of Knoop et al. (2012).



Figure 6.2 Variation of VAs per link.

Figure 6.3 shows the correlation of each attribute with relative travel time per trip, $RTT_{pT}(a)$ arising from individual link closure. The coefficient of determination, R^2 , for each attribute reflects its strength of association with $RTT_{pT}(a)$. As an example, VA_1 has the highest R^2 (=0.5447) followed by VA_3 (=0.4403), then VA_4 (=0.4206). Meanwhile, VA_2 has a low R^2 (=0.191). Both VA_5 and VA_6 have a negligible correlation, with R^2 equal to 0.0039 and 0.0148, respectively. These findings highlight the need to develop a single vulnerability indicator taking into account all the four main attributes proposed in this research, whilst VA_5 and VA_6 would contribute little to the indicator.

The set of weights calculated above are not universal but network dependent. However, they can be used for the same network to consider different scenarios, for example to test the effectiveness of different policy or the impact of implementing new technology.

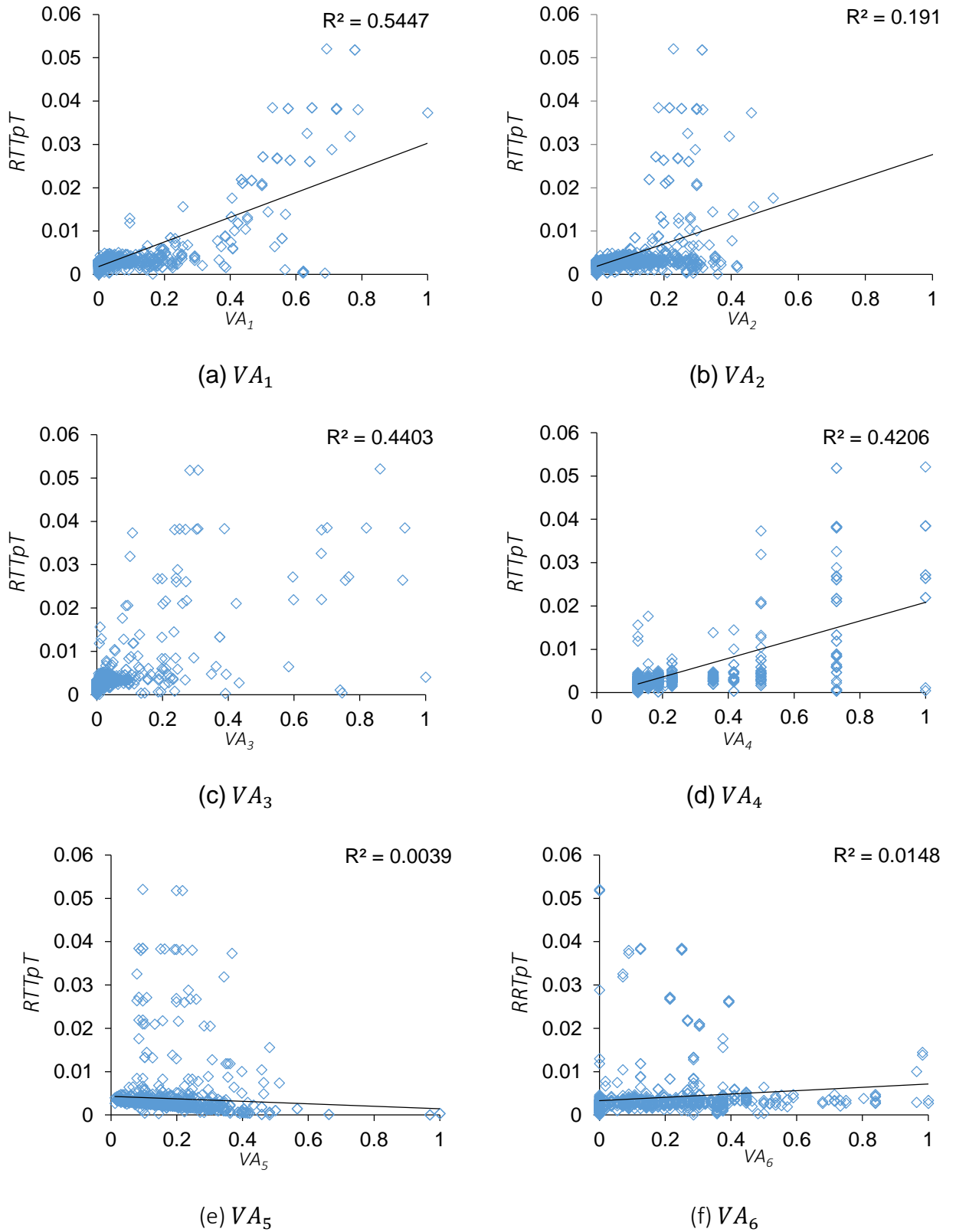


Figure 6.3 Correlations between VAs and $RTTpT$ for each link closure.

Figure 6.4 shows the correlation between the calculated vulnerability indicator, VI , for each link based on the combined weights of the four vulnerability attributes VA_1 to VA_4 and the relative travel time per trip. VA_5 and VA_6 are not considered in the derivation of VI as their correlation with RTT_{pT} is very weak, as described above. The relatively low value of R^2 presented in Figure 6.4 reflects the fact that the increase in the total travel time may not be the only consequence arising from link closure. For example, the closure of some links is likely to lead to the disconnection of some zones creating unsatisfied demand and a misleading value of reduced total travel time because of a lower overall load on the network. However, this is a feature of the physical layout of the network and would therefore vary in magnitude for different links and with the application of the method in different cities. Figure 6.5 further illustrates the relationship between the relative travel time for different link closure scenarios with associated unsatisfied demand and the vulnerability indicator. Links with high VI and low RTT_{pT} are associated with unsatisfied demand.

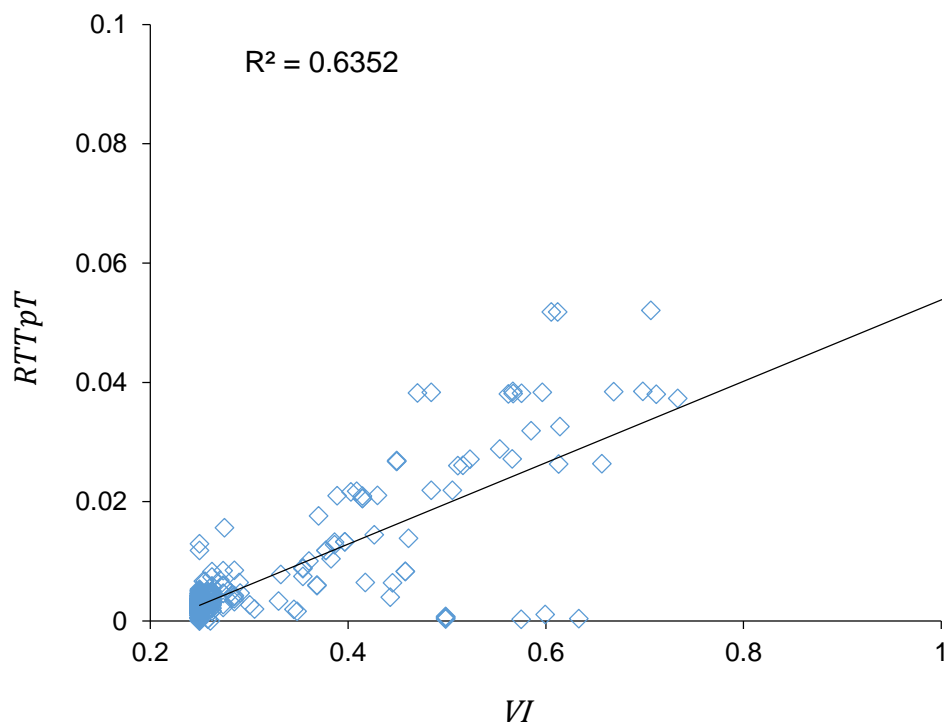


Figure 6.4 Link vulnerability Indicator and RTT_{pT} for all links.

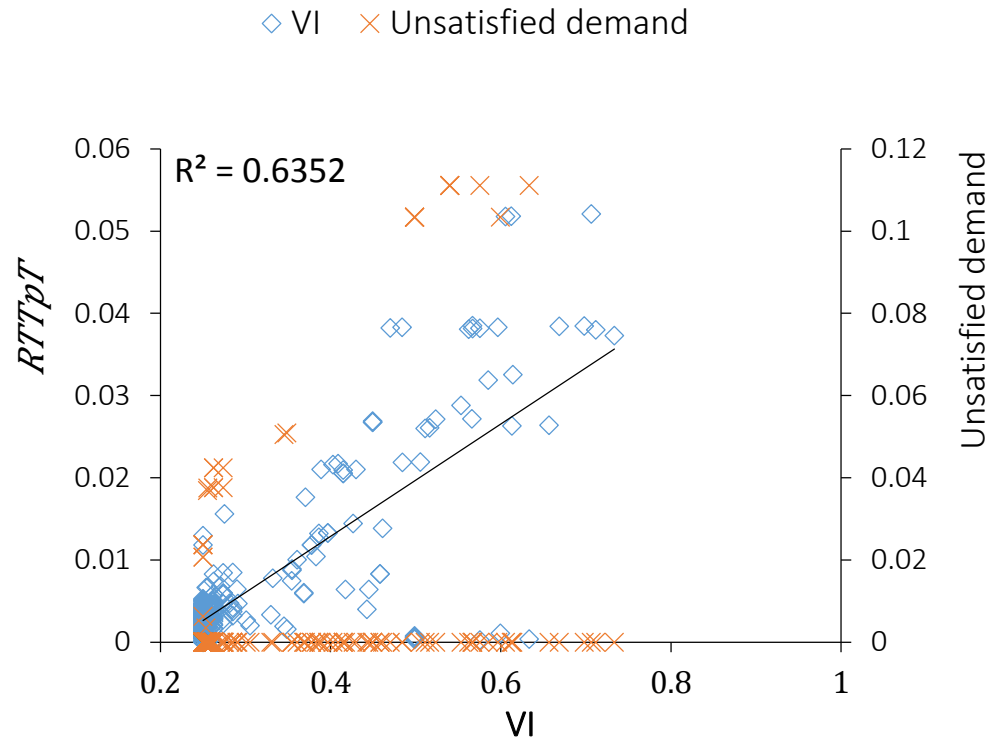


Figure 6.5 RTT_{pT} , unsatisfied demand and VI for the network links.

When the results of the 'cut' links (i.e. links that when closed result in zone disconnection, creating unsatisfied demand) are removed from the data regression analysis, the coefficient of determination R^2 increases to 0.8667 as depicted in Figure 6.6.

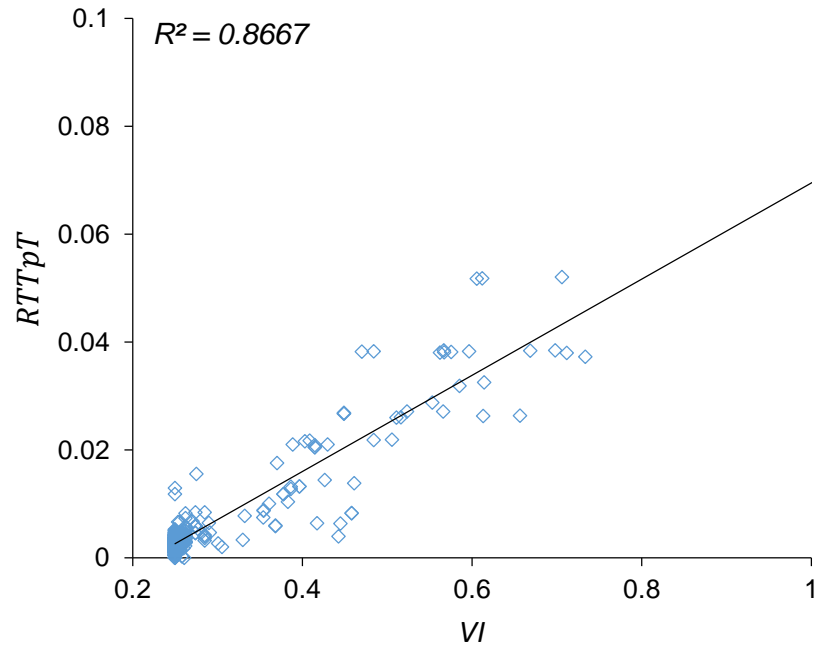


Figure 6.6 Correlation between *VI* and *RTTpT* excluding cut links.

However, excluding cut links from the estimation of *VI* could also be undesirable due to their importance in the vulnerability of the overall network cut links create unsatisfied demand which in turn (intuitively) increases network vulnerability. As a result, modelling the impact of unsatisfied demand is essential to give a more realistic *VI*. From the literature, there are two possible ways to overcome this issue, the first is to quantify the impact of link closure by two indicators; one for the cut links and the other for the remaining links (Jenelius et al., 2006). The other approach is to estimate the cost of time due to a particular link closure (Jenelius, 2009). In the current research, the second approach is adopted to obtain the total impact for all links in the network. The increase in total travel time due to the closure of links (cut links) is then modelled by adding the proposed unsatisfied demand impact (*UnSDI*), calculated by Eq. (6.12) below, to the total travel time.

$$UnSDI = d_a \tau \left(\tau + \frac{TTpT_a}{L_a} * l_a \right) \quad (6.12)$$

where d_a is the unsatisfied demand due the unavailability of link a (vehicle/hour), τ is the closure period, $TTpT_a$ is the total travel time per trip

during the closure of link a , l_a is the length of link a and L_a is the total network length without link a .

The inclusion of the UnSDI in the total travel time calculation leads to an improvement in the correlation between NVI and the modified relative travel time, increasing R^2 to 0.9125 as shown in Figure 6.7.

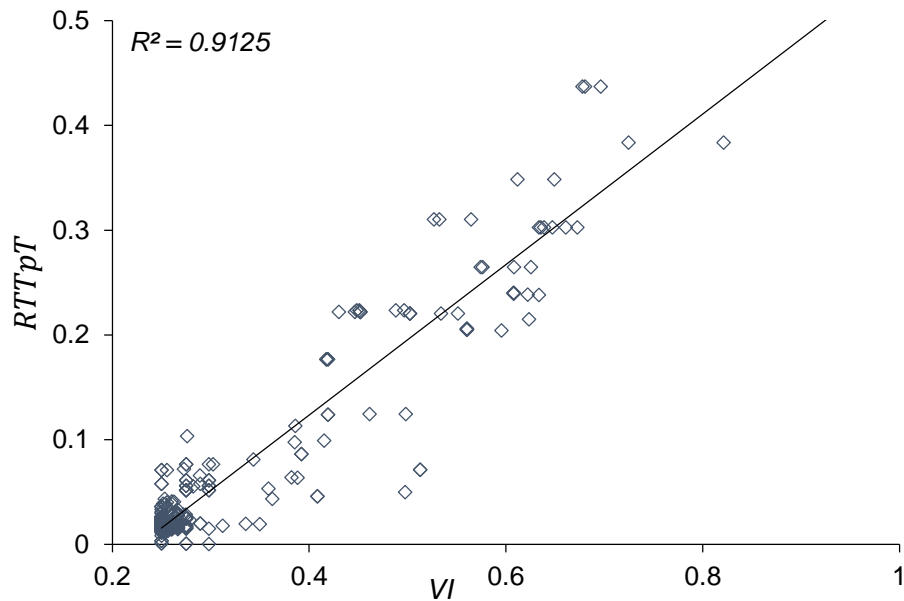


Figure 6.7 Correlation between VI and modified $RTTpT$.

The influence of network configuration is implicitly included by considering unsatisfied demand, as the percentage of unsatisfied demand reflects the ability of the network to offer alternative routes during a certain link closure. For example, zero unsatisfied demand highlights the ability of the network to offer alternative routes for all OD pairs during a link closure.

6.4.1.2 Group Two Scenarios

Here the impact of variations in demand on NVI_{PH} and NVI_{OP} is investigated using different departure rates during the morning peak. NVI_{PH} and NVI_{OP} are calculated using Eqs. (6.10) and (6.11). Figure 6.8 shows both NVI_{PH} and NVI_{OP} under uniformly distributed departure rates, whilst Figure 6.9 plots the variations of NVI_{PH} and NVI_{OP} under different departure rates, with and without UnSDI. The vulnerability level is measured by both indicators (NVI_{PH} and NVI_{OP}) and increases in line with the rate of increase in the departure

rate, as depicted in Figure 6.9. It is also apparent that the inclusion of UnSDI increases the vulnerability level. This leads to the conclusion that both indicators are able to reflect the impact of increases in demand on the level of vulnerability.

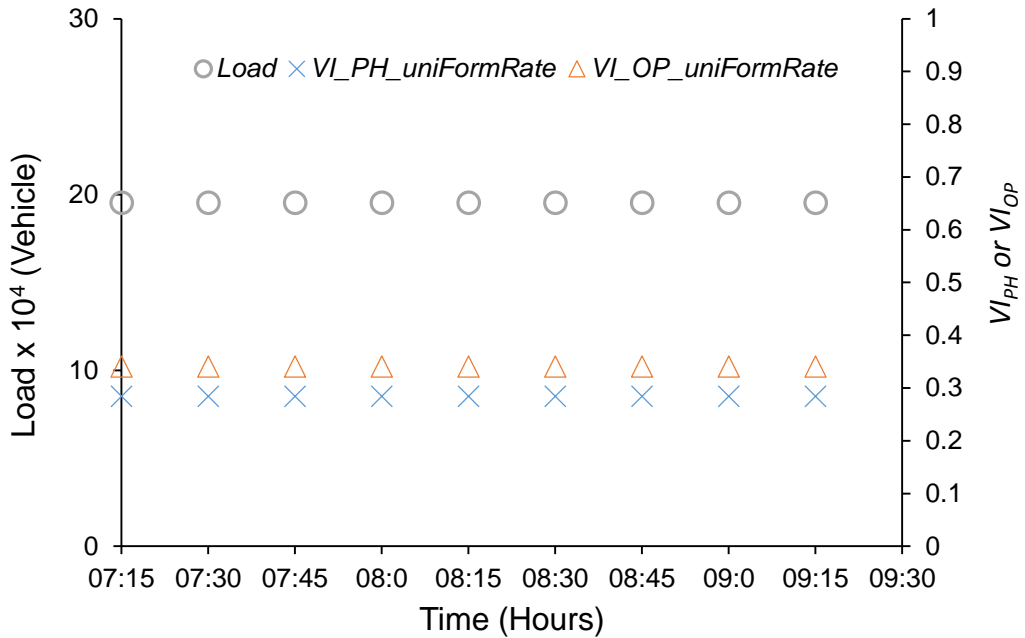


Figure 6.8 NVI_{PH} and NVI_{OP} under uniform distributed departure rates.

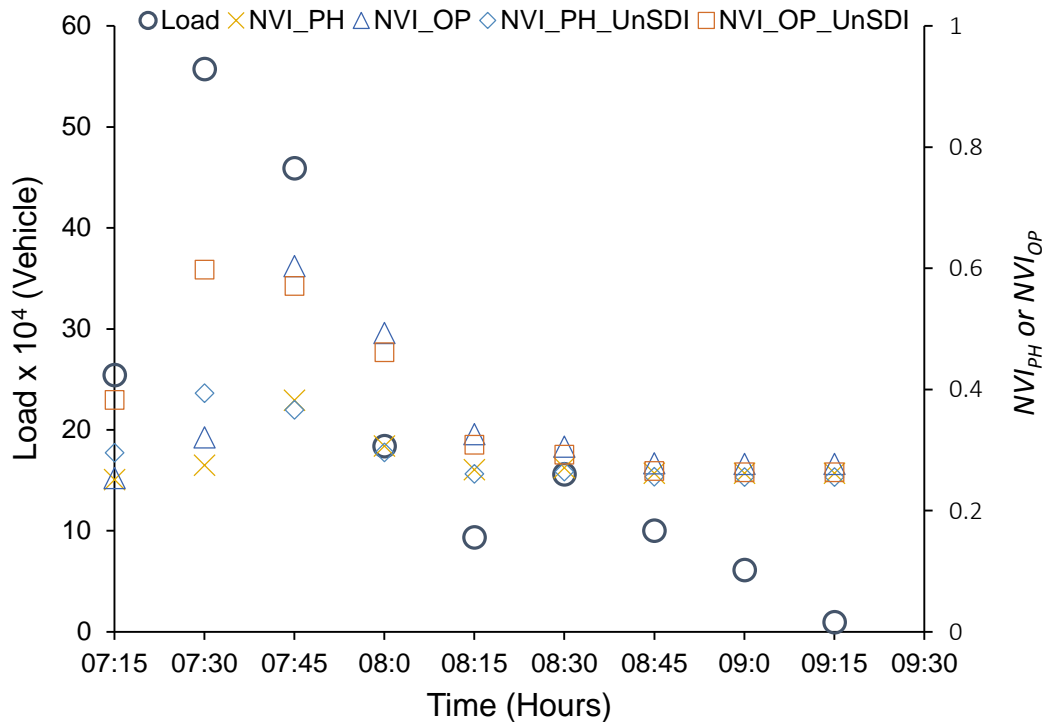


Figure 6.9 NVI_{PH} and NVI_{OP} under different departure rates, with and without UnSDI.

6.4.1.3 Group Three Scenarios

In this analysis the ability of NVI to capture the impact of reductions in network capacity under the same variations in demand is investigated. Overall network capacity could be reduced in practice due to the effects of network wide events such as heavy rain or snowfall. The level of reduction in network capacity and speed were assumed based on evidence in the literature (Enei et al., 2011; Pisano and Goodwin, 2004; Koetse and Rietveld, 2009). This group of scenarios was undertaken using reduced capacity in addition to a reduction in saturation flow or free flow speed by 10%, in order to model the impact of a weather related event. Figure 6.10 shows the variations of NVI_{PH} and NVI_{OP} under different departure rates and variations in supply. The vulnerability level measured by both indicators, NVI_{PH} and NVI_{OP} , increases in the case of reduced capacity compared with full network capacity. Furthermore, the difference between the vulnerability indicators (i.e. full network capacity and reduced capacity) increases with increased in demand and diminishes at low demand. This leads to the conclusion that the NVI_{PH} and NVI_{OP} indicators are both able to reflect the impact of varying reductions in supply and demand on the level of vulnerability.

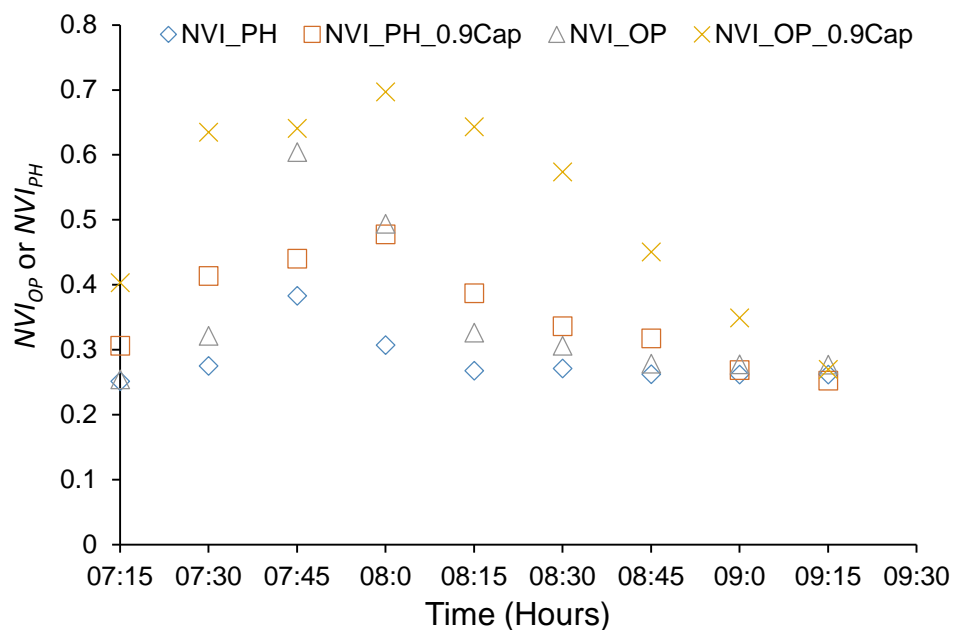


Figure 6.10 NVI_{PH} and NVI_{OP} under different departure rates and network capacity.

6.5 Conclusions

A new methodology for assessing the level of vulnerability of road transport networks has been introduced which is able to reflect the importance of network links. The proposed technique is a two-stage process where a link vulnerability indicator is first developed and subsequently network vulnerability indicators are estimated. The development of the link vulnerability indicator is based on a fuzzy membership grade and exhaustive optimisation search. It allows the identification of the relative weights of vulnerability attributes when combined in a single vulnerability indicator for each link in the network. The proposed methodology is able to accommodate further attributes in order to reflect wider vulnerability related issues, such as road type and the economic value of the traffic flow. Two overall network vulnerability indicators, namely physical and operational vulnerability indicators, are then developed. The technique has been successfully demonstrated on a representative road transport network.

Correlations between each attribute and the total travel time due to link closure in a synthetic Delft city network are investigated. It was found that none of the attributes on its own is able to justify the full impact of link closure. These findings reveal the need to develop a single vulnerability indicator that is able to take into account a number of attributes. A term to reflect the impacts of unsatisfied demand has also been proposed to model the decrease in the total travel time that arises when particular cut links result in unsatisfied demand. An exhaustive search optimisation technique for attribute weight identification produced a high correlation between the single vulnerability indicator and the total travel time, with an R^2 value of 0.9125. Two attributes (related to link length and the shortest paths) yielded a low contribution to the single vulnerability indicator, as they are heavily dependent on the network configuration and infrastructure characteristics. It is therefore suggested that the number of link lanes may be combined with the link length in order to enhance their overall contribution to the vulnerability indicator.

It should be noted that the relative weights of the vulnerability attributes are not universal but network dependent. However, the weights calculated for each attribute can be used with a particular network in order to consider the

impacts of different scenarios - for example to test the effectiveness of different policies or the impact of introducing new technology.

Finally, the estimated network physical and operational vulnerability indicators show a good correlation with variations in both supply and demand. These indicators represent a potential tool that could be used to gauge the total network vulnerability under different scenarios. It can also be used to assess the effectiveness of different policies or technologies to improve the overall network vulnerability. Furthermore, the developed vulnerability indicators will be also included with other resilience characteristics, namely redundancy (Chapter 5) and mobility (Chapter 7) in the development of composite resilience index of the road transport networks in Chapters 8.

Chapter 7: Mobility of Road Transport Networks

7.1 Introduction

Mobility is essential to economic growth and social activities, including commuting, manufacturing and supplying energy (Rodrigue et al., 2009). Higher mobility (or in other words, a better ability of the network to deliver an improved service) is a very important issue for decision makers and operators as it relates to the main function of the road transport network. Consequently, an assessment of road transport network mobility is essential in order to evaluate the impact of disruptive events on network functionality and to investigate the influence of different policies and technologies on the level of mobility. Disruptive events may be classified as manmade or climate change related events, the scale of which will also have an impact on road transport network mobility as presented in Section 3.2.

Mobility could have two dimensions (Berdica, 2002). Firstly, mobility as “the ability of people and goods to move from one place (origin) to another (destination) by use of an acceptable level of transport service” - commonly measured by vehicle kilometres and evaluated through surveys (Litman, 2008). Secondly, from the road transport network perspective, mobility is defined as the ability of a road transport network to provide connection to jobs, education, health service, shopping, etc., therefore travellers are able to reach their destinations at an acceptable level of service (Kaparias et al., 2012, Hyder, 2010). Therefore, mobility is a measure of the performance of the road transport network in connecting spatially separated sites, which is normally identified by system indicators such as travel time and speed. However, here the mobility concept is used as a key performance indicator to measure the functionality of the road network under a disruptive event, as in the second case above. It is therefore used to reflect the ability of a network to offer users a certain level of service in terms of movement.

7.2 Mobility Assessment

As with many transport concepts, there are no universally agreed indicators to assess road transport network mobility from a network perspective. According to the National Research Council (2002), mobility assessment should take into account system performance indicators such as time and costs of travel. They proposed that the mobility level is inversely proportional to variations in travel time and cost, whereas, Zhang et al. (2009) suggested that travel time and average trip length are two key indicators to evaluate system mobility. The study (Zhang et al., 2009) developed a performance index to evaluate the mobility of an intermodal system, measured by the ratio of travel speed to the free flow speed weighted by truck miles travelled. However, the performance index (*PI*) could be adopted to measure road transport mobility by considering total traffic flow rather than average daily truck volume. In line with this approach, Wang and Jim (2006) used the average travel time per mile as a mobility indicator, where the distance is the geographic distance rather than actual distance travelled. The use of the geographic distance rather than travel distance could lead to an overestimation of mobility, as the geographic mileage is generally shorter than the actual travel distance between two locations.

Cianfano et al. (2008) suggested a number of indicators based on link travel time and speed to evaluate road network mobility. Specifically, they (Cianfano et al., 2008) introduced a vehicle speed indicator, *VSI*, measuring the variation in speed compared to free flow conditions. A value of *VSI* of 1 would indicate that vehicles are experiencing a travel speed across the network equal to the free flow speed (i.e. the average free flow speed of the network). Under extreme conditions $VSI = 0$ indicates a fully congested road network. Cianfano et al. (2008) also proposed a mobility indicator based on travel time. According to Lomax and Schrank (2005), transport performance measures based on travel time fulfil a range of mobility purposes. However, other researchers (Zhang et al., 2009; Cianfano et al., 2008) have used simple and applicable indicators that could be easily implemented at a real-life network scale. They only considered the impact of traffic flow conditions (presented as the variation in travel speed compared with free flow speed) and took into

account the impact of unconnected zones. If some links are not available (e.g. closed due to an incident) they are omitted from the indicator calculations, producing misleading values.

Murray-Tuite (2006) proposed a number of indicators to estimate the mobility characteristic under disruptive events, some of which were scenario based measures such as the time needed to vacate a towns' population and the capability of emergency vehicles (ambulance, police) to pass from one zone through to another. Murray-Tuite (2006) also suggested that the average queue time per vehicle, the queue length on the link and finally, the amount of time that a link can offer average speeds lower than its nominal speed limit could also be considered as mobility indicators.

Chen and Tang (2011) introduced the notion of link mobility reliability, calculated using a statistical method based on historical data i.e. speed data for 3 months derived from floating cars. They also investigated the possible influencing factors on mobility reliability. Their results showed that the mobility reliability of an urban road network is correlated with network saturation (volume/capacity ratio) and road network density.

At the operational level, TAC (2006) carried out a survey including Canadian provincial and territorial jurisdictions regarding current practices in performance measurement for road networks related to six outcomes; mobility being one of them. The study found that average speed and traffic volume are widely used as measures of mobility. The study also found that the concepts of accessibility and mobility are used interchangeably in practice, which could conflict with academic practice, where accessibility and mobility are very different concepts. For example, Gutiérrez (2009) emphasised that the mobility concept relates to the actual movements of passengers or goods over space, whereas accessibility refers to a feature of either locations or individuals (the facility to reach a destination). In other words, accessibility could be defined as the potential opportunities for interaction (Hansen, 1959) that are not only influenced by the quality of the road transport network, but also by the quality of the land-use system (Straatemeier, 2008). Widespread communication technologies could play a crucial role in virtual accessibility (Janelle and Hodge, 2000).

A number of further mobility indicators have been reported, namely origin-destination travel times, total travel time, average travel time from a facility to a destination, delay per vehicle mile travelled, lost time due to congestion and volume/capacity ratio (TAC, 2006). Meanwhile, Hyder (2010) suggested three indicators to measure the mobility of the road transport network, namely maximum volume/capacity ratio, maximum intersection delay and minimum speed. The study (Hyder, 2010) used linguistic expressions to evaluate the indicators (as shown in Table 7.1) and suggested that mobility is gauged by the lowest value of these indicators.

Table 7.1 Linguistic expressions and corresponding values of mobility indicators (Hyder, 2010).

Mobility indicator	Low	Medium	High
Maximum volume/capacity	>75%	50-75%	<50%
Maximum intersection delay	>300 seconds	60-300 seconds	<60 seconds
Minimum speed	<25 kph	25-50 kph	>50 kph

However, none of this existing research has considered the impact of the road transport network infrastructure, such as road density, on network mobility. Therefore, the research presented here considers the impact of network infrastructure and network configuration using graph theory measures alongside traffic conditions indicators, as discussed above. The use of the network configuration and traffic flow conditions will reflect the impact of different kinds of disruptive events. For example, in case of a flood, some parts of the network could become totally disconnected whilst other parts of the network could benefit from lower network loading. Therefore, the impact of such an event could be masked if the mobility indicator only considers traffic conditions. In the case of adverse weather conditions the overall network capacity could decrease (Enei et al., 2011) leading to congested conditions, but not necessarily affecting travel distance. Consequently, the consideration

of both attributes, i.e. physical connectivity and traffic conditions, is necessary to cover both cases. In section 7.3 below, mobility attributes are introduced.

7.3 Mobility Modelling of Road Transport Networks

In the research here, the mobility concept is treated as a performance measure expressing the level of road transport network functionality under a disruptive event. Therefore, mobility is used as a concept to reflect the ability of a network to offer its users a certain level of service in terms of movement. To obtain a single mobility indicator a number of mobility attributes are used to capture a range of mobility issues, as outlined above.

7.3.1 Mobility Attributes

Based on the definition of mobility (i.e. the ability of the road transport network to move road users from one place to another with an acceptable level of service), two attributes are proposed. Firstly, an attribute is used to evaluate physical connectivity, i.e. the ability of road transport to offer a route to connect two zones. The second attribute is implemented as a measure of the road transport network level of service, based on traffic conditions. Figure 7.1 shows a schematic diagram of the mobility attributes and the various factors affecting them. In the following sub sections, both attributes are presented and a justification for their selection is provided.

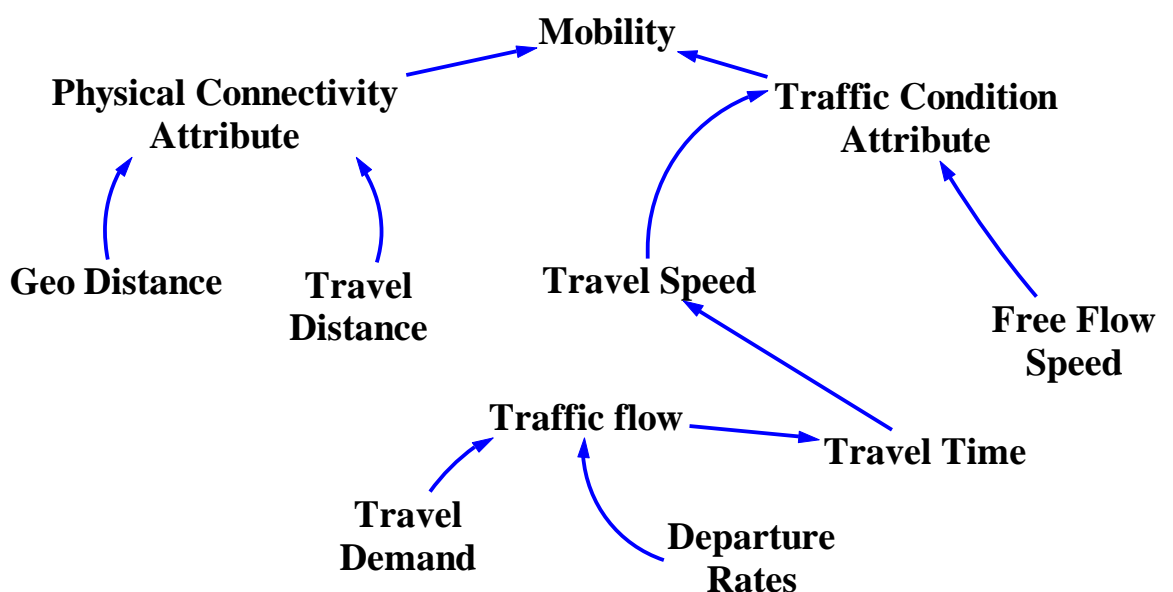


Figure 7.1 Conceptual framework for the proposed mobility model.

7.3.1.1 Physical Connectivity

The physical connectivity (i.e. existence of a path between OD pairs), is a key factor on the level of network mobility. For example, the unavailability of a certain route may lead to unsatisfied demand, economic loss or safety concerns arising from the disconnection of a group of travellers who are then effectively trapped.

Physical connectivity can be measured by a number of indicators based on graph theory, as shown in Levinson (2012). The influence of network configuration on connectivity could be studied by calculating the gamma index (γ). The γ index is measured as the percentage of the actual number of links to the maximum number of possible links (Rodrigue et al., 2009). The γ index is a useful measure of the relative connectivity of the entire network, as a transport network with a higher gamma index has a lower travel cost under the same demand (Scott et al., 2006). However, γ is not able to reflect the zone-to-zone level of connectivity and its impact on overall connectivity. Road density also has drawbacks in similarity to the γ index. The detour index (also referred to as the circuitry measure) is defined as the ratio of the network distance to the Euclidean distance, or Geo-distance. It is widely used to investigate the impacts of network structure. According to Rodrigue et al. (2009), the detour index is a measure of the ability of road transport to overcome distance or the friction of space. Meanwhile, Parthasarathi and Levinson (2011) concluded that the network detour index measures the inefficiency of the transport network from a travellers' point of view.

In the research here a physical connectivity attribute, *PCA*, is developed based on the detour index but modified to consider zone-to-zone connectivity (see Eq. 7.1 below).

$$PCA_{ij}(r) = \frac{GD_{ij}}{TD_{ij}(r)} \quad (7.1)$$

where GD_{ij} is the geographic distance between zone i and zone j . TD_{ij} is the actual travel distance between zone i and zone j using route r . The value of $PCA_{ij}(r)$ varies from 1 (representing 100% physical connectivity), to zero (where there is no connectivity). In the case of a high impact disaster, the

degree of connectivity would intuitively be expected to be zero. In such a case, the actual travel distance, $TD_{ij}(r)$, may be mathematically assumed to be infinity to express the unsatisfied demand and, accordingly, the value of $PCA_{ij}(r)$ becomes zero.

To explain the importance of physical connectivity (represented by PCA), 9 routes listed in Table 7.2 with very similar free flow travel speeds were investigated to eliminate the impact of traffic conditions on mobility. The data for the 7 routes was obtained using google maps, i.e. travel distance (TD), free flow travel time ($FFTT$), as shown in Figure 7.2 for the Leeds to Birmingham route. The free flow travel and actual travel speeds, ($FFTS$ and TS) were calculated based on the traffic from the google map website (maps.google.co.uk). The GD_{ij} between each OD pair was calculated using the Euclidean distance based on Pythagorean theorem (i.e. $GD_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$) where x and y are the National Grid Coordinates obtained using a “gazetteer” query that allows search for and download particular records from the Ordnance Survey's 1:50,000 Landranger series maps⁴.



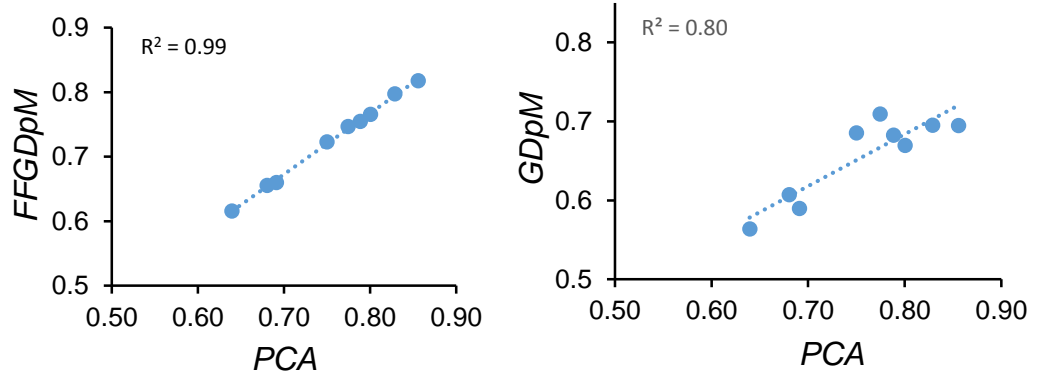
Figure 7.2 Routes from Leeds to Birmingham (Source: Google Map, 2014).

⁴ © Crown Copyright and database rights 2014; an Ordnance Survey/EDINA-supplied service.

Table 7.2 *GD*, traffic information, *PCA*, *FTDpM* and *TDpM* for different routes.

Route	<i>GD</i> (mi)	<i>TD</i> (mi)	<i>FFTS</i> (mi/hr)	<i>TS</i> (mi/hr)	<i>PCA</i>	<i>FFGDpM</i> (mi/min)	<i>GDpM</i> (mi/min)
Bradford-Birmingham	88.46	128	57.31	51.2	0.69	0.66	0.59
Brighton-Birmingham	133.01	208	57.78	52.88	0.64	0.62	0.56
Leeds-Birmingham	90.48	133	57.83	53.56	0.68	0.66	0.61
Brighton-Bradford	210.64	272	57.87	54.95	0.77	0.75	0.71
Leeds-London	166	195	57.64	48.95	0.86	0.82	0.69
London-Manchester	160.05	200	57.42	50.21	0.80	0.77	0.67
Brighton-Manchester	199.48	266	57.82	54.85	0.75	0.72	0.69
London-Bradford	168.23	203	57.7	50.33	0.83	0.80	0.70
Bath-Manchester	142.69	181	57.46	51.96	0.79	0.75	0.68

The *PCA* was then calculated for each route using Eq. (7.1) with GD_{ij} and TD_{ij} . Furthermore, the mobility indicator developed by Wang and Jim (2006) (average travel time per mile of Geo distance, i.e. TT_{ij}/GD_{ij}) was also calculated for free flow conditions and under different traffic conditions. For compatibility, an inverse of the indicator developed by Wang and Jim (2006) should be considered for comparisons with the *PCA*. For example, the higher the Geo distance per minute (*GDpM*), the more miles are travelled in a minute, hence a higher mobility level. The trend for *PCA* in comparison with *GDpM* and the free flow Geo distance per minute (*FFGDpM*) can then be calculated, as shown in Figure 7.3.



(a) *PCA* and *FFGDpM*

(b) *PCA* and *GDpM*

Figure 7.3 Relationship between *PCA* and *GDpM*, *FFGDpM*.

The coefficient of determination R^2 was used to reflect the correlation between *PCA* and *FFGDpM*. A very high correlation ($R^2 = 0.99$) between *PCA* and *FFGDpM* is shown in Figure 7.3(a), highlighting the importance of *PCA* in estimating the mobility level in the case of the free flow conditions. R^2 decreases to 0.8, however, in the case of traffic flow with a lower travel speed. The travel speeds presented in Table 7.2 are close to the free flow speeds and, consequently, the correlation is still relatively high. As traffic speed decreases, the correlation is expected to be weaker. These findings indicate that *PCA* is insufficient to assess the level of mobility under different traffic flow conditions. As a result, the impact of traffic conditions should also be taken into account, as explained below.

7.3.1.2 Traffic Conditions Attribute

A wide range of mobility attributes has been developed that are based on traffic conditions, as discussed in section 7.2. Some of these are defined using link data, such as *VSI* (Cianfano et al., 2008), while others are based at zone level such as the performance index (*PI*) (Zhang et al., 2009). As physical connectivity is calculated at zone level, the variation in travel speed between each OD pair can be adopted to indicate the level of service, given it is widely accepted as a mobility attribute (TAC, 2006). The travel speed between each OD pair (TS_{ij}) can then be calculated using Eq. (7.2) and the traffic condition attribute (*TCA*) is obtained using Eq. (7.3) below.

$$TS_{ij}(r) = \frac{TD_{ij}(r)}{TT_{ij}(r)} \quad (7.2)$$

$$TCA(r) = \frac{TS_{ij}(r)}{FFTS} \quad (7.3)$$

where TS_{ij} is the travel speed between zone i and zone j for a route r , TT_{ij} is the actual travel time between zone i and zone j for a route r and $FFTS$ is the free flow travel speed in the network considered. For example, in the case of motorways, $FFTS$ could be taken as 70 mi/hr. The value of TCA varies between 1 and zero. A value of $TCA = 1$ indicates that vehicles have a travel speed across the network equal to the free flow speed (i.e. the average free flow speed of the network). Under extreme conditions $TCA = 0$, indicating a fully congested road network.

A number of routes with a very high PCA (≈ 0.80) are presented in Table 7.3 to show the impact of TCA in the case of high physical connectivity. A very high correlation was found between TCA and $GDpM$ in the case of routes with very high PCA , as shown in Figure 7.4(a). A low correlation was, however, obtained between TCA and $GDpM$ in the case of routes with low PCA values as presented in Table 7.2 ($R^2 = 0.0061$, see Figure 7.4(b)). Consequently, it could be concluded that the combined impact of both PCA and TCA on mobility is not linear and requires a flexible approach that has the ability to estimate the impact of each attribute according to its level.

Table 7.3 GD , traffic information, PCA , $GDpM$ and TCA for different routes.

	<i>GD</i> (mi)	<i>TD</i> (mi)	<i>FFTS</i> (mi/hr)	<i>TS</i> (mi/hr)	<i>PCA</i>	<i>GDpM</i> (mi/min)	<i>TCA</i>
Brighton-Bath	101.99	127	43.05	35.61	0.80	0.48	0.51
Leeds-Bath	168.029	209	49.37	43.09	0.80	0.58	0.62
London-Manchester	160.06	200	57.42	50.21	0.80	0.67	0.72
Leeds-Bradford	8.62	10.8	25.92	20.90	0.80	0.28	0.30
London-Leeds	166	208	56.73	49.33	0.80	0.66	0.70



(a) *TCA* and *GDpM* for routes in Table 7.3 (b) *TCA* and *GDpM* for routes in Table 7.2

Figure 7.4 Correlation between *TCA* and *GDpM* for routes presented in Tables 7.3 and 7.2.

7.4 Mobility Indicator Using Fuzzy Logic Approach

Each attribute (i.e. physical connectivity or traffic conditions), can be considered to individually reflect the level of mobility from a certain perspective. Suitable measures can then be introduced to improve the mobility level related to each attribute. However, there is still a need to estimate the overall mobility level by combining the impact of both *PCA* and *TCA*. *TCA* is able to clearly reflect the effects of a congested/free flow network, but could underestimate the impact of certain events. For example a link closure could lead to detours with some trips rescheduled or cancelled. As a consequence, network loading will decrease, leading to improved flow in some parts of the network. To reflect these effects on the mobility indicator, *PCA* should also be considered. Consequently, the mobility indicator *MI* should be estimated with consideration to both *PCA* and *TCA*. To deal with the complexity and uncertainty of traffic behaviour, the randomised nature of traffic data and to simulate the influences of both *PCA* and *TCA*, a fuzzy logic approach was implemented to scale both attributes and combine their impact at the mobility level. The fuzzy logic approach has the ability to interpolate the inherent vagueness of the human mind and to determine a course of action, when the existing circumstances are not clear and the consequence of the course of action have not been identified (Zadeh, 1965). In other words, a fuzzy logic approach deals with the type of uncertainty, which arises when the boundaries of a class of objects are not sharply defined (Nguyen and Walker, 1997).

7.4.1 Fuzzy Logic Applications in Transport Context

The use of the fuzzy logic approach in transport started with Pappis and Mamdani (1977) and was followed by many other applications. These applications could be categorized into two main areas, namely soft and hard applications. Hard applications refer to the use of fuzzy logic in hardware design such as dynamic traffic signal control. Examples include: a fuzzy controller for a traffic junction (e.g. Zuyuan et al., 2008), ramp metering and variable speed limit control (Ghods et al., 2007). Soft applications refer to the use of fuzzy logic in modelling the uncertainty associated with various parameters such as travel demand. According to Kalic´ and Teodorovic (2003), the fuzzy logic technique is successfully used in transport modelling including route choice, trip generation, trip distribution, model split and traffic assignment.

However, like any other approach, the fuzzy logic approach has its own merits and drawbacks. Davarynejad and Vrancken (2009) highlighted a number of these merits and drawbacks based on a comprehensive review. For example, it is a simple method as it uses an easy modelling language and is a powerful tool due to its ability to model experience and knowledge of human operator. It also has the ability to deal with imprecise information. The criticism by Davarynejad and Vrancken (2009) of the fuzzy logic approach focused on its application in hardware, for example, its limited use in traffic control signal or isolated ramp metering rather than traffic control due to the complexity of describing large-scale applications using quantitative information.

The fuzzy logic approach includes four main steps, namely fuzzification, fuzzy rule base, fuzzy inference engine and defuzzification. The first step, fuzzification, converts *PCA* and *TCA* crisp values to degrees of membership by means of a lookup to one or more of several membership functions. In the fuzzy rule base, all possible fuzzy relationships between *PCA* and *TCA* form the input whilst the output for the mobility indicator *MI* is then found using an 'IF-THEN' format. The fuzzy inference engine collects all the fuzzy rules in the fuzzy rule base and learns how to transform a set of inputs to related outputs. The final step, defuzzification, converts the resulting fuzzy outputs from the fuzzy inference engine to a crisp number representing the mobility

indicator MI . A brief introduction on the implementation of these steps to estimate a single mobility indicator MI from the proposed two attributes, PCA and TCA is described below.

7.4.2 Fuzzy Membership of Mobility Attributes

In the proposed method, both PCA and TCA are expressed by fuzzy sets labelled using gradual linguistic terms, i.e. the crisp values of PCA and TCA are converted to fuzzy values, for example high, medium and low. Each attribute is divided into a number of fuzzy subsets and represented by membership grade functions. Various membership functions have been proposed in the literature (Ross, 2010), for example triangular, trapezoid, Gaussian distribution and sigmoid functions. However, the triangular and trapezoid membership functions were adopted to fuzzify different assessed levels of the mobility attributes and indicator, as they are by far the most common forms encountered in practice. They also have the benefit of simplicity for grade membership calculations (Ross, 2010; Torlak et al., 2011). Other membership functions may also be used, however, previous research (Shepard, 2005) indicated that real world systems are relatively insensitive to the shape of the membership function. Membership functions were also recently determined using optimization procedures, provided that a comprehensive database is available (Jiang et al., 2008). The fuzzy triangular and trapezoidal membership grade functions for each attribute (PCA , TCA , and MI), are presented in Figure 7.5. Five assessment levels i.e. very low, low, medium, high and very high were proposed to model PCA , TCA and MI , where each level is defined by a fuzzy function having membership grades varying from 0 to 1. The membership grade function adopted can be adjusted or re-scaled to reflect real life conditions and expert opinion.

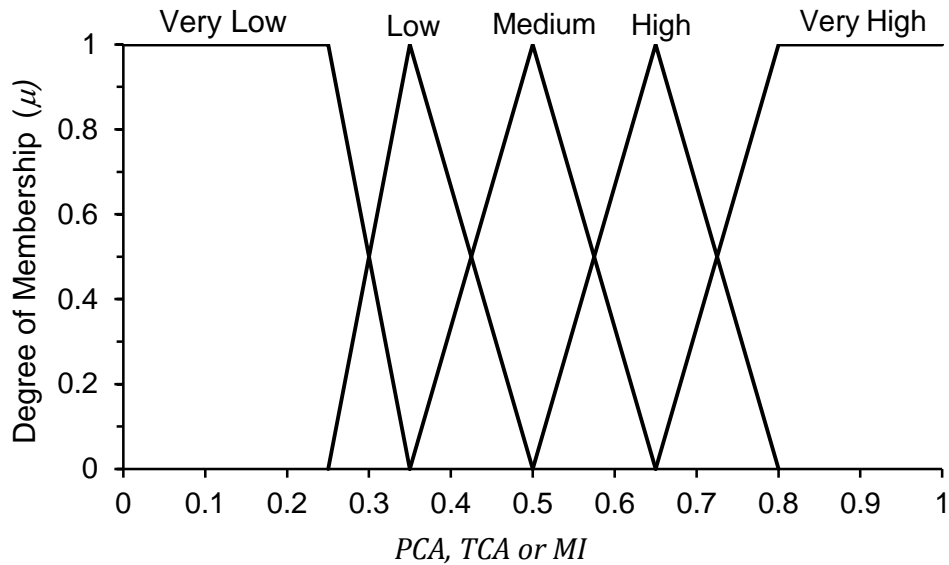


Figure 7.5 Triangular and trapezoidal membership functions for *PCA*, *TCA* and *MI*.

7.4.3 Fuzzy Inference System and Fuzzy Rule Base

A fuzzy inference system (FIS) is concerned with developing explicit rules in the form of IF-Then statements. These rules convert implicit knowledge and expertise of the particular application then build a block of rules determining the decision outputs. The FIS adopted here is based on Mamdani and Assilian (1975) as it is the most common in practice and literature (Ross, 2010).

Generally, there are m^n fuzzy rules where m is the number of subsets used to define the ' n ' input parameters. As the number of subsets m used for either *PCA* or *TCA* is 5, the total number of fuzzy rules is 25. These fuzzy base rules have the following descriptive form:

R¹ **IF** *PCA* is Very Low and *TCA* is Very Low **Then** *MI* is Very Low

R² **IF** *PCA* is Very Low and *TCA* is Low **Then** *MI* is Very Low

...

R²⁵ **IF** *PCA* is Very High and *TCA* is Very High **Then** *MI* is Very High

The Mamdani method has several functions that qualify as fuzzy intersection, referred to in the literature as t-norms as introduced by Menger (1942), (quoted in Ross, 2010). T-norms are used for the connectives of inputs; for

example 'min' or 'product' operator. The 'product' t-norm was chosen for the fuzzy inference rules determined here as it makes the output sensitive to every input, whereas, only one input controls the conclusion in case of the 'min' t-norm operator.

Figure 7.6 shows a surface plot representation of all these rules using the 'product' t-norm operator. This figure reflects the importance of both *PCA* and *TCA* on the mobility indicator *MI*, as high mobility can only be achieved when both *PCA* and *TCA* are high. The maximum values of *PCA* or *TCA* could only, however, achieve a medium to low mobility level on their own. The above rules are only used for demonstration purposes of the effective application of fuzzy logic in determining the mobility indicator. However, the validity of these rules were studied using data from a real life case study, as presented in Section 7.6. Following the fuzzification of the two input parameters using the membership functions shown in Figure 7.5, the applicable rules were activated and the results generated.

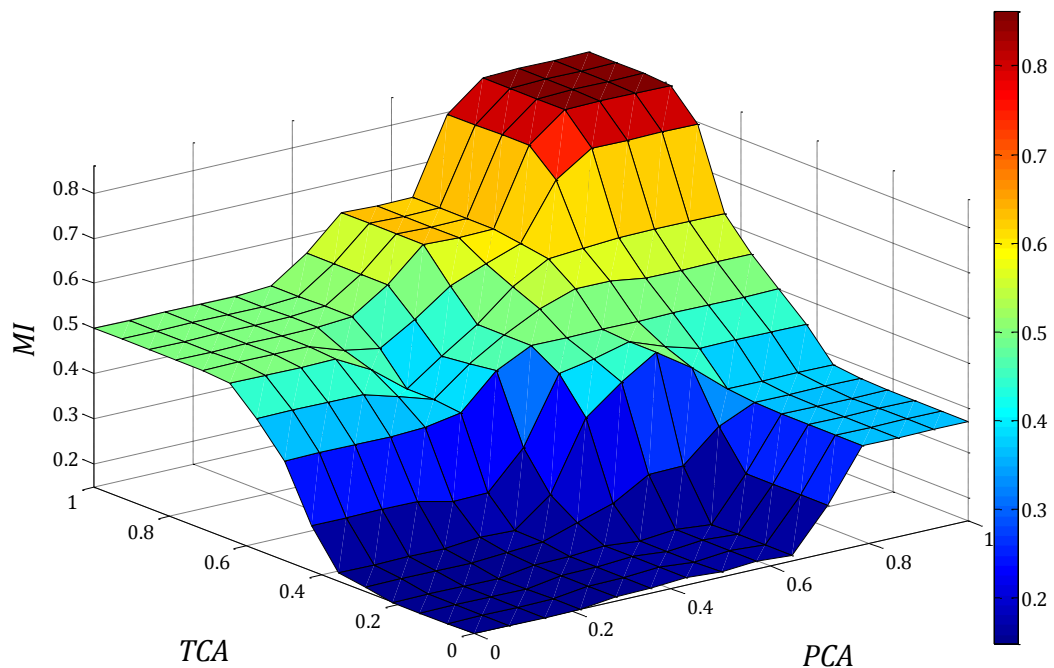


Figure 7.6 Surface plot of PCA, TCA and the mobility indicator.

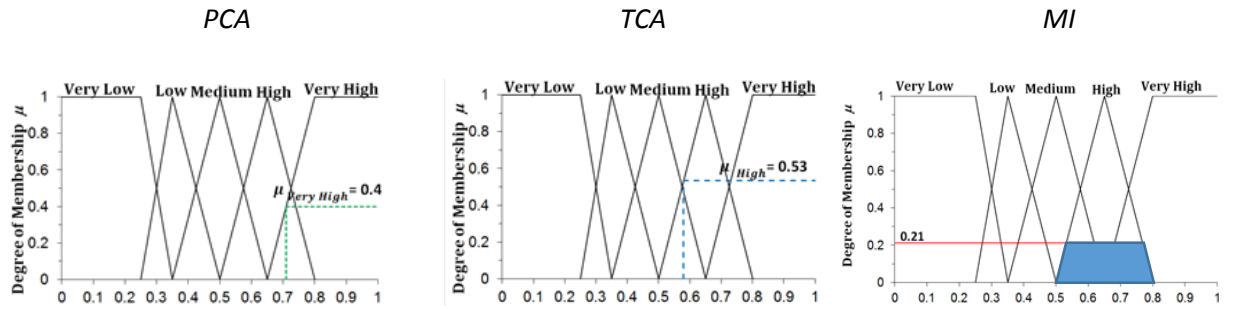
7.4.4 Defuzzification of Mobility Indicator

Defuzzification is the inverse process of fuzzification, whereby the calculated fuzzy values of the mobility indicator are converted to crisp values. There are

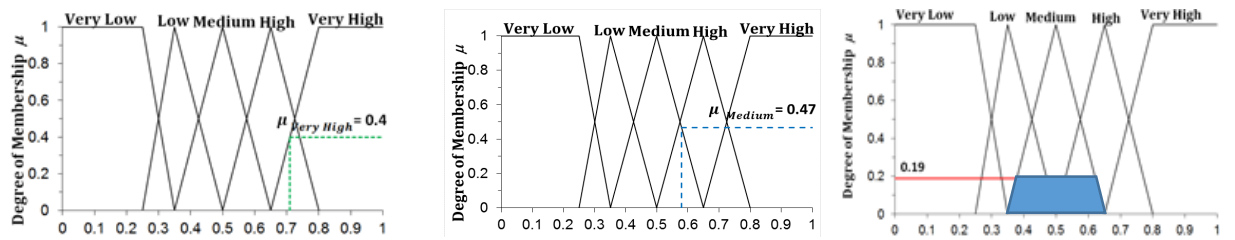
a number of defuzzification techniques, such as the max membership principle, centroid method (centre of area or centre of gravity) and weighted average method. For more details of these techniques and their uses, see Ross (2010). Here the centroid method, that calculates the centre of gravity for the area under the curve, was used as it allows for an accumulating effect for each assessment level on the calculated *MI* (Ross, 2010). It is also the most prevalent and appealing technique (Ross, 2010).

7.4.5 Illustrative Example of FL Processes

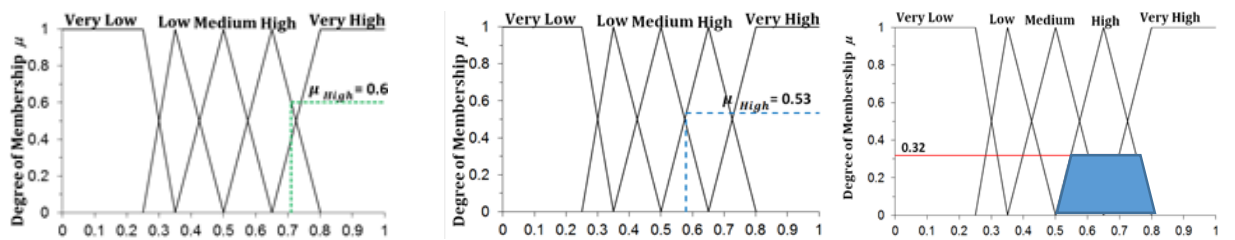
In this section, a numerical example is used to demonstrate the main steps of the fuzzy logic approach in combining the two attributes to estimate the mobility indicator. The route between Birmingham and London was chosen for this purpose. The full details of the route are presented in Tables 7.4 and 7.5 (route 3 between the two cities) where $PCA = 0.71$ and $TCA = 0.58$. Based on Figure 7.7, defuzzification of $PCA = 0.71$ gives a membership grade of the very high and high subsets of 0.55 and 0.40, respectively. Similarly defuzzification of $TCA = 0.58$ provides a membership grade of the high and medium subsets of 0.53 and 0.47, respectively. Consequently, four If-Then rules were activated, as listed in Figure 7.7. These four rules identify the mobility level to be members of the high and medium subsets. For each rule, the compatibility of the rule was calculated using the 'product' t-norm, for example for rule 1, the compatibility level for the mobility high subset is $0.53 \times 0.40 = 0.21$. For each rule, a trapezoid conclusion was truncated based on the rule compatibility value. The truncated membership functions for each rule were then aggregated using the 'min' operator. The centre of gravity technique was, then, employed to defuzzificate the aggregated membership function obtained and the value of the mobility indicator was calculated, as presented in Figure 7.7.



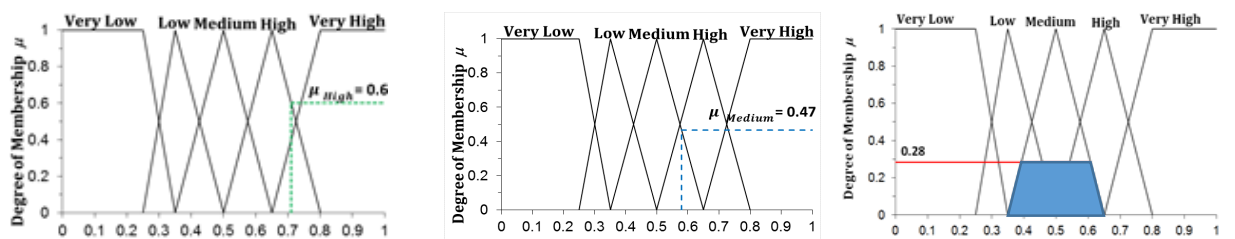
IF *PCA* is Very high and *TCA* is High Then *MI* is High



IF *PCA* is Very high and *TCA* is Medium Then *MI* is Medium



IF *PCA* is high and *TCA* is High Then *MI* is High



IF *PCA* is high and *TCA* is Medium Then *MI* is Medium

$PCA = 0.71$

$TCA = 0.58$

$MI = 0.57$

Figure 7.7 Graphical representation of fuzzy reasoning.

The fuzzy logic toolbox Graphical User Interface (GUI) in MATLAB environment was used to build the FIS described and to model MI from the two attributes PCA and TCA . To test the validity of the proposed model a number of scenarios of real transport networks were studied, as presented in more detail in Section 7.6 below.

7.5 Network Mobility Indicator

Despite the importance of an OD based mobility indicator, a network wide indicator could be needed to assess the level of mobility under different conditions. To evaluate network mobility, the network mobility indicator (NMI) was estimated from the mobility indicator MI obtained from the fuzzy logic inference system described above. Each MI_{ij} is aggregated based on the level of demand between each OD pair, as presented in Eq. (7.4) below:

$$NMI = \frac{\sum_{i \neq j} MI_{ij} d_{ij}}{\sum_{i \neq j} d_{ij}} \quad (7.4)$$

d_{ij} is the demand between zone i and zone j .

7.6 Case Study 1

Different routes between 7 British cities, namely London, Bath, Leeds, Birmingham, Bradford, Brighton and Manchester were chosen to show the applicability of the proposed technique. For each OD pair (e.g. Brighton and Manchester), various alternative routes available in Google maps in both directions were considered. For example, Figure 7.8 shows different routes from Bath, Birmingham, Bradford, Leeds, Brighton and Manchester to London. For each route, the travel distance in addition to the free flow travel time is shown in Figure 7.8. The travel time for each route was obtained from the google maps website based on the traffic conditions at the time of data collection (between 8:00am and 10:00am on 10 March 2014). Table 7.4 presents the routes' characteristics including travel distance, time and speed, in addition to the free flow time and speed. Table 7.5 shows a numerical example of the calculated values of PCA , TCA and $GDpM$ for the routes

presented in Table 7.4, in addition to the estimated values of MI produced using the FIS. Figure 7.9 shows the correlation between MI and $GDpM$. The numerical example shows the efficiency of the proposed technique in estimating MI , with an R^2 value of 0.9 between the estimated value of MI and $GDpM$.



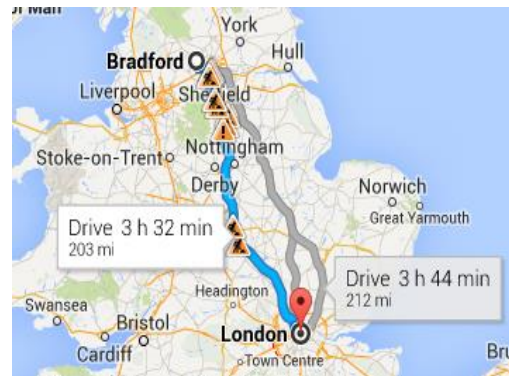
(a) Bath-London routes



(b) Birmingham-London routes



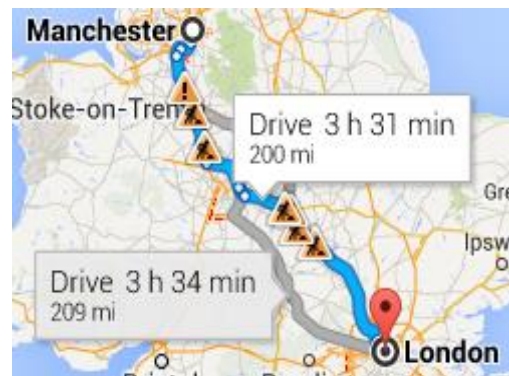
(c) Leeds-London routes



(d) Bradford-London routes



(e) Brighton-London routes



(f) Manchester-London routes

Figure 7.8 Route maps with travel distance and free flow travel time (Source: Google Map, 2014).

Table 7.4 Different routes to London City with their traffic performance measures.

<i>i</i> \ <i>j</i>	London												
	GD _{ij} (mi)	Route 1				Route 2				Route 3			
		TD _{ij} (mi)	TT _{ij} (min)	FFTT _{ij} (min)	TS _{ij} (mi/hr)	TD _{ij} (mi)	TT _{ij} (min)	FFTT _{ij} (min)	TS _{ij} (mi/hr)	TD _{ij} (mi)	TT _{ij} (min)	FFTT _{ij} (min)	TS _{ij} (mi/hr)
Bath	96.23	116	154	130	45.19	122	174	149	42.41	-*	-*	-*	-*
Birmingham	98.48	118	162	127	43.70	139	204	157	40.88	152	204	164	47.35
Bradford	168.23	203	261	212	46.67	212	283	222	43.04	216	287	228	45.16
Brighton	45.70	53.3	127	87	25.18	63.2	130	94	29.17	-*	-*	-*	-*
Leeds	166.00	195	239	203	48.95	195.	250	150	46.80	225	253	229	53.36
Manchester	160.10	200	242	211	49.59	202.	258	223	46.98	209	240	214	52.25

-* indicates no third route between the two cities at the time of data collection (between 8:00am and 10:00am on 10 March 2014).

Table 7.5 *PCA, TCA, MI and GDpM* values for routes presented in Table 7.4.

<i>i</i> \ <i>j</i>	London											
	Route 1				Route 2				Route 3			
	<i>PCA_{ij}</i>	<i>TCA_{ij}</i>	<i>MI_{ij}</i>	<i>GDpM_{ij}</i>	<i>PCA_{ij}</i>	<i>TCA_{ij}</i>	<i>MI_{ij}</i>	<i>GDpM_{ij}</i>	<i>PCA_{ij}</i>	<i>TCA_{ij}</i>	<i>MI_{ij}</i>	<i>GDpM_{ij}</i>
Bath	0.83	0.65	0.63	0.62	0.79	0.60	0.58	0.55	-*	-*	-*	-*
Birmingham	0.83	0.62	0.60	0.61	0.78	0.69	0.75	0.63	0.71	0.58	0.57	0.48
Bradford	0.83	0.67	0.70	0.64	0.83	0.61	0.59	0.59	0.79	0.63	0.61	0.59
Brighton	0.86	0.36	0.38	0.36	0.72	0.42	0.47	0.35	-*	-*	-*	-*
Leeds	0.85	0.7	0.77	0.69	0.85	0.67	0.70	0.66	0.74	0.76	0.84	0.66
Manchester	0.80	0.71	0.79	0.66	0.79	0.67	0.70	0.62	0.77	0.75	0.85	0.67

-* indicates no third route between the two cities at the time of data collection (between 8:00am and 10:00am on 10 March 2014)

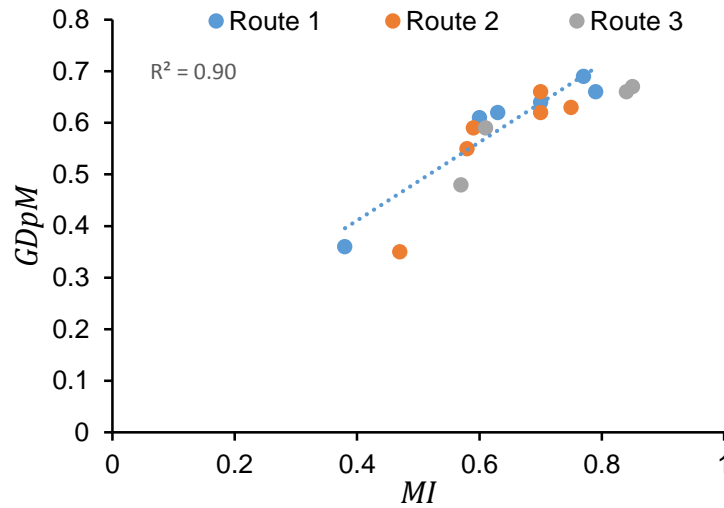


Figure 7.9 Correlation between *MI* and *GDPm*.

To check the validity of the technique on a wider scale, all the routes between the seven cities (110 routes) were used. Figure 7.10 shows the correlation between the mobility indicator and travel distance per minute for all the routes between the seven cities: Figure 7.10(a) for free flow conditions and Figure 7.10(b) with current traffic conditions. Figure 7.10(a) shows a high correlation between the mobility level under free flow conditions *FFMI* and *FFGDPm* ($R^2=0.90$) whereas Figure 7.10(b) shows a high correlation under different traffic flow conditions. These findings further support the successful application of the proposed technique.

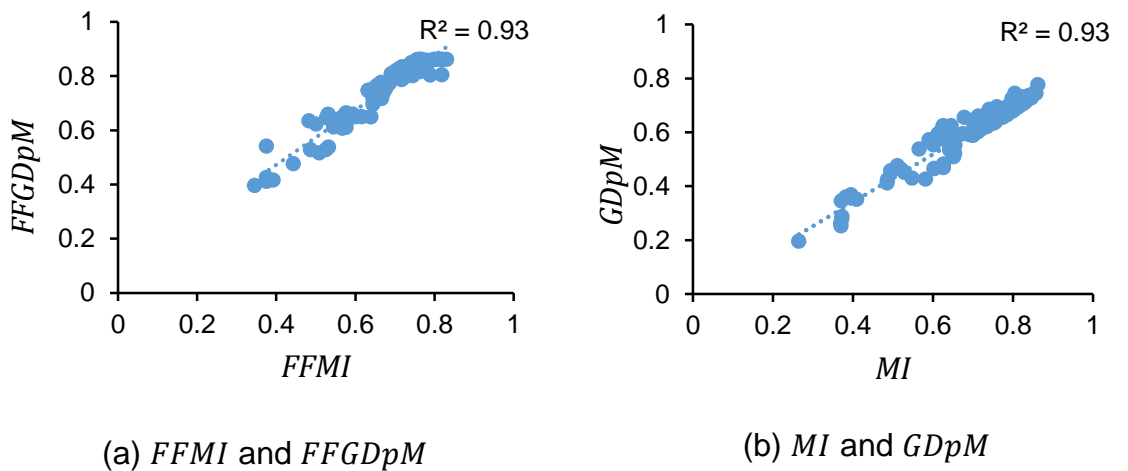


Figure 7.10 Correlation between *MI* and *GDPm* for the 110 routes between the seven cities.

7.7 Case Study 2

Case study 1 (explained above) was used to show the validity of the proposed technique in a real life application. However, there is still a need to check the variation of MI under different scenarios. To achieve this, a synthetic road transport network for Delft city was employed to illustrate the mobility of the road network under different scenarios using the proposed methodology. The full details about the Delft city road transport network are given in Chapter 4 along with a detailed discussion on OmniTRANS Software.

A dynamic assignment model (MaDAM), available in the four steps transport modelling software OmniTRANS (version 6.026), was implemented to investigate the ability of MI to respond to variations in demand i.e. applying different departure rates every 5 minutes. A full discussion about the OmniTRANS software is introduced in Chapter 4.

7.7.1 Demand Variation Scenario

Different departure rates every 5 minutes were used to investigate the impact of demand variations on the network mobility indicator estimated by FIS. 15 minute aggregated travel data (i.e. travel time and distance between each OD in the network) were obtained. A computer programme was developed using MATLAB (R2011a) to calculate PCA and TCA (Eqs. 7.1, 7.2 and 7.3) for each OD pair (i.e. 484 routes for each time step; in total 9 time periods from 7:00pm to 9:00pm) and MI was then estimated using the FIS developed. The network mobility indicator, NMI , was calculated using Eq. (7.4). Similar to the real life case study, a very high correlation was achieved between NMI and $GDpM$ for the 9 time steps, as presented in Figure 7.11.

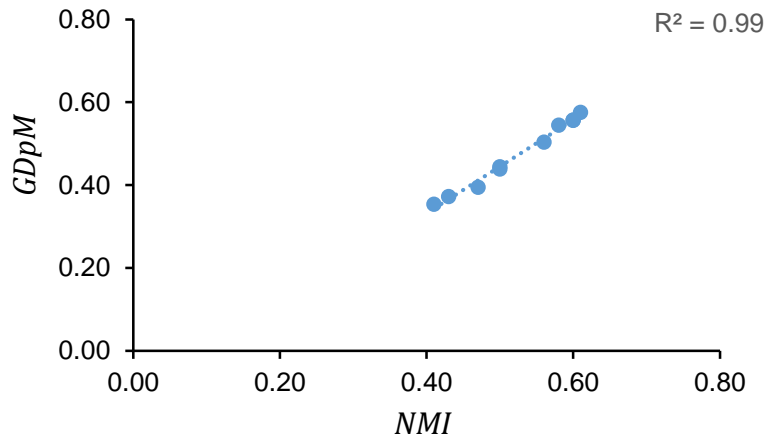


Figure 7.11 Correlation between *NMI* and *GDpM*.

Figure 7.12 presents the variations in *TCA* and hence the mobility level under different departure rates. *PCA* does not show any change with demand variations as route choice does not change within the MaDAM model in OmniTRANS (Version 6.026) (as explained earlier). Consequently, the network mobility indicator *NMI* shows the same trend as *TCA*. Figure 7.12 also demonstrates that the proposed *NMI* decreases as the departure rate increases, reflecting the ability of the network to accommodate the increase in demand. However, as the departure rate decreases, for example between 7:30 and 8:15, *NMI*, is seen to increase.

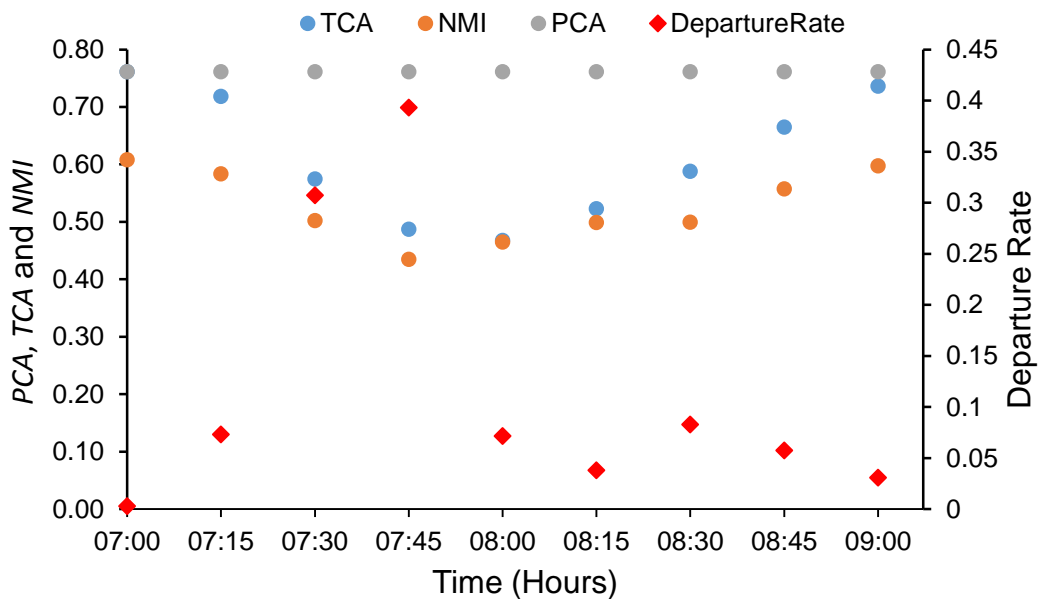


Figure 7.12 Variation of the mobility attributes and indicator against time.

7.7.2 Disruptive Events

The road transport network may be exposed to a wide range of disruptive events, which varies in type, magnitude and consequences. Disruptive events can be classified as manmade (i.e. a traffic accident) or natural events such as climate change related events (e.g. floods and extreme weather conditions) as explained in details in Section 3.2. In this section, an accident impact will be modelled using a single link closure, whereas a natural event impact is simulated using network wide capacity reductions, as explained below.

7.7.2.1 Link Closure

A number of links were selected to investigate the ability of the proposed attributes to reflect the impact of link closure on mobility. 10 link closure scenarios were carried out using a static assignment model for the morning peak for the purposes of illustration, though many more links could be considered if needed. In each scenario, only one link was blocked, e.g. closed due to a road accident or roadwork (see Figure 7.13 for link closure). Both attributes, the physical connectivity attribute (*PCA*) and traffic condition attribute (*TCA*), were calculated based on the zone level data output. Table 7.6 and Figure 7.14 show the results for *PCA*, *TCA* and *NMI* due to 10 link closures. The impact of link closure on both attributes, *PCA* and *TCA*, is seen to vary from one link to another. For example, links 1 and 5 have the greatest impact on *PCA* as the closure of these links leads to a 5% decrease in *PCA* when compared with full network operation. The closure of links 3, 4, 6 and 7 has the highest impact on *TCA* as each link closure leads to a 10% reduction in *TCA* in comparison to full network operation. The highest aggregated impact of a link closure, measured by the corresponding decrease in *NMI*, occurs with the closure of links 2, 3, 4, 6 and 7.

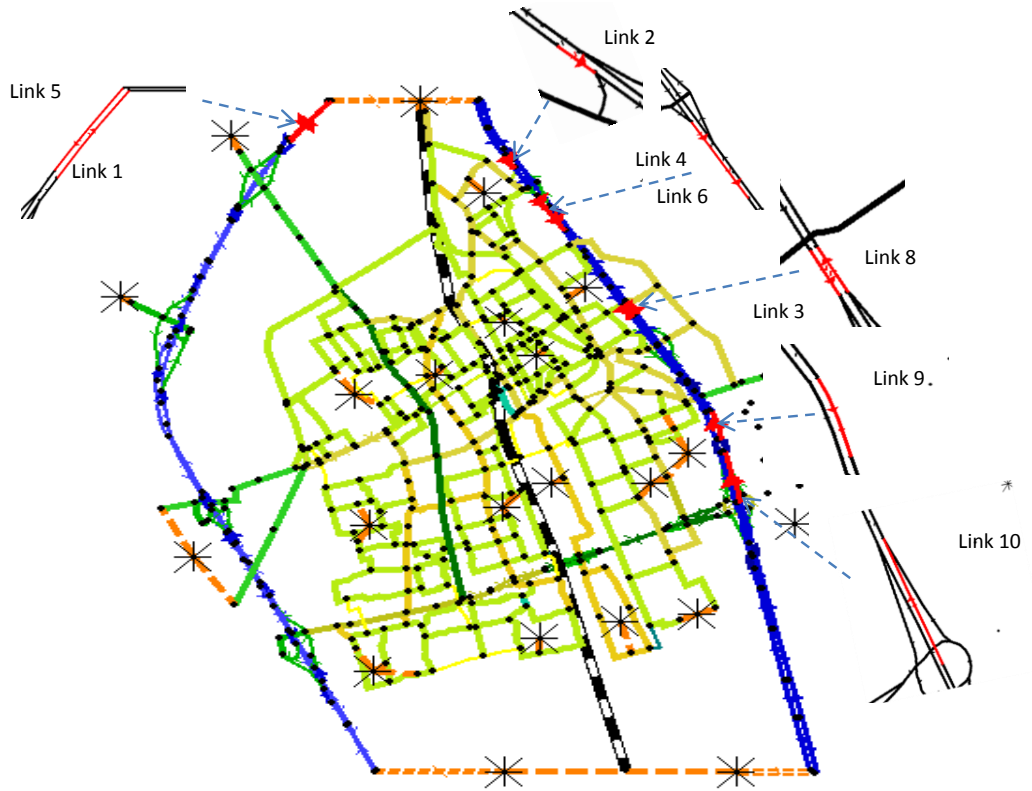


Figure 7.13 Delft road transport network with Link closure.

Table 7.6 PCA, TCA and NMI variations arising from individual link closure.

	PCA	TCA	NMI
Full Network	0.76	0.65	0.61
Link 1	0.71	0.58	0.54
Link 2	0.72	0.56	0.53
Link 3	0.75	0.55	0.53
Link 4	0.75	0.55	0.53
Link 5	0.71	0.61	0.56
Link 6	0.75	0.55	0.53
Link 7	0.75	0.55	0.53
Link 8	0.74	0.60	0.57
Link 9	0.74	0.56	0.55
Link 10	0.75	0.59	0.57

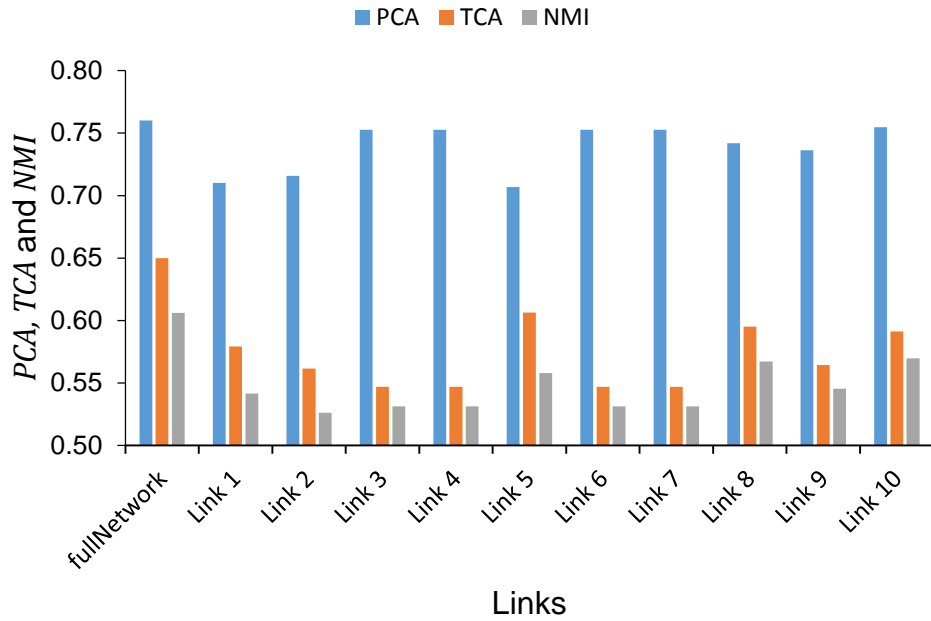


Figure 7.14 *PCA, TCA and NMI variations due to link closure.*

7.7.2.2 Impact of a Network Wide Disruptive Event

Overall network capacity could be reduced in real life due to the effect of network wide events such as heavy rain or snowfall. The levels of reduction in network capacity and speed were assumed based on evidence in the literature (Enei et al., 2011; Pisano and Goodwin, 2004; Koetse and Rietveld, 2009). The main aim of this analysis was to examine the ability of *NMI* to capture the impact of a reduction in network capacity under similar variations in demand. This group of scenarios involved a reduction in capacity of 5%, 10% and 15 % in order to model the impact of a weather related event. Figure 7.15 shows the variations in the network mobility indicator, *NMI*, for the reduced network capacity and variations in the departure rate as illustrated in Figure 7.15. From Figure 7.15, *NMI* shows variations during the modelling period (7:00-9:00) for reduced capacity compared with the full network capacity. In general, the largest reduction in the level of network mobility occurs with a 15% capacity reduction under different departure rates. It is worth noting that the response rate in terms of improvement in mobility associated with a decrease in the departure rate is dependent on network capacity. For example, when the reduction in network capacity is 15%,

network mobility does not improve much with varying departure rates in comparison with lower reductions in network capacity.

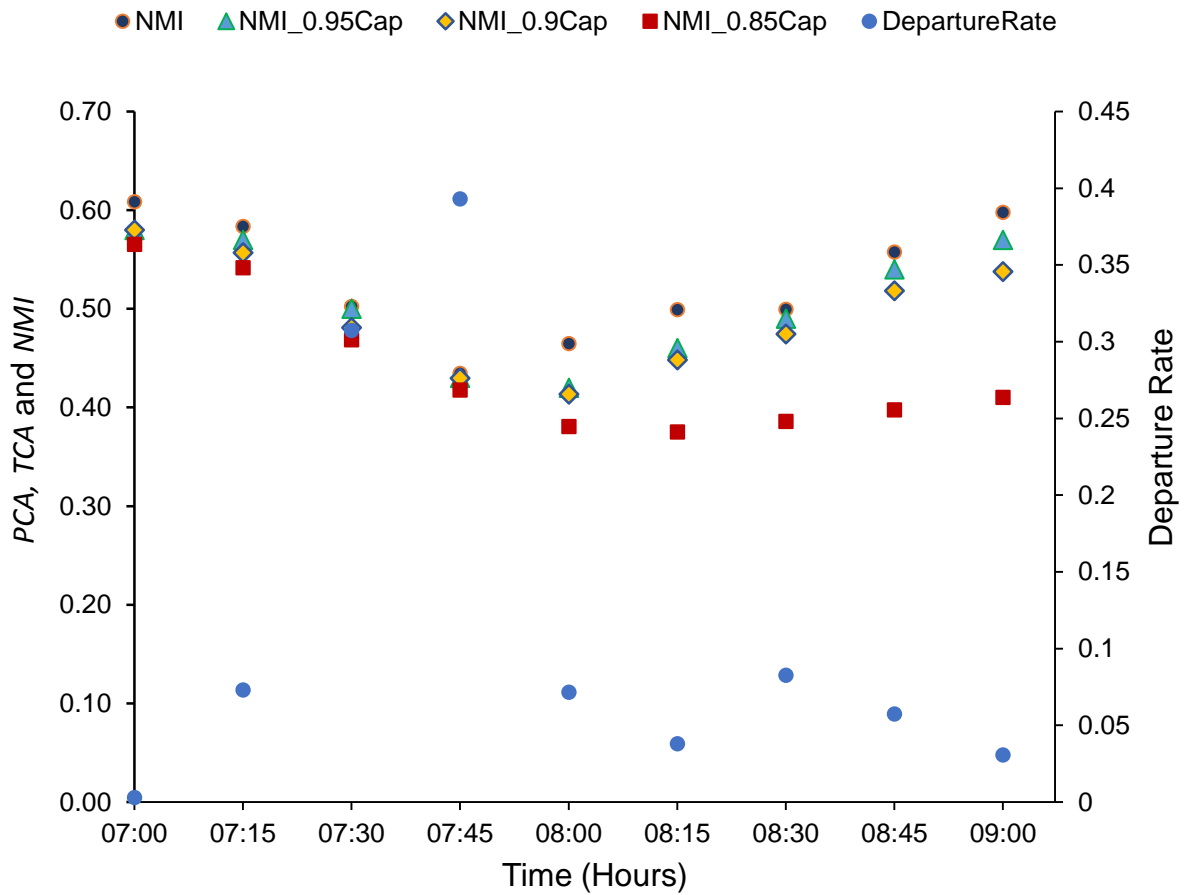


Figure 7.15 Variation in mobility indicator against time for different levels of network capacity.

7.8 Conclusions

This chapter introduces a new mobility indicator based on two attributes: a physical connectivity attribute (*PCA*) and a traffic condition attribute (*TCA*), accounting for both network configuration and traffic flow conditions. The merit of using both attributes is to allow the inclusion of different types of disruptive events and their impacts on network mobility. The use of two attributes also allows identification of the causes of low mobility under different scenarios. This is in contrast to the case of a single mobility attribute that may refer to the level of mobility without providing insight to the cause. A flexible technique

based on a fuzzy logic approach was therefore implemented to estimate a mobility indicator *MI* based on *PCA* and *TCA*. In contrast with alternatives such as the use of different weights for each attribute, FL was able to accommodate variation of both attributes under different conditions. As an example, under free flow conditions, the technique was able to estimate the level of mobility that is more influenced by the physical connectivity than the traffic condition.

Two case studies were considered to validate the technique. The first case (based on real traffic data between seven British cities) showed strong correlation between the estimated mobility indicator and travel distance per minute, confirming the applicability of the proposed mobility indicator. The second case study concerned a synthetic road transport network for Delft city. It demonstrated that the network mobility indicator changes with demand variations; as the departure rate increases, the network mobility indicator decreases. Furthermore, the network mobility indicator changes with supply side variations (i.e. network capacity reduction and link closure). Together these findings indicate that the *NMI* behaves in an intuitively correct manner. It has also been observed that individual link closures have different impacts on *PCA* and *TCA*, i.e. the closure of some links had more impact on *PCA* whereas other link closures resulted in greater reductions in *TCA* than *PCA*. This emphasises the importance of considering both attributes in assessing the level of mobility.

NMI could be used by policy makers, local road authorities or strategic Highway Agencies to evaluate the overall effectiveness of particular policies or, for example, to assess the implementation of new technologies.

Chapter 8: A Composite Resilience Index and ITS influence on the road transport network resilience

8.1 Introduction

This chapter discusses the interdependence of the proposed resilience characteristics and explain their role in identifying the resiliency level of road transport networks. Furthermore, this chapter presents a composite resilience index of road transport networks based on the three resilience characteristics, redundancy, vulnerability and mobility, introduced in Chapters 5, 6 and 7, respectively.

The chapter also investigates the role of real-time travel information systems on the resilience characteristics and the developed composite resilience index of road transport networks. The chapter benefits from the very recent version of the OmniTRANS software (Version 6.1.2) which became available in May 2014. The new version has included a route choice model in the dynamic traffic assignment (DTA) framework. A full discussion about the difference between OmniTRANS 6.1.2 and the previous versions is introduced in Chapter 4 along with a summary of the impact of using different versions on the research.

8.2 Interdependence of the Resilience Characteristics

Figure 8.1 illustrates the relationship between road transport network resilience, the three characteristics and their attributes using the bottom-up level of the attributes for each characteristic as presented in Chapters 5, 6 and 7. For example link flow changes affect the redundancy characteristic by increasing or decreasing the link spare capacity (i.e. ρ_{am}^i calculated by Eq. 5.6) and several attributes of vulnerability characteristic as shown in Figure 8.1. Variations in traffic flow can result in a change to the travel speed on a link, affecting the level of mobility by increasing or decreasing the traffic condition attribute (TCA calculated by Eq. 7.3). However changes in mobility

could also vary under the same level of traffic flow due to the network configuration, measured by the physical condition attribute. Similarly, a decrease in network capacity due to the closure of one or more links (e.g. due to an accident, floods or adverse weather conditions) could also influence the three characteristics, as shown in the case studies presented in Chapters 5, 6, and 7. Table 8.1 summarises the attributes used to quantify the three resilience characteristics as explained in each respective chapter for the three characteristics. The table also shows the level of measurement and importance of each characteristic. The level at which the redundancy and vulnerability indicators are calculated (i.e. junction level and link level respectively) suggests that both characteristics reflect resilience from the perspective of planners, decision makers and stakeholders. However as mobility is calculated at OD level it could be considered to be reflecting resilience from the travellers point of view (see Table 8.1). Given that the proposed indicators are calculated at different levels, each indicator has finally been aggregated to the network level as explained in each respective chapter.

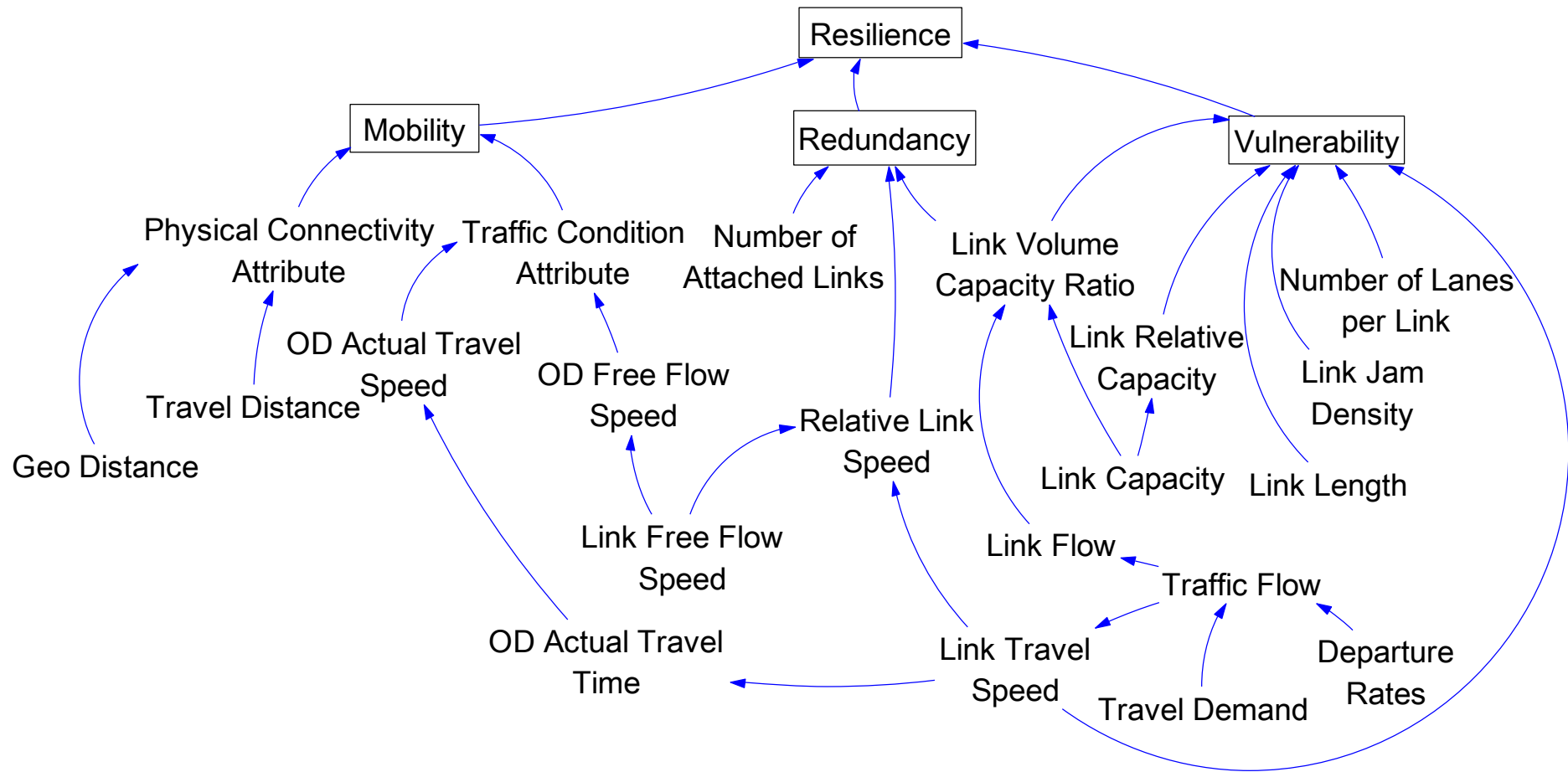


Figure 8.1 Resilience dependency on various characteristics and attributes (Source: the author).

Table 8.1 Resilience characteristics (indicators, level of measures, attributes and importance).

Resilience Characteristics	Indicators	Level of measure	attributes	Importance
Redundancy	Junction redundancy indicator	Junction level	<ul style="list-style-type: none"> • Number of links attached to the junction, • Attached link capacity, • Attached link flow, • Attached links speed. 	The ability of the network to adapt the change in demand or supply.
Vulnerability	Link vulnerability indicator	Link level	<ul style="list-style-type: none"> • Link flow, • Link capacity, • Link number of lanes, • Link jam density, • Link length, • Link free flow speed. 	The ability of road transport network to recoup with the distribution of the traffic across the network /Sensitivity of the network to disruptive events.
Mobility	OD mobility indicator	OD level	<ul style="list-style-type: none"> • OD travel distance, • OD travel speed. • OD geo distance. • OD free flow travel time. 	The overall functionality of the network.

The three characteristics represent three interconnected capabilities of road transport networks, as presented in Table 8.1. Redundancy can be considered as the ability of the network to adapt to a change in demand or supply, e.g. the availability of several routes to a junction under different scenarios. It is intended to reflect the influence of the configuration of the road transport network and its interaction with the level of demand. As such, the redundancy indicator could be used to gauge the level of adaptability of the network in the case of a disruptive event such as road closure due to flooding or an accident. An increase in redundancy may allow the re-assignment of traffic to other routes where a disruptive event has occurred. A high level of network redundancy could result in links being less vulnerable given there is the possibility for traffic to be distributed more widely over the network links rather than congestion concentrated on certain routes. The vulnerability characteristic indicates the ability of the network to recoup as it captures the interaction between the distribution of traffic and the capacity of the road transport network. Mobility is also essential to fulfil the resilience concept as it assesses the main function of the road transport network.

The case studies presented in Sections 8.4 and 8.5 demonstrate that the interdependency of the three characteristics cannot be interpreted as essentially measuring the same phenomena but at different levels, i.e. junction, link and OD levels. The characteristics could be influenced by some common factors, as will be shown using principal component analysis in Section 8.3.2. However the magnitude of the impact of these common factors on the characteristics can vary from one characteristic to another, as demonstrated in the case study presented later in this chapter. Moreover, the type of impact (i.e. positive or negative), may change from one period of time to another for the same characteristic, reflecting the complex relationships inherent in the road transport network under different conditions. As an example, the reassignment of traffic due to an accident could, in some cases, lead to a decrease in the level of vulnerability compared with the 'no accident' scenario as will be shown in case study 1 presented in Section 8.4. This set of dependencies and levels of measurement provides the rationale for a composite resilience index (based on various characteristics) in order to

assess the functionality of a road transport network under different disruptive events.

8.3 A Composite Resilience Index for Road Transport Networks

Despite the importance of measuring the level of each characteristic separately, it could be useful to estimate the overall level of resilience using a composite resilience index. Smith (2002) outlined the advantage and disadvantages of a composite index in general. The advantages focus on its role as a communication tool that offers an overall rounded assessment of performance and in giving an indication of the behaviour of the system under consideration. It can be used to summarize multi-dimensional issues and include more information, allowing a comparison between different scenarios or places (Saisana and Tarantola, 2002). Despite the advantages of a composite index, a number of disadvantages also have to be taken into account. For example the use of a composite index only may lead to simplistic policy conclusions (Saisana and Tarantola, 2002) and may not be adequate to identify the changes required for improvements (Mitchell, 1996). Consequently it might be useful to consider both aggregate and disaggregate levels, (i.e. indicators for individual resilience characteristics in addition to a composite resilience index) in the assessment of road transport networks. In order to produce an aggregate index it is necessary to consider the method of aggregation and in particular the potential use of weights. Smith (2002) claimed that methodologies for estimating weights could be inadequate and reflect a single set of preferences.

To obtain the composite index, a number of steps should be considered (Saisana and Tarantola, 2002), namely the development of a conceptual framework, the selection of an appropriate set of indicators, and then the use of a suitable aggregation method. In the current research, the conceptual framework is presented in Chapter 3 followed by another 3 chapters, each to develop an indicator for each resilience characteristic. Consequently, this chapter focuses on the aggregation step. In the following section a number of aggregation methods are briefly reviewed; then two methods, namely equal

weighting and principal component analysis are implemented to develop a composite resilience index of road transport networks.

8.3.1 Aggregation Approaches

Aggregation often involves the use of weights on individual components rather than simple addition. According to Saisana and Tarantola (2002), weighting techniques can be classified into three main categories, statistical methods (e.g. principal component analysis), methods based on experts' opinions (e.g. analytical hierarchy processes) or equal weighting amongst variables. In the resilience literature, several weighting approaches have been adopted to obtain a composite index. Briguglio et al. (2009) used a simple average (i.e. equal weighting) to obtain a composite economic resilience index, whilst Stolker (2008) used analytical hierarchical process to estimate the overall operational resilience of an organization. In McManus (2008), the estimated values of the resilience characteristics are multiplied together to obtain the relative overall resilience for an organization. Hyder (2010) added the number of "Low" scores for ten characteristics to estimate a vulnerability index for each link as a method to estimate the resilience of road transport networks.

The equal weighting method is widely used in many disciplines, for example, it is used for developing a composite index for assessing social–ecological status (Estoque and Murayama, 2014) and organizational resilience (Briguglio et al., 2009) due to its simplicity and transparency (see Section 8.3.1.1). However, the equal weighting method suffers from potential double counting effects in the final index. In addition, it does not necessarily reflect the relative priorities of different indicators (Saisana and Tarantola, 2002). Hermans et al. (2008) concluded that equal weighting could be used where the results from other weighting methods were invalid and also suggested that the approach could yield good results whether the indicators are correlated or uncorrelated.

Statistical methods such as principal component analysis have been widely used in many applications, including the development of a transport sustainability index (e.g. Reisi et al., 2014). The mathematical formulation of this method is presented in Section 8.3.1.2. Principal component analysis has many advantages as it does not involve any manipulation of weights through subjective process, unlike methods based around experts' opinions and

overcomes the double counting effect inherent to the equal weighting method. However, the method is sensitive to the dataset used, as the weights may change according to the dataset from which the indicators have been derived. Analytical hierarchy processes (AHP) (as an example of a method based on experts' opinions) is also widely used in many disciplines (Saisana and Tarantola, 2002). AHP is based on structuring the indicators in a hierarchal way, then assigning weights for each indicator compared with other indicators at the same level. The weights are based on experts' opinion and use a semantic scale to form the comparison matrix (Saaty, 1980). For example, if AHP is used to develop *RCI*, experts judge the relative contribution of each resilience characteristics compared with other characteristic as illustrated in Table 8.2. For example, the vulnerability is 2 times more important than redundancy, and consequently redundancy has 0.5 the importance of the vulnerability.

Table 8.2 illustrative example of Comparison matrix of three resilience characteristics (semantic scale).

	Redundancy	Vulnerability	Mobility
Redundancy	1	0.5	0.25
Vulnerability	2	1	0.33
Mobility	4	3	1

Using the resulting comparison matrix, the relative weights for indicators are calculated using an eigenvector technique. The use of eigenvalues allows checks on the consistency of the comparison matrix as a number of comparisons are generated. This is equal to $n(n - 1)/2$ for a matrix size of $n \times n$, where the $n - 1$ comparisons are required to establish weights and n is the number of indicators considered. The excess number of comparisons is analogous to calculating a number using the average of repeated observations, resulting in a set of weights less sensitive to judgement errors (Saisana and Tarantola, 2002; Saaty, 1980). The ability to use quantitative and qualitative data in addition to the degree of transparency are the main advantages of AHP, whereas subjectivity is the main drawback (Nardo et al.,

2005). Further details about AHP and its applications are widely available in the literature, e.g. Saaty, 1980, Saisana and Tarantola, 2002 and Nardo et al., 2005.

A wide range of further methods can be used to develop a composite index using many indicators, such as regression, conjoint analysis, benefit of the doubt and data envelopment analysis (see Saisana and Tarantola, 2002; Nardo et al., 2005). However, the choice of an appropriate weighting method could be a challenge as no agreement on the ideal aggregation method has been reached so far (Hermans et al., 2008). To construct a composite resilience index based on the three proposed characteristics in this research, two methods of weighting are adopted i.e. equal weighting, and principal component analysis. The equal weighing method was chosen due to its simplicity and transparency which could facilitate its use in practice. Principal component analysis has also been implemented as it allows the elimination of interdependence among the indicators for the characteristics (see Section 8.3.1.2).

8.3.1.1 Equal Weighting Method

In line with the approach taken by Briguglio et al. (2009), the equal weighting method (EWM) is used here to combine redundancy, vulnerability and mobility indicators into a composite resilience index (CRI_{eq}). The method is based on allocating equal weights to all the indicators considered, as given by Eq. (8.1).

$$CRI_{eq} = \frac{((1-NVI)+NRI+NMI)}{3} \quad (8.1)$$

where NVI , NRI and NMI are the vulnerability, redundancy and mobility indicators for the road transport network respectively. As vulnerability is inversely proportional to resilience, the value $1 - NVI$ is used.

However the use of the EWM could result in double counting with implications for the value of the composite index (as previously discussed). In order to avoid this weakness, principal component analysis is also implemented as a

second approach (Section 8.3.1.2) and a comparison is then made with use of the EWM.

8.3.1.2 Principal Component Analysis

The main aim of the principal component analysis approach (PCA) is to convert a set of data of possibly correlated variables into a set of values of linearly uncorrelated variables, called principal components (Tabachnick & Fidell, 2007). The principal components calculated are still able to capture all the information present in the original variables. However, the first principal component accounts for the largest possible variance whilst the last component accounts for the least variance. It should also be noted that each principal component is orthogonal to the preceding one (Tabachnick & Fidell, 2007).

The applicability of PCA is based on correlation among the original variables, i.e. it is recommended when the original variables are correlated, positively or negatively. The first step in PCA is therefore to measure the sample adequacy using Kaiser-Meyer-Olkin⁵ (Reisi et al., 2014), with high values between 0.6 and 1.0 required in order to apply PCA. The second step is concerned with the extraction of a number of principal components to fully represent the original variables:

$$PC_j = \sum_{i=1}^n a_{ij} X_i \quad (8.2)$$

where PC_j is the principal component j , X_i represents the original variables (e.g. NVI , NRI and NMI) and a_{ij} is the weight for the j th principal component and the i th indicator X_i . As vulnerability is inversely proportional to resilience in this context, the corresponding variable is assumed to be 1 minus the vulnerability index (as explained for the EWM). The mobility and redundancy indicator values are input directly. The number of principal components could be as many as the number of original variables, n . The weights a_{ij} are

⁵ Kaiser-Meyer-Olkin measure is a ratio of the sum of squared correlations to the sum of squared correlations plus the sum of squared partial correlations (Tabachnick & Fidell, 2007).

calculated from the eigenvectors of the covariance matrix of the original data. a_{ij} is given by Eq. (8.3) below (Reisi et al., 2014):

$$a_{ij} = \frac{\varepsilon_{ij}^2}{\lambda_j} \quad (8.3)$$

where ε_{ij} represents the factor loadings and λ_j is the corresponding eigenvalue of the covariance matrix for the data. The above weights are normalised with respect to the sum of weights in order to scale them between 0 and 1. The method developed by Nicoletti et al. (2000) is then adopted to calculate a composite index of road transport network resilience from the principal components obtained using the original data for the three characteristics. The aggregated PC_j (based on its eigenvalues) can then be used to calculate the composite resilience index, as presented in Eq. (8.4) below:

$$CRI_{pc} = \sum_{j=1}^m \frac{\lambda_j}{\sum_{j=1}^m \lambda_j} PC_j \quad (8.4)$$

where CRI_{pc} is the composite resilience index using aggregated principal components.

More discussion on PCA is given in Tabachnick & Fidell (2007). The method is also applied by Nicoletti et al. (2000) and Reisi et al. (2014) to develop summary indicators of the strictness of product market regulations and a transport sustainability index respectively.

In the following sections, two case studies are presented, a simple network with one OD pair and a synthetic road transport network of Delft city case study with multi OD pairs and a wide variety of road types and junctions. In the first case study, the impact of an accident on the resilience characteristics is investigated with or without real-time travel information. Whereas the second case study explores the impact of demand increase with and without real-time travel information on the resilience characteristics and composite index using a synthetic road transport network of Delft city.

8.4 Case Study 1

A simple road transport network shown in Figure 8.2 is considered to investigate the impact of real-time travel information on the resilience characteristics. It consists of two zones, namely zone 1 and zone 2 representing the origin and the destination, respectively, with three routes available between the two zones as presented in Figure 8.2. The values of travel distance (TD), free flow travel time ($FFTT$) and free flow travel speed ($FFTS$) are calculated⁶ and presented in Table 8.3.

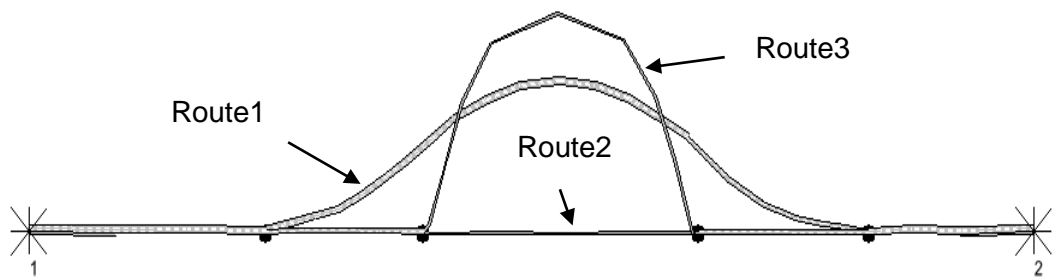


Figure 8.2 A simple road transport network.

Table 8.3 TD , $FFTT$ and $FFTS$ for the 3 routes.

Route1			Route2			Route3		
TD km	$FFTT$ min	$FFTS$ km/hr	TD km	$FFTT$ min	$FFTS$ km/hr	TD km	$FFTT$ min	$FFTS$ km/hr
25.58	12.78	120	26.11	20	78	31.29	21.87	90

The Geo distance (GD) between zones 1 and 2 is also calculated to be 25 km from the assumed coordinates of zones 1 and 2, using the Euclidean distance based on Pythagorean Theorem as explained in Section 7.3.1.1.

⁶ (i.e. identify the sequences of links for each route and sum up its free flow travel time to obtain $FFTT$ and its lengths to obtain TD per route and then divide TD by $FFTT$ to get $FFTS$)

8.4.1 Scenarios Implemented

Table 8.4 presents the group of scenarios to investigate the impact of real-time travel information on the resilience characteristics. Four different scenarios have been implemented for this case study by varying the network conditions and route choice stages. In scenarios S1_a and S2_a, the full network capacity has been considered in case of real-time travel information (route choice updating every 900 seconds) and without real-time travel information (i.e. the route choice has been identified for the whole simulation period at the start), respectively. Moreover, a link closure (e.g. due to accident or roadwork) takes place in the other two scenarios, S1_b and S2_b, along with and without travel time information updating, respectively. Figure 8.3 highlights the location of the link closure in route 1, between 7:00am and 8:00am.

Table 8.4 Scenarios with different real-time travel information updating.

Scenarios	Route choice moments	Network Conditions
S1_a	900 seconds	Full network capacity
S1_b	900 seconds	Link closure
S2_a	17100 seconds	Full network capacity
S2_b	17100 seconds	Link closure

Figure 8.4 presents the departure rates for different time intervals (6:00am to 10:00am) implemented in all scenarios. However, the period between 6:30am and 9:00am is only considered in the analysis to avoid the impact of loading and emptying of the network as the way that StreamLine⁷ simulates the emptying of the network was shown to be unrealistic (Dijkhuis, 2012). OmniTRANS software (Version 6.1.2) was used to simulate each scenario and a number of link data reports (15 minutes aggregated link data such as average link speed, travel time and flow) were produced. A special job was also written in OmniTRANS to extract route data for different time intervals

⁷ StreamLine is dynamic traffic assignment implemented in OmniTRANS as explained in Section 4.4.2.2.

such as the link sequences, route travel time and demand fraction of each route.

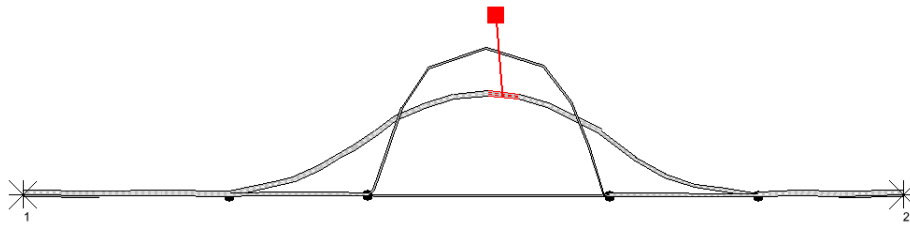


Figure 8.3 Link closure location.

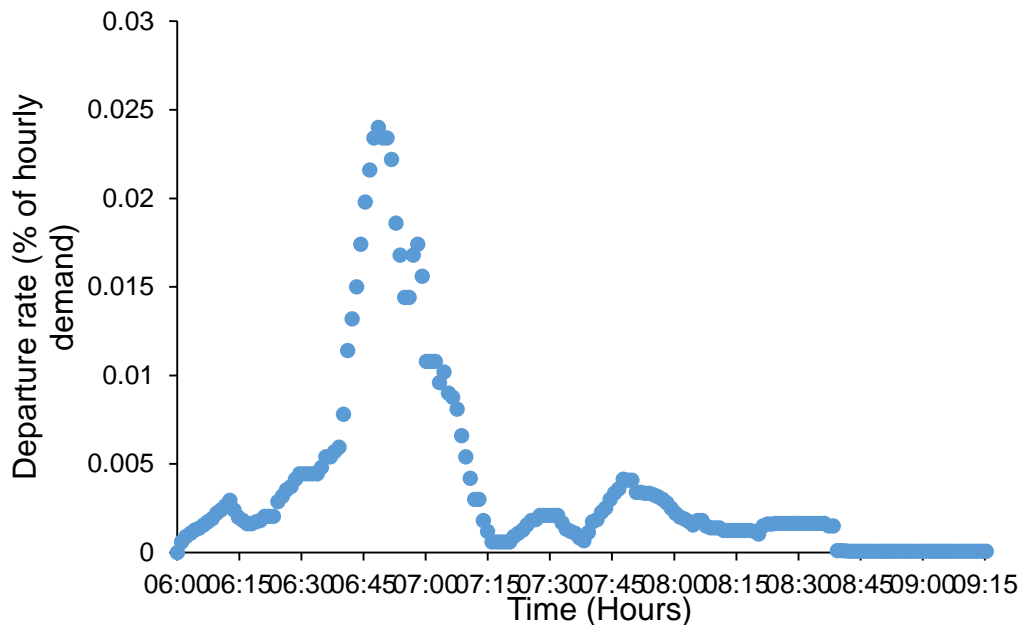
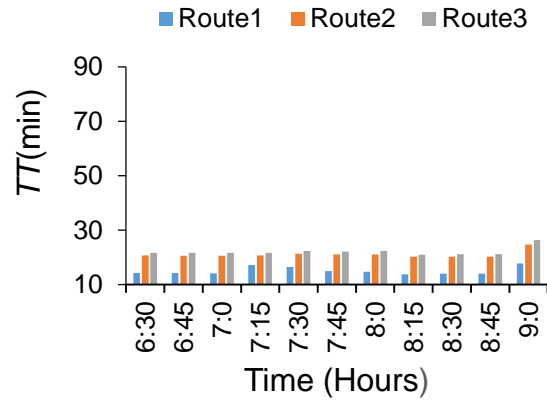


Figure 8.4 Departure rate of different time intervals.

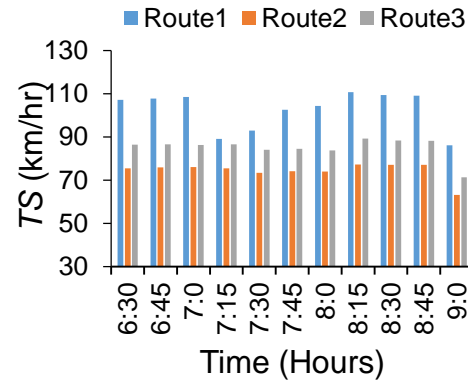
8.4.2 Results and Discussion

Based on the data produced from OmniTRANS software, the values of travel time (TT) and travel speed (TS) for each route for different time intervals for the four scenarios described in Table 8.3 calculated using a MATLAB code are shown in Figures 8.5 to 8.8. In the case of full network conditions, there are slight variations in route choice when real-time travel information is used (Figure 8.5(c)) whereas route fractions stayed the same without the real-time travel information as expected (Figure 8.7(c)). The impact of real-time travel information has a greater impact on route choice in case of link closure scenario as depicted from Figure 8.6(c) in line with other investigations (e.g.

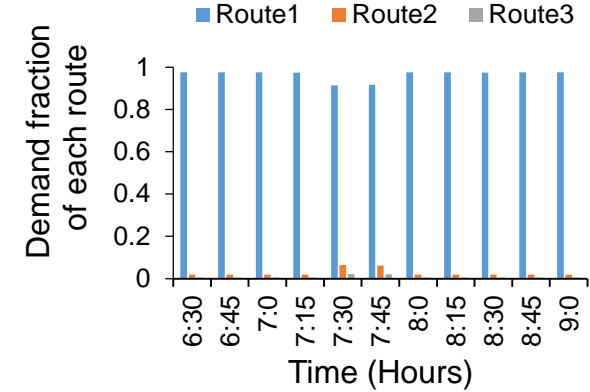
Gao, 2012). For example, the demand redistributed over routes 2 and 3 for the time period between 7:30 to 8:30 in S2_a scenario (see Figure 8.6(c)) whereas, in case of S2_b scenario, there is no change in route choice as expected (see Figure 8.8(c)).



(a) Travel time (TT)

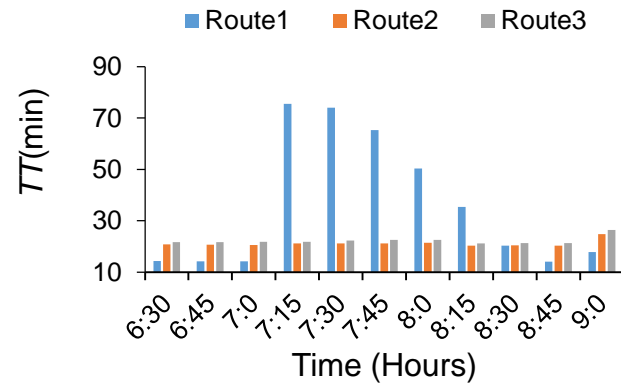


(b) Travel speed (TS)

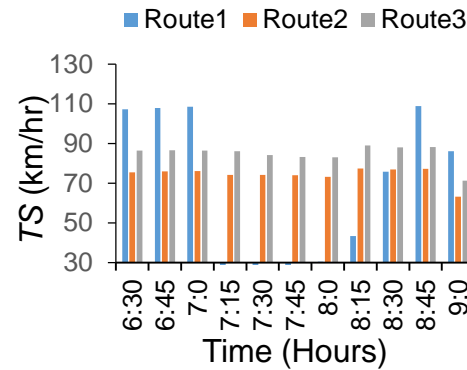


(c) Demand fraction of each route

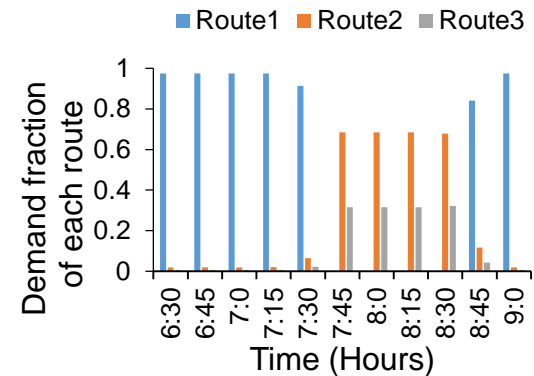
Figure 8.5 Travel Speed, travel time and demand fraction of each route for scenario S1_a.



(a) Travel time (TT)



(b) Travel speed (TS)



(c) Demand fraction of each route

Figure 8.6 Travel Speed, travel time and demand fraction of each route for scenario S1_b.

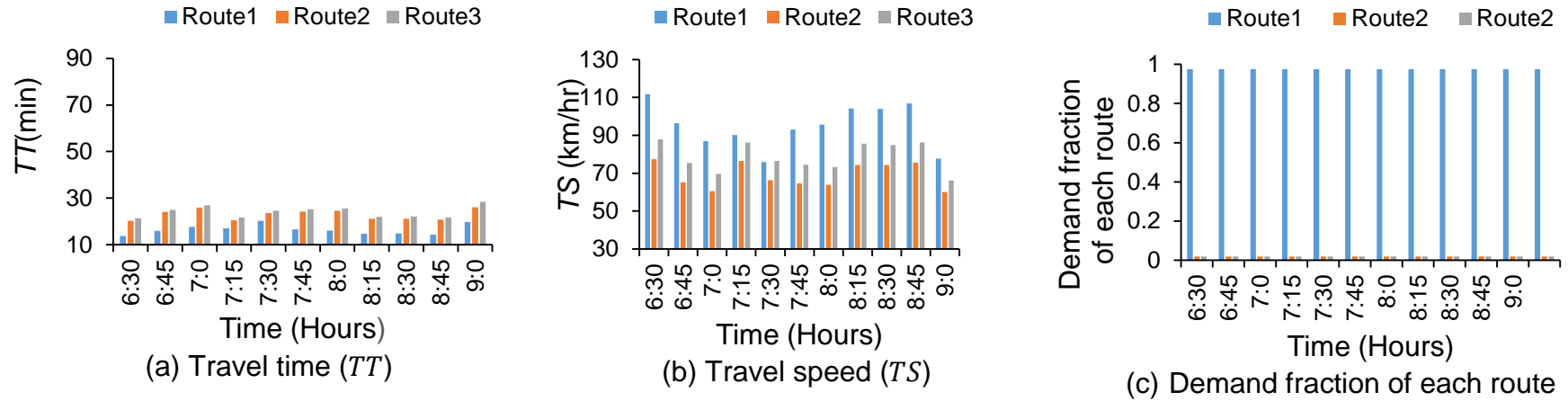


Figure 8.7 Travel speed, travel time and demand fraction of each route for scenario S2_a.

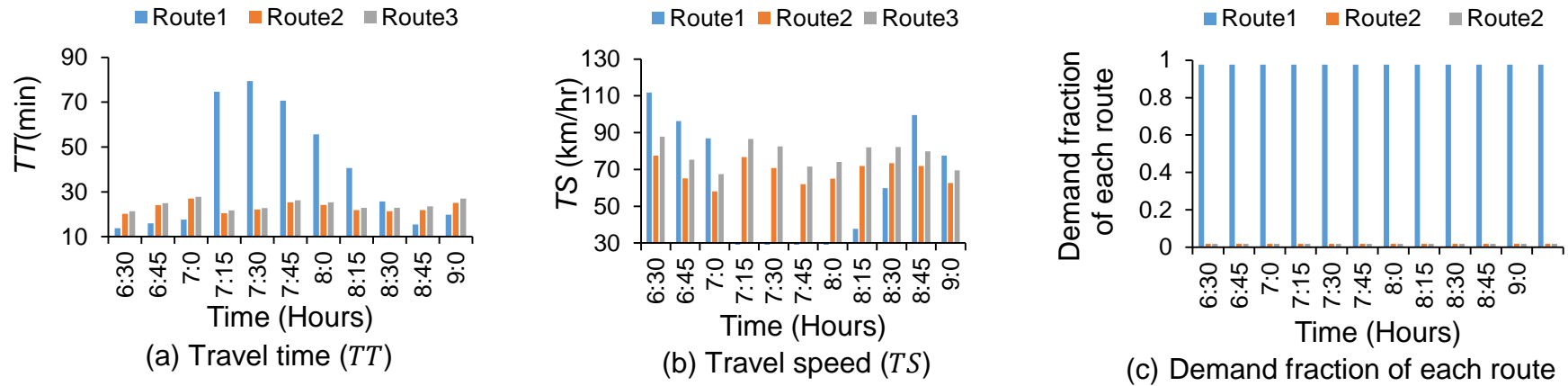


Figure 8.8 Travel speed, travel time and demand fraction of each route for scenario S2_b.

The traffic data obtained from the previous simulation for cases with and without real-time travel information were used in the MATLAB codes developed to calculate the values of the redundancy, vulnerability and mobility indices as described in Chapters 5, 6 and 7, respectively. Figure 8.9 shows that the variation of network mobility indicator, *NMI*, for the 4 scenarios studied. Under normal conditions, (all links are operating i.e. S1_a and S2_a), the impact of real-time travel information has more influence during high demand, for example at 7:00am, *NMI* for S1_a scenario is around 0.82 whereas *NMI* for S2_a scenario equals to 0.63 as suggested by other literature (Ben-Elia and Shiftan, 2010). While, under low departure rates (i.e. the time period between 7:30am to 9:00am), *NMI* for S1_a and S2_a are similar. Reflecting the fact that, under low demand, there is no variation in the real-time travel information, and consequently the information updating has very low impact on network mobility as intuitively expected and in line with the literature (Ben-Elia and Shiftan, 2010; Mahmassani and Jayakrishnan, 1991). In contrast, under link closure scenarios (S1_b and S2_b), the real-time travel information has a significant impact on *NMI* during the link closure period as depicted from Figure 8.9 in line with the literature (e.g. Güner et al., 2012).

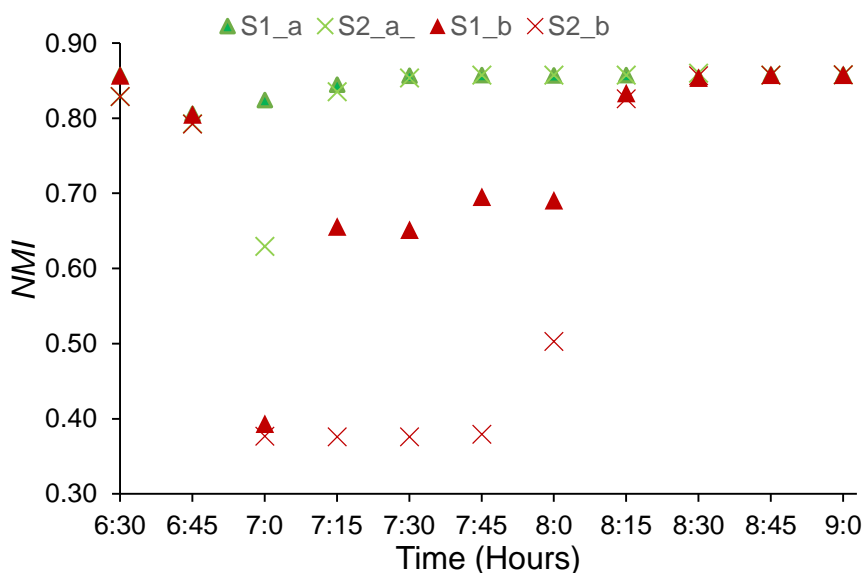


Figure 8.9 *NMI* variations under different scenarios.

The updating of real-time travel information has no impact on the network redundancy indicator, NRI_3 , of the simple network as depicted from Figure 8.10. In contrast, the link closure leads to a considerable reduction in redundancy under both travel time information scenarios (S1_b and S2_b). However, it is very difficult to generalize this as the simple network has only four junctions that might not be very representative of a real life network.

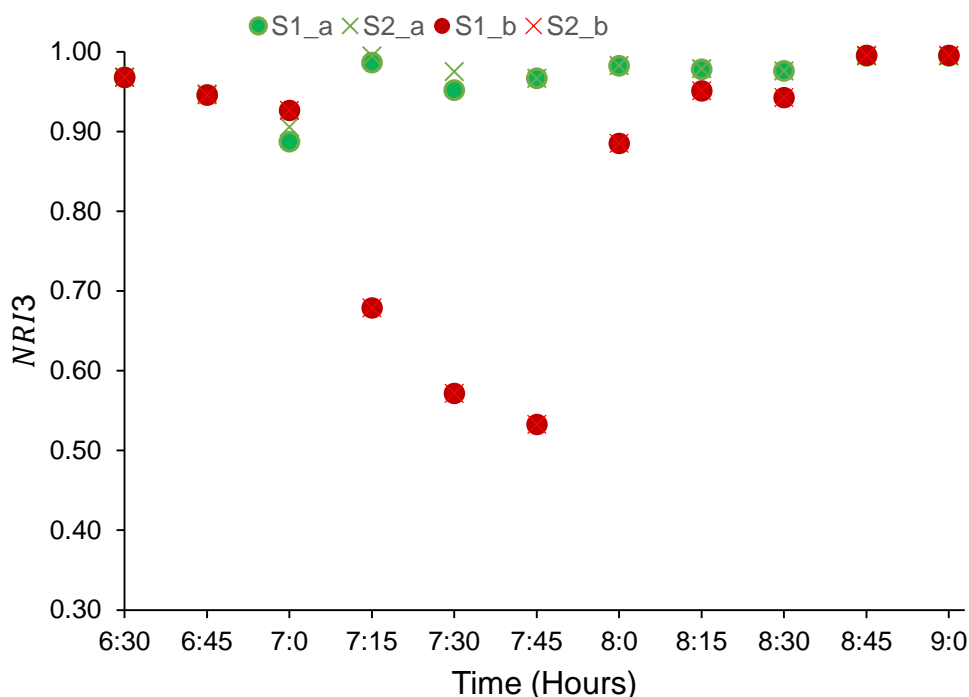


Figure 8.10 NRI_3 variations under different scenarios.

Figure 8.11, plotting the variation of network vulnerability indicator, NVI_{OP} , for the 4 scenarios, indicates that NVI_{OP} has higher values for S1_a and S2_a (full network capacity) than for link closure scenarios (S1_b and S2_b) for most time periods. This may be attributed to the fact that, in normal conditions, nearly all the traffic has been allocated to route 1 as depicted from Figures 8.6(c) and 8.8(c), whereas, under link closure scenarios, the traffic has been allocated to the other two routes in different proportions. However, at the end of the link closure period (8:00am to 8:15am) both NVI_{OP} values for S1_b and S2_b are

higher than NVI_{OP} values under S1_a and S2_a scenarios showing the capability of the alternative routes availability to recoup with a slight increase in the traffic demand.

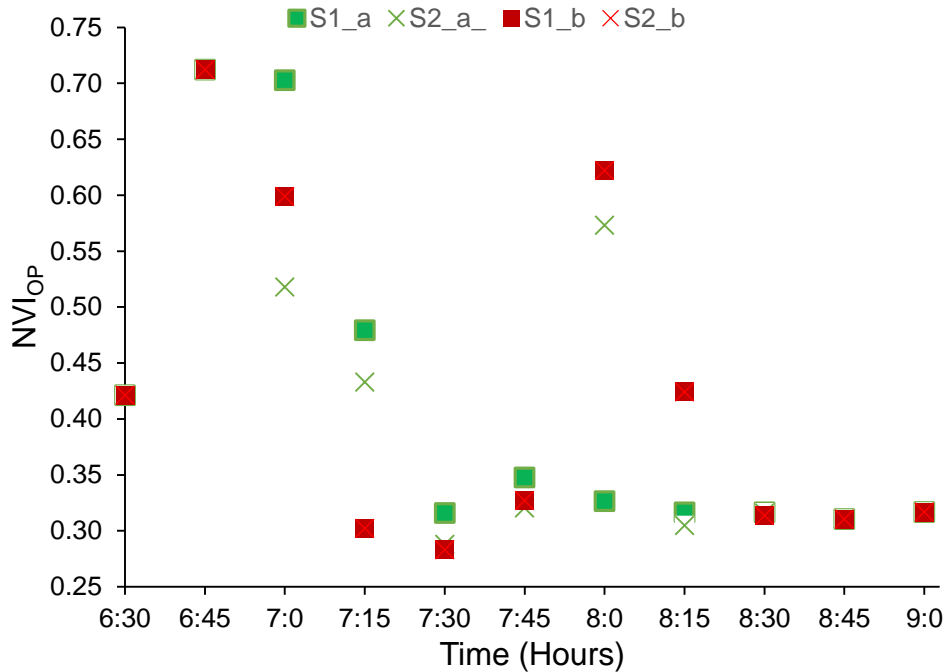


Figure 8.11 NVI_{OP} variations under different scenarios.

The above analysis reflects the importance of considering the three proposed characteristics, redundancy, vulnerability and mobility in investigating the resilience of the road transport network. In the following section, a synthetic road transport network of Delft city described in Chapter 4 is considered to investigate the impact of real-time travel information on a multi origin-destination network.

8.5 Case Study 2

In this section, a synthetic road transport network of Delft city (see Chapter 4 for full description of the network) is used to investigate the impact of real-time travel information on variation in the three resilience characteristics.

8.5.1 Implemented Group 1 Scenarios

Sixteen scenarios are used to investigate the impact of real-time travel information on the three characteristics in the case of an increase in demand with the same departure rates. Table 8.5 presents the scenarios showing the travel time updating conditions and the percentage increase in demand, whilst Figure 8.12 shows the departure rates used. The first group of scenarios (i.e. S1_a to S1_h) have the same travel time updating schedule of every 900 seconds, whilst traffic demand increases from 0% (normal demand) to 50% (as listed in Table 8.5). The remaining 8 scenarios have similar demand increases to the first group, but no real-time travel information is provided.

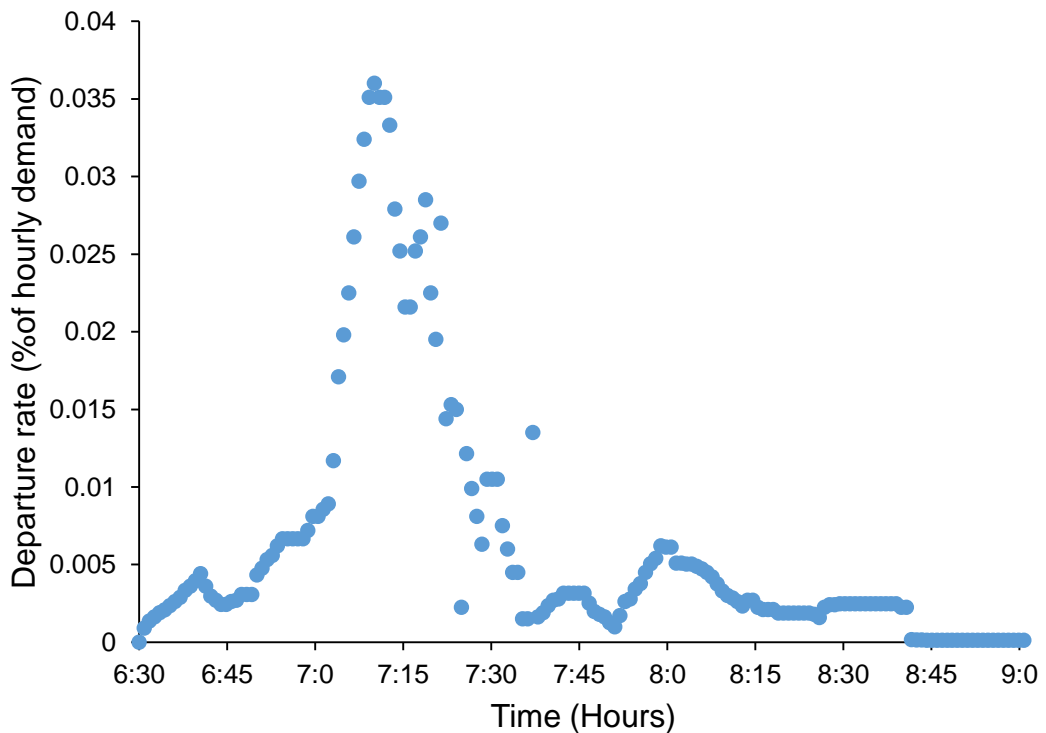


Figure 8.12 Departure rate for different time intervals.

Table 8.5 Scenarios according to increases in demand and real-time travel information updating.

Scenarios	Travel Time updating	Demand increase
S1_a	900 seconds real-time travel information updating	Normal demand.
S1_b	900 seconds real-time travel information updating	5% increase
S1_c	900 seconds real-time travel information updating	10 % increase.
S1_d	900 seconds real-time travel information updating	15 % increase.
S1_e	900 seconds real-time travel information updating	20 % increase.
S1_f	900 seconds real-time travel information updating	30 % increase.
S1_g	900 seconds real-time travel information updating	40 % increase.
S1_h	900 seconds real-time travel information updating	50 % increase.
S2_a	No real-time travel information updating	Normal demand.
S2_b	No real-time travel information updating	5% increase.
S2_c	No real-time travel information updating	10% increase.
S2_d	No real-time travel information updating	15 % increase.
S2_e	No real-time travel information updating	20 % increase.
S2_f	No real-time travel information updating	30 % increase.
S2_g	No real-time travel information updating	40 % increase.
S2_h	No real-time travel information updating	50 % increase.

8.5.1.1 Results and Discussion

For each scenario 9 reports (a 15 minute aggregated report for the time period between 7:00 to 9:00am) are produced from the OmniTRANS software (Version 6.1.2). This includes link travel time, speed and load, in addition to the number of lanes, direction, length, free flow speed, capacity, and upstream and downstream junctions. An OmniTRANS task was written to obtain the full set of

routes for each OD pair, with the fraction of the demand used for each route for each time period under different scenarios (22760 routes for every scenario). The data obtained from OmniTRANS were implemented in MATLAB code to calculate network redundancy indices $NRI3$ and $NRI6$, network vulnerability indices NVI_{PH} and NVI_{OP} and the network mobility indicator NMI using the methodologies detailed in Chapters 5, 6 and 7, respectively.

The calculated indicators, $NRI3$, $NRI6$, NVI_{OP} and NMI , for different scenarios are presented in Figures 8.13, 8.14, 8.15 and 8.16, respectively. These figures show that the demand increase has an impact on the characteristic indicators by different degrees and in line with the results of the corresponding indicators without real-time travel information, as presented in Chapters 5, 6 and 7.

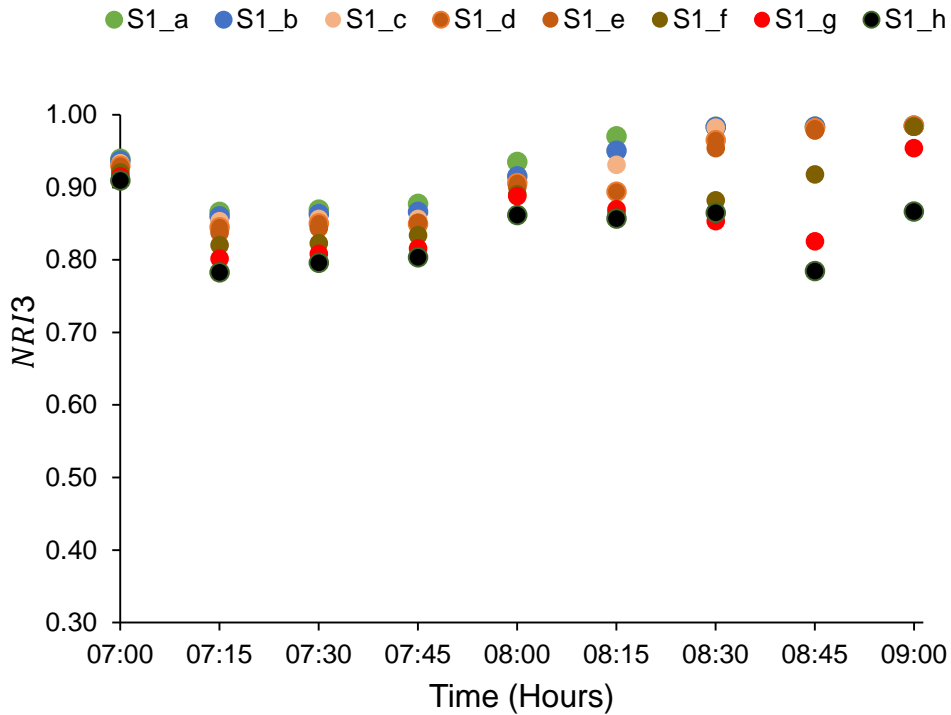


Figure 8.13 $NRI3$ of Delft road transport network under different demand increase scenarios with 15 minute travel time updating.

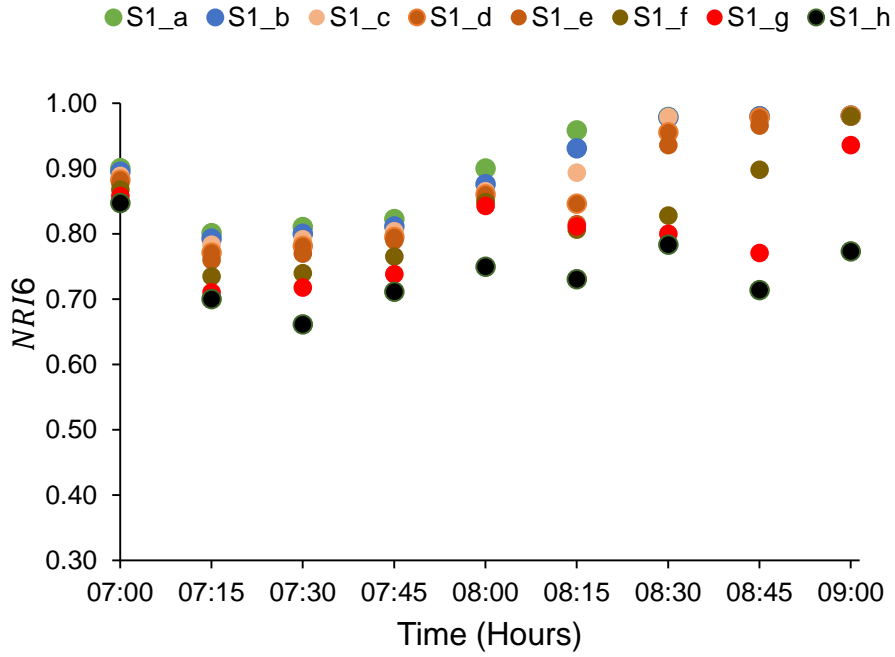


Figure 8.14 NRI_6 of Delft road transport network under different demand increase scenarios with 15 minute travel time updating.

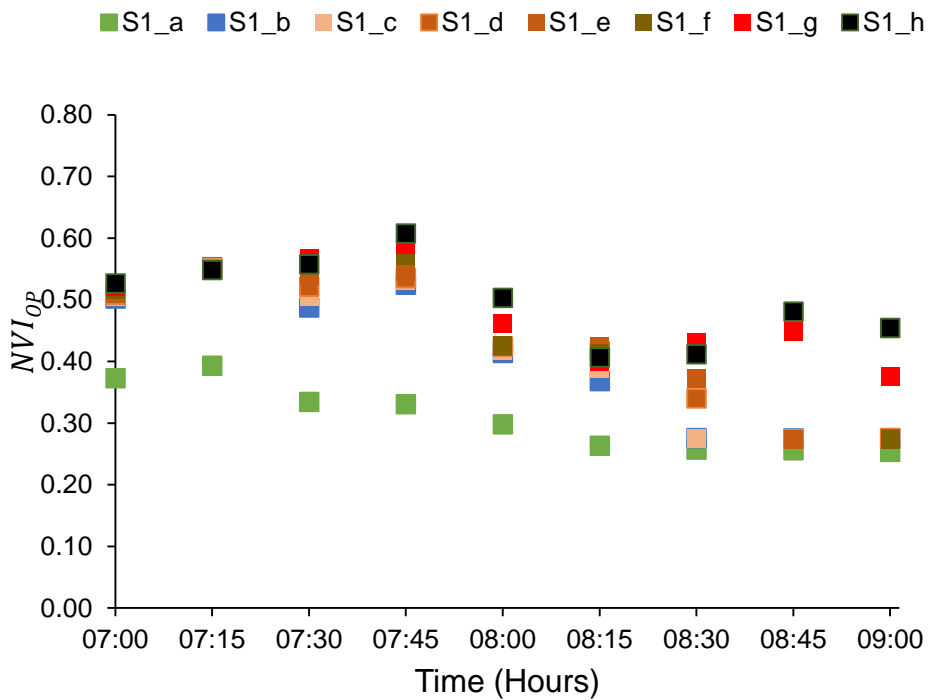


Figure 8.15 NVI_{OP} of Delft road transport network under different demand increase scenarios with 15 minute travel time updating.

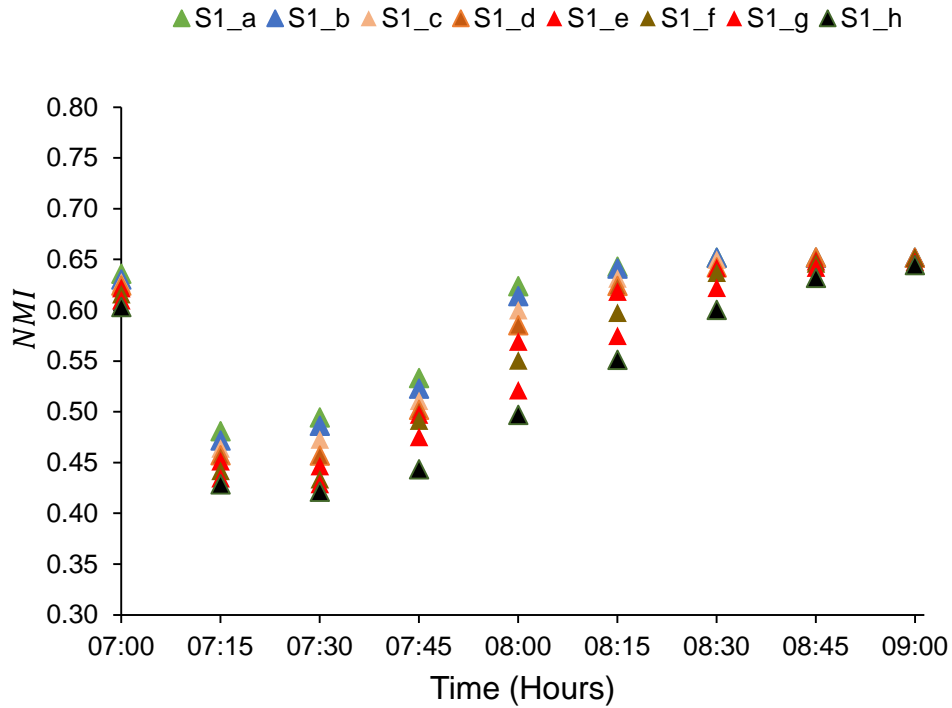


Figure 8.16 *NMI* of Delft road transport network under different demand increase scenarios with 15 minute travel time updating.

To investigate the impact of demand increase along with the level of real-time travel information updating on the three characteristics, six scenarios from the sixteen cases listed in Table 8.5 were selected and compared. These are: normal demand, 20% and 50% demand increase, without and with travel time updating schedule of every 900 seconds. Other scenarios with a small demand variation (5% change) exhibited small variations in the resilience characteristics, therefore only large variations in demand (as listed above) will be emphasized in the following discussion.

The use of real-time travel information (updating every 900 seconds) generally leads to an improvement in *NRI3* and *NRI6* as shown in Figures 8.17 and 8.18. This is as intuitively expected and in line with the M42 (Junction 3a) motorway case study results presented in Chapter 5. However, the level of improvement

varies according to different departure rates in each scenario as explained below:

- Between 7:00am and 7:15am, both indicators (*NRI3* and *NRI6*) have responded inversely to the increase in demand but with no notable changes arising from the use of real-time travel information (e.g. *NRI*s for scenarios S1_a and S2_a have almost the same value). This could be attributed to the fact that the traffic has been allocated based on dynamic user equilibrium (DUE) in all scenarios, which could offset the advantage of the real-time travel information in less-congested network conditions, as concluded by Mahmassani and Jayakrishnan (1991).
- However at 7:30am where the loading of the network increases, the use of real-time travel information has a positive impact in all three scenarios. This could be attributed to a better route choice by all travellers owing to level of information received, leading to less congestion on particular routes.
- The positive impact continues in the following time period (starting at 7:45am) for both normal demand and a 20% increase in demand (S1_a and S1_e compared with S2_a and S2_e, respectively). However there is no significant impact under the 50% demand increase scenario (S1_h compared with S2_h). This could be related to the ability of the road network to offer alternative uncongested routes to accommodate the network loading under scenarios S1_a and S1_e. In contrast, the use of real-time travel information may not offer improvements in S1_h due to the congested conditions that can result from residual traffic, as suggested by other literature (Yang and Jayakrishnan, 2013).
- Conditions in the subsequent time periods (i.e 8:00 - 8:30am) confirm the previous justification, given the road transport network has lower loading in S1_a and S1_e where the impact of real-time travel information is minimum (i.e. minor change under normal conditions and a 20% demand). Moreover, congestion could be relieved under a low

departure rate and reduced residual traffic, leading to a significant improvement in the case of S1_h.

This reflects the complex relationship between increases in demand and the level of real-time travel information, as real-time travel information does not necessarily increase *NRI3* and *NRI6* for each scenario and under different network loadings.

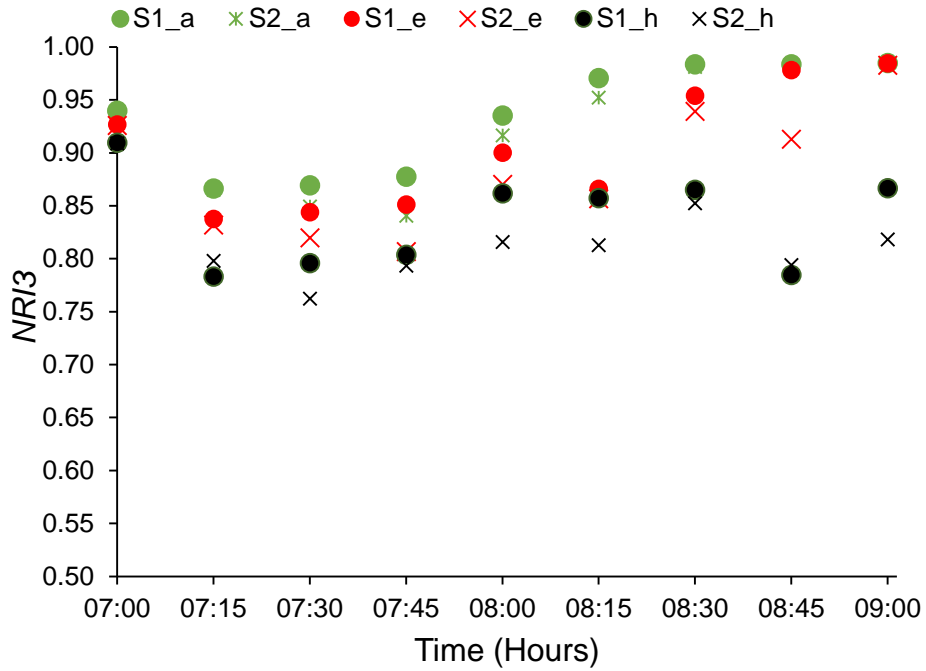


Figure 8.17 *NRI3* of Delft road transport network under different scenarios,1 with and without travel time information.

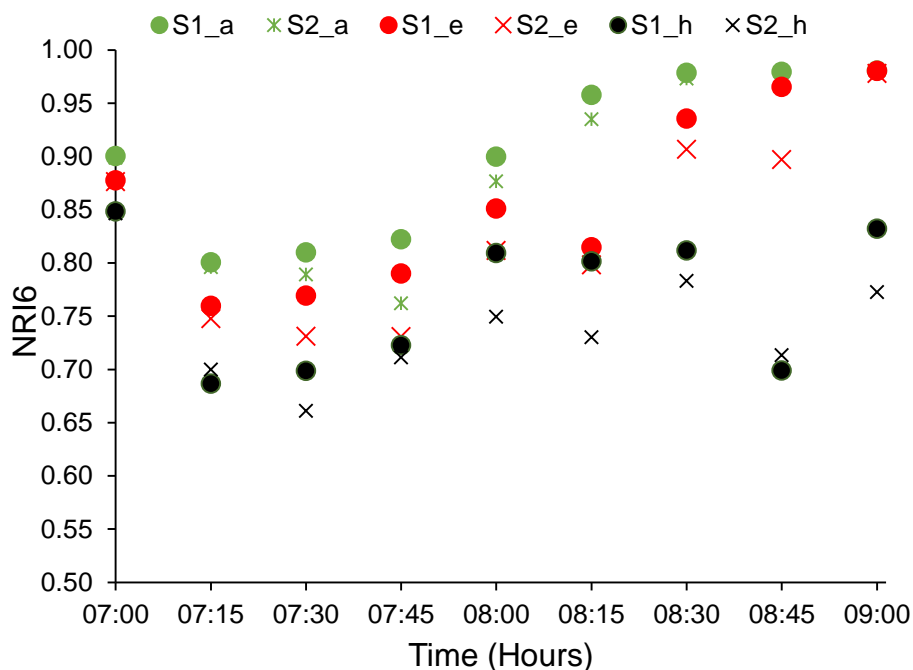


Figure 8.18 *NRI6* under different scenarios with and without travel time information.

The vulnerability indicator, NVI_{OP} , shows variations under different departure rates when calculated for the six scenarios, as depicted in Figure 8.19. For example, using real-time travel information leads to a reduction in NVI_{OP} at 7:30am and 8:15am under the normal demand scenario, and at 7:45am and 8:45am for a 20% increase in demand. It also leads to a decrease in NVI_{OP} under a 50% demand increase scenario at 8:00am and 8:15am, as shown in, as shown in Figure 8.19.

The variation in NVI_{OP} may be related to that of $NRI3$ and $NRI6$. For example, when the use of real-time travel information has a positive impact on $NRI3$ or $NRI6$, it could be assumed that travellers have a better route choice. This may result in less vulnerable links in some cases, such as at 7:30am and 7:45am for the S1_a and S1_e scenarios respectively. However, the use of real-time travel information could also lead to a negative impact on NVI_{OP} (i.e. increase in NVI_{OP}) in some cases. For example the value of NVI_{OP} for the S1_a scenario is higher than that of NVI_{OP} for the S2_a scenario at 7:45am, as depicted by

Figure 8.19. This is in contrast with the value of $NRI3$ or $NRI6$ at the same time under the same scenarios. This observation is in line with the accident scenario presented in Section 9.4.1, where the vulnerability of links decreases due to the assignment of traffic to less attractive routes due to the lack of real-time travel information (S2_a at 7:45am) or link closure (i.e. case study 1 in Section 9.4).

Furthermore, the variation of NVI_{PH} is mainly influenced by the demand increase with nearly no impact of real-time travel information as depicted from Figure 8.20. This could be due to the fact that the aggregation of link vulnerability indicator is obtained based on the number of lanes of links and length of links (Eq. 6.10). Consequently it might be more appropriate in case of supply side changes such as capacity reduction (e.g. group three scenarios presented in Section 6.4.1.3) due to the adverse weather condition). However, further investigation is needed to confirm these findings.

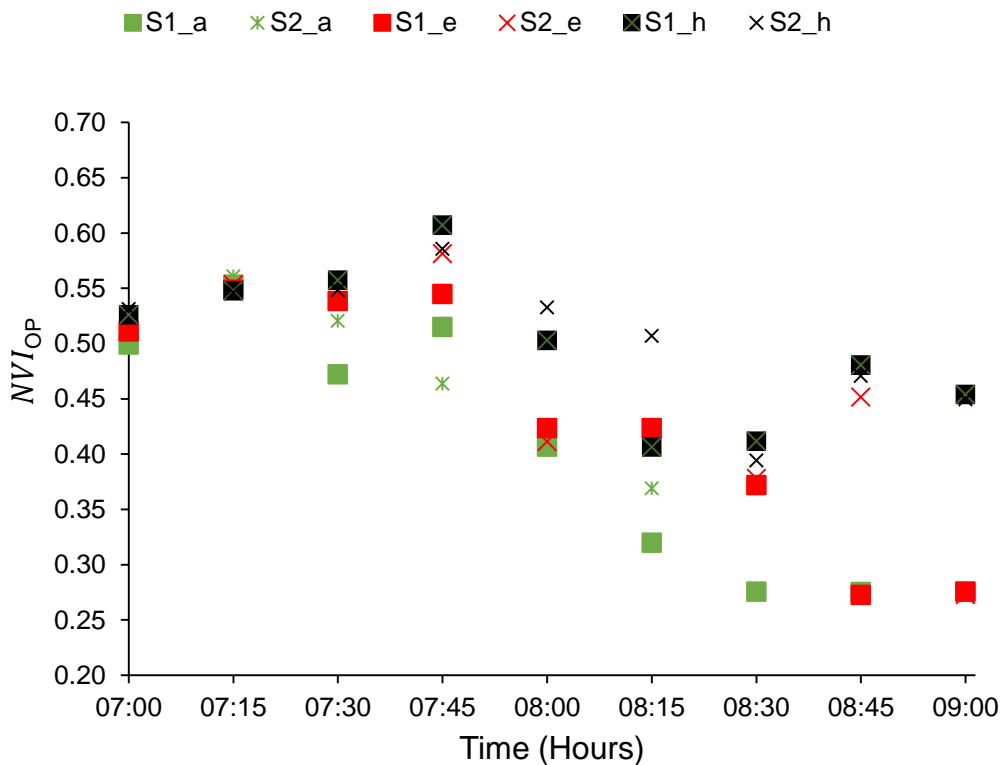


Figure 8.19 NVI_{OP} under different scenarios with and without travel time information.

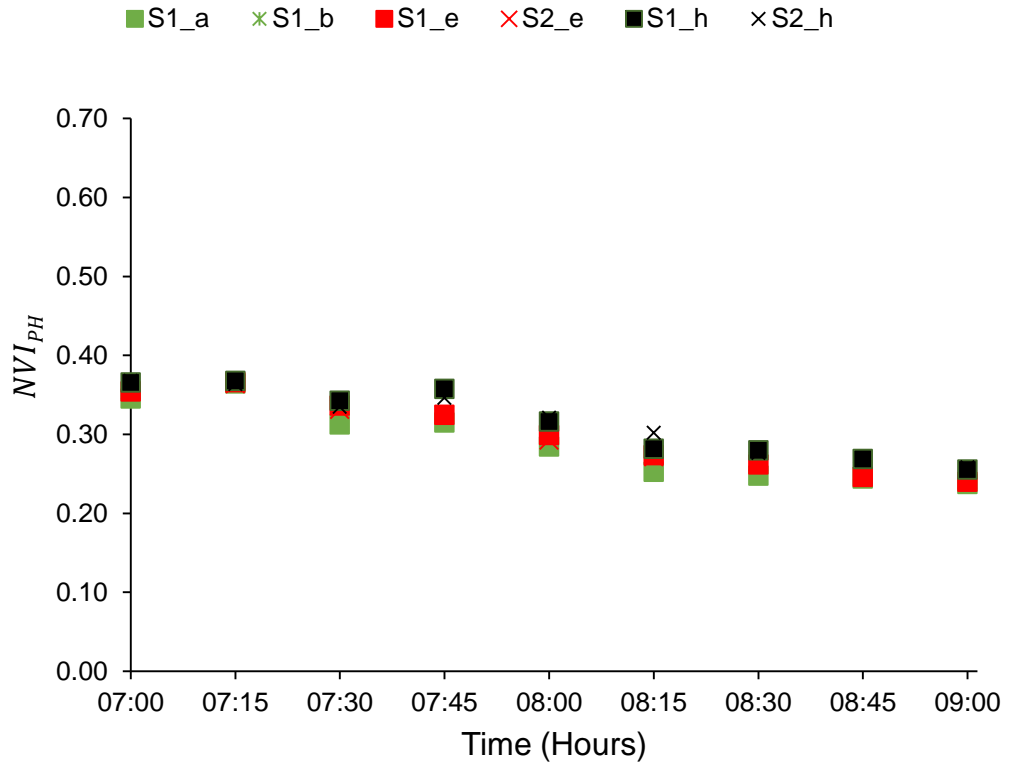


Figure 8.20 NVI_{PH} under different scenarios with and without travel time information.

For the mobility indicator, NMI , the importance of real-time travel information updates increases with the increase in demand, as shown in Figure 8.21. NMI has a similar trend to $NRI3$ and $NRI6$ but with different values. However, at 7:45am for $S1_a$, NMI does not show any improvement with the use of real-time travel information in contrast to $NRI3$ and $NRI6$, indicating the impact of the increase. NVI_{op} .

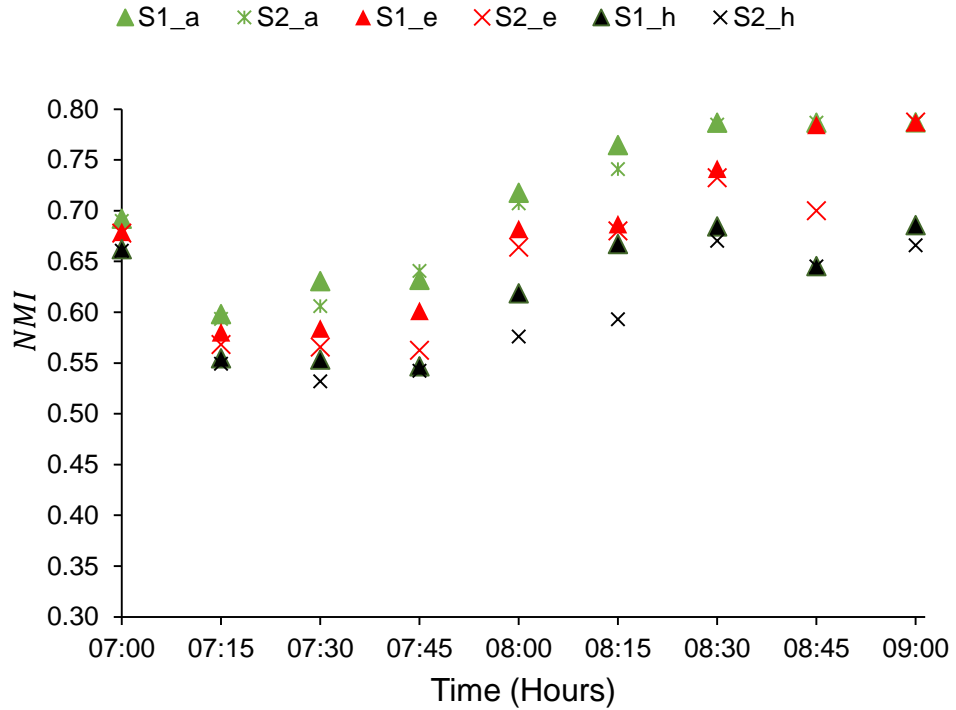


Figure 8.21 *NMI* under different scenarios with and without travel time information.

8.5.2 Implemented Group 2 Scenarios

In this group, six scenarios are compared to investigate the impact of traveller behaviour under real-time travel information availability. Three scenarios, namely S1_a, S1_e and S1_h, have already presented in Table 8.5 where all travellers follow the real-time travel information under different demand increase conditions. Furthermore, another three scenarios presented in Table 8.6 represent 50% of the travellers comply with real-time travel information under three demand increases, namely 0, 20 and 50%.

Table 8.6 Additional scenarios with different demand increase and traveller behaviour.

Scenarios	Travellers behaviour	Demand increase
S1_i	50% comply with the information	Normal demand.
S1_j	50% comply with the information	20% increase.
S1_k	50% comply with the information	50% increase.

Figures 8.22 and 8.23 show the variation in *NRI3* and *NRI6* under different demand increases, with 100% and 50% travellers following the real-time travel information, respectively. A little variation in *NRI3* and *NRI6* occurred in the case of no demand increase and 20% demand increase compared with 50% demand increase. This could be related to a similarity among the route alternatives between each OD pair. However, for some time periods, 100% use of real-time travel information has achieved a higher *NRI3* and *NRI6* (e.g. at 7:45am) compared with 50% of travellers complying with real-time travel information for the 0% and 20% demand increase scenarios. For a 50% demand increase, the benefit due to the 100% use of real-time travel information has been shown at 8:00am.

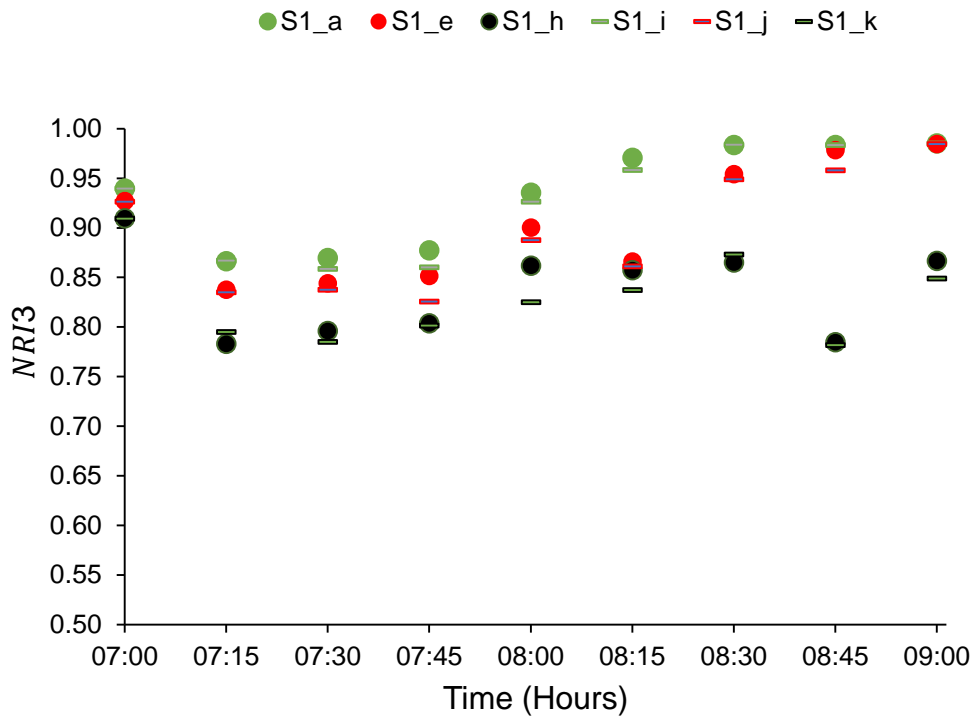


Figure 8.22 *NRI3* under 50% traveller complying and different demand increase.

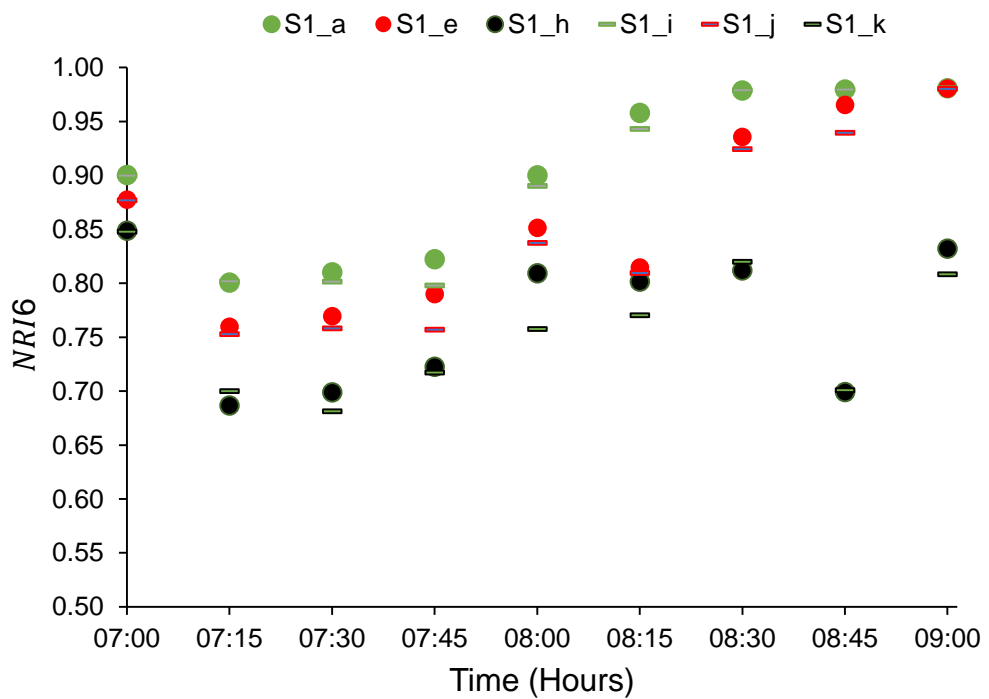


Figure 8.23 *NRI6* under 50% traveller complying and different demand increase.

The impact of the percentage of travellers complying with the real-time travel information on NVI_{OP} varied, as depicted in Figure 8.24. For example, there is no change in NVI_{OP} due to the increase in the use of real-time travel information from 50 to 100% for the time periods 7:00am and 7:15am. However, at 7:45am, there is a slight increase in NVI_{OP} due to 100% use compared with 50% use under no increase and 50% demand increase confirming the analysis of NVI_{OP} presented in Section 9.5.1 and in line with the literature (Yang and Jayakrishnan, 2013). However, the decrease of NVI_{OP} for all scenarios as 8:15am refer to the ability of the road transport network to accommodate all the informed travellers (i.e. 100% complying with the real-time travel information). Under this variation, it might be difficult to conclude the effect of traveller heterogeneity on the vulnerability of road transport network.

In line with the group 1 results presented in Section 9.5.1, NVI_{PH} does not show a noticeable variation due to the real-time travel information or demand increase as depicted in Figure 8.25.

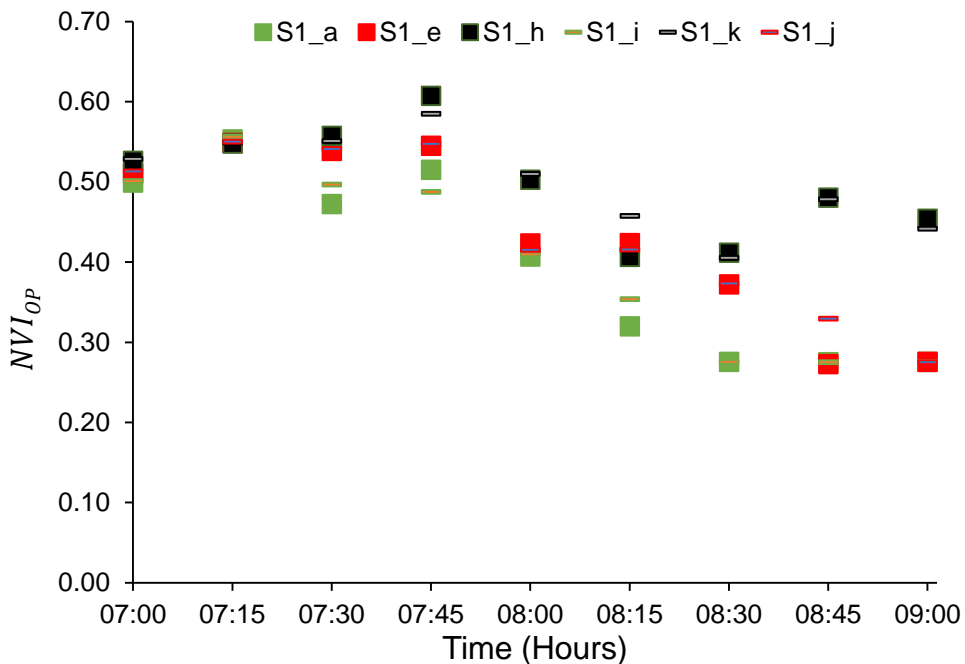


Figure 8.24 NVI_{OP} under 50% traveller complying and different demand increase.

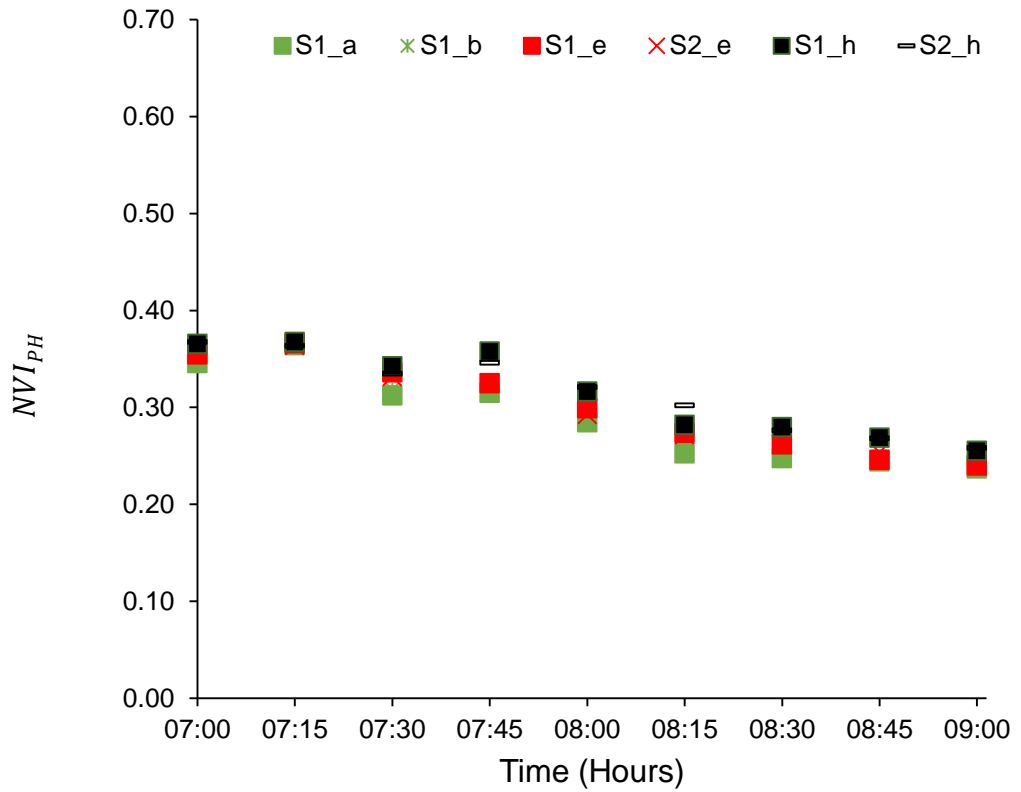


Figure 8.25 NVI_{PH} under 50% traveller complying and different demand increase.

For mobility indicator NMI , the importance of the percentage of travellers using the real-time travel information increases with the demand increase, as shown in Figure 8.26. For example, there is no difference in NMI for 50% and 100% traveller information compliance for no demand increase, and a slight increase in the mobility indicator for the 20% demand increase scenario. The greatest increase in NMI occurs under the 50% demand increase scenario.

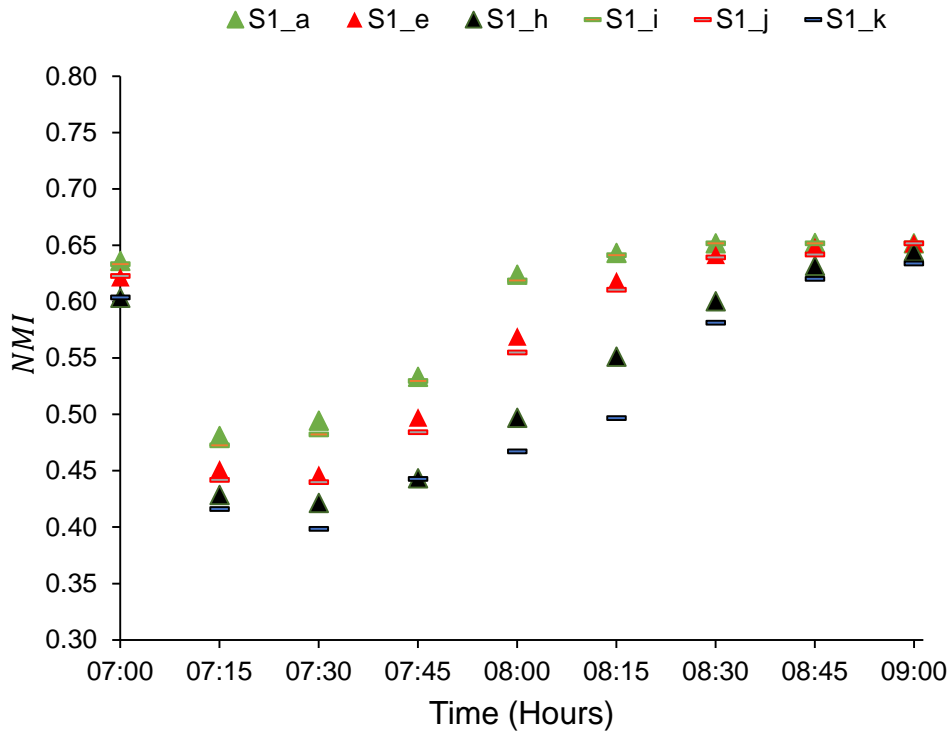


Figure 8.26 *NMI* under 50% traveller complying and different demand increase.

The analysis of the three characteristics under different scenarios presented above shows that the variation of each characteristic may be different. For example, at 7:45am using real-time travel information under normal demand condition has led to the increase of network redundancy indicators and, at the same time, also increase the network vulnerability indicator whereas has nearly no influence on the network mobility (S1_a and S2_a scenarios). Under such a case, it could be a challenge to gauge the resilience of road transport networks under different conditions or to evaluate the role of real-time travel information in improving the network resilience without having a composite resilience index. To aggregate the influence of the three characteristics and estimate a composite resilience index, two methods are used, equal weighting and principal component analysis. In the following section, the influence of real-time travel information on the composite resilience index is explored.

8.6 Composite Resilience Index for Delft Road Transport Network

The results of the three resilience characteristics with and without real-time travel information for Delft case study (case study 2 presented above) are used to estimate the composite resilience index using the two techniques presented, EWM and PCA. NRI_3 , NVI_{OP} and NMI are used in both techniques as the main characteristics indicators, however, other proposed indicators (i.e. NRI_6 and NVI_{PH}) could also be used instead of the corresponding indicator.

8.6.1 Results and Analysis

Before calculating the composite resilience index, the Kaiser-Meyer-Olkin (KMO) measure was estimated for the three characteristic indicators to examine sampling adequacy and the applicability of principle component analysis. For the 6 scenarios, the values of KMO was found to be between 0.63 (S1_a) and 0.76 (S1_e), indicating the suitability of this approach as presented in Table 8.7.

Table 8.7 Kaiser-Meyer-Olkin (KMO) measure for 9 scenarios.

Scenarios	KMO
S1_a	0.63
S1_e	0.76
S1_h	0.66
S2_a	0.74
S2_e	0.72
S2_h	0.64

The values of loading factors, eigenvalues and eigenvectors are calculated using the PRINCOMP function available in MATLAB. a_{ij} and RCI_{pc} are then calculated based on Eqs. 8.3 and 8.4. Table 8.8 presents the characteristics weights estimated from the factor loading matrix as presented in Eq. 8.3 along

with the % of variance ($= \frac{\lambda_j}{\sum_{j=1}^m \lambda_j}$) for each *PC*. The weighting of each characteristics varies for each scenario as depicted from Table 8.8. For example, for *PC1* (accounting for a maximal amount of total variance in the characteristics indicators), the vulnerability indicator has the highest values for scenarios S1_a, S1_e and S2_a, whereas for scenario S2_e both vulnerability and mobility indicators have nearly the same weight (0.43 and 0.41). In contrast, the mobility has the highest influence on *PC1* for scenarios S1_h and S2_h. Overall, the redundancy characteristic has the lowest influence on *PC1* compared with the other two characteristics. This may be attributed to the fact that the network considered is a road transport network of a city where alternative routes are normally available. It should be noted these findings are valid for the synthetic road transport network of Delft city under different scenarios considered.

Table 8.8 Characteristics weights

	Resilience Characteristics	PC1	PC2	PC3
S1_a	Redundancy	0.14	0.07	0.79
	Vulnerability	0.63	0.34	0.02
	Mobility	0.23	0.59	0.19
	% of variance	0.92	0.07	0.01
S1_e	Redundancy	0.15	0.01	0.84
	Vulnerability	0.56	0.39	0.06
	Mobility	0.30	0.60	0.10
	% of variance	0.91	0.07	0.02
S1_h	Redundancy	0.07	0.023	0.91
	Vulnerability	0.29	0.71	0.0
	Mobility	0.64	0.26	0.09
	% of variance	0.80	0.12	0.08
S2_a	Redundancy	0.15	0.15	0.70
	Vulnerability	0.62	0.38	0.01
	Mobility	0.23	0.47	0.29
	% of variance	0.91	0.07	0.02
S2_e	Redundancy	0.16	0.03	0.0.81
	Vulnerability	0.43	0.55	0.02
	Mobility	0.41	0.42	0.17
	% of variance	0.87	0.11	0.022
S2_h	Redundancy	0.05	0.68	0.69
	Vulnerability	0.17	0.25	0.15
	Mobility	0.77	0.07	0.16
	% of variance	0.82	0.12	0.06

Figure 8.27 presents the composite resilience index CRI_{pc} calculated using PCA under different scenarios (see Table 8.5 for full details scenarios). In general, the variation in CRI_{pc} under different increases in demand reflects the ability of the index to respond to variations in departure rates in addition to increases in demand as listed below:

- At 7:00am, all the scenarios have equal values for CRI_{pc} reflecting that the network is able to recoup with the demand increase where the departure rate is low, with no or minimum residual effect.
- CRI_{pc} has the lowest values for a 50% demand increase in both with and without real-time travel information scenarios (S1_h and S2_h), compared with its value under normal demand and other percentage increases.
- Interestingly, for the period between 7:15am and 7:30am, CRI_{pc} increases in response to decreasing departure rates under normal demand. It almost has the same value with a 20% increase in demand, with a slight reduction in value for a 50% increase in demand. This could be related to the ability of the road transport network to bounce back to its performance prior to the increase in departure rate. This ability seems to be inversely proportional to the increase in demand e.g. CRI_{pc} for the S1_a scenario increases more rapidly than that for the S1_h scenario, responding to a departure rate decrease.

The influence of real-time travel information is seen to vary from one scenario to another under different departure rates, reflecting the complexity of the effect of information on the road transport network performance and in line with the literature (e.g. Mahmassani and Jayakrishnan, 1991). The use of real-time travel information could have a positive impact on CRI_{pc} , for example at 7:30am under S1_a compared with the S2_a scenario and from 8:00am to 9:00am for S1_h compared with the S2_h scenario. Under normal demand conditions for S1_a and S2_a scenarios, CRI_{pc} has improved due to the use of real-time travel information at some intervals, (e.g. 7:30am), whereas there is no change for other intervals (e.g. 8:30am). This is similar to the variation in $NRI3$ for

scenarios S1_a and S2_a between 7:00am and 7:15am as outlined above. However, the use of real-time travel information might also cause adverse effects, for example CRI_{pc} has a lower value in the case of real-time travel information than its value without travel information in the case of a 50% demand increase (S1_h and S2_h) at 7:45am. This could be due to the fact that all travellers receive the same information concerning the best routes without considering the rerouting effect (Yang and Jayakrishnan, 2013), resulting in a more congested network. This could be demonstrated using a vulnerability analysis as the highest NVI_{OP} for all the scenarios occurs at this point (i.e. at 7:45am for S1_h), showing the concentration of traffic in certain routes. Together, these findings indicate that CRI_{pc} behaves in an intuitively expected manner and according to related previous research.

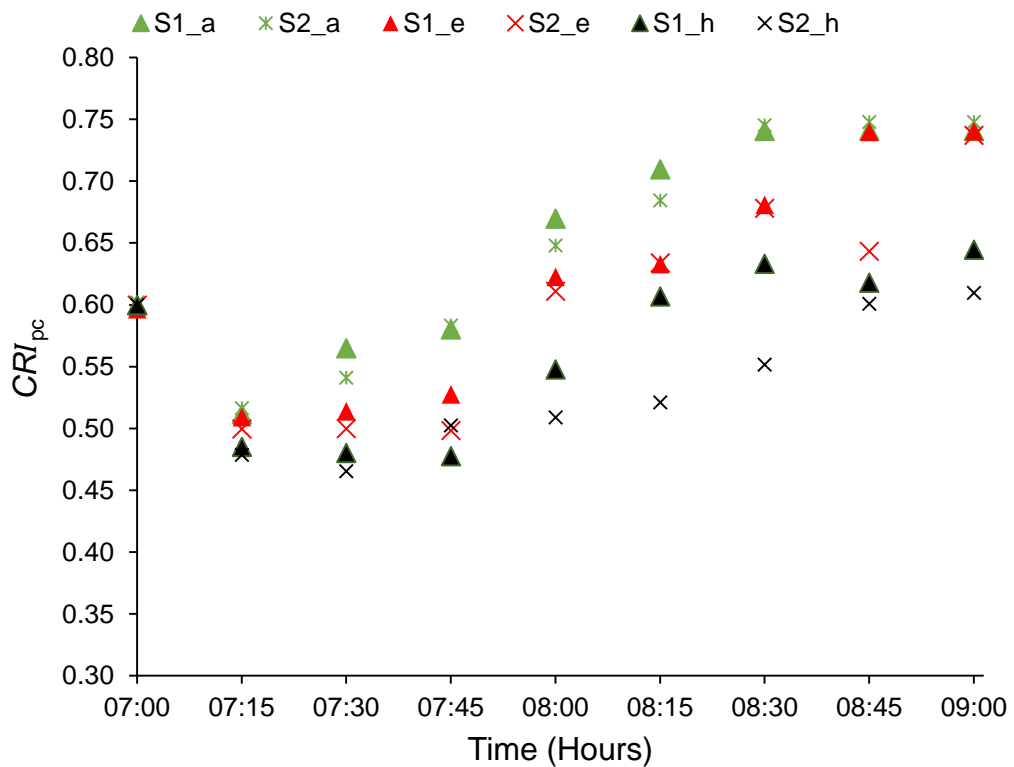


Figure 8.27 CRI_{pc} for Delft road transport network case study under different scenarios.

Figure 8.28 shows the composite resilience index (CRI_{eq}) using equal weights for different scenarios. The variation in CRI_{eq} exhibits a similar trend to that of CRI_{pc} , under different demand increases. This reflects the ability of CRI_{eq} to respond to variations in the departure rate in addition to increases in demand. However, the values of CRI_{eq} are always higher than these of CRI_{pc} , as shown in Figure 8.29 potentially highlighting the impact of double counting using EWM. Furthermore, the correlation between the two indices, CRI_{pc} and CRI_{eq} , was found to be strong with the coefficient of determination $R^2 > 0.96$ for all scenarios.

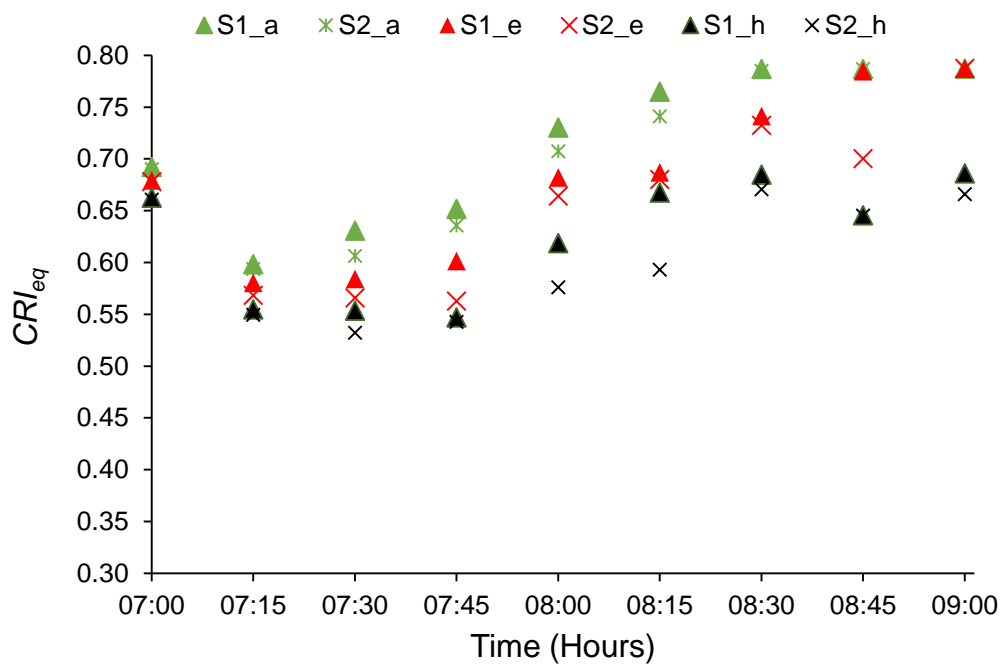


Figure 8.28 CRI_{eq} for Delft road transport network case study under different scenarios.

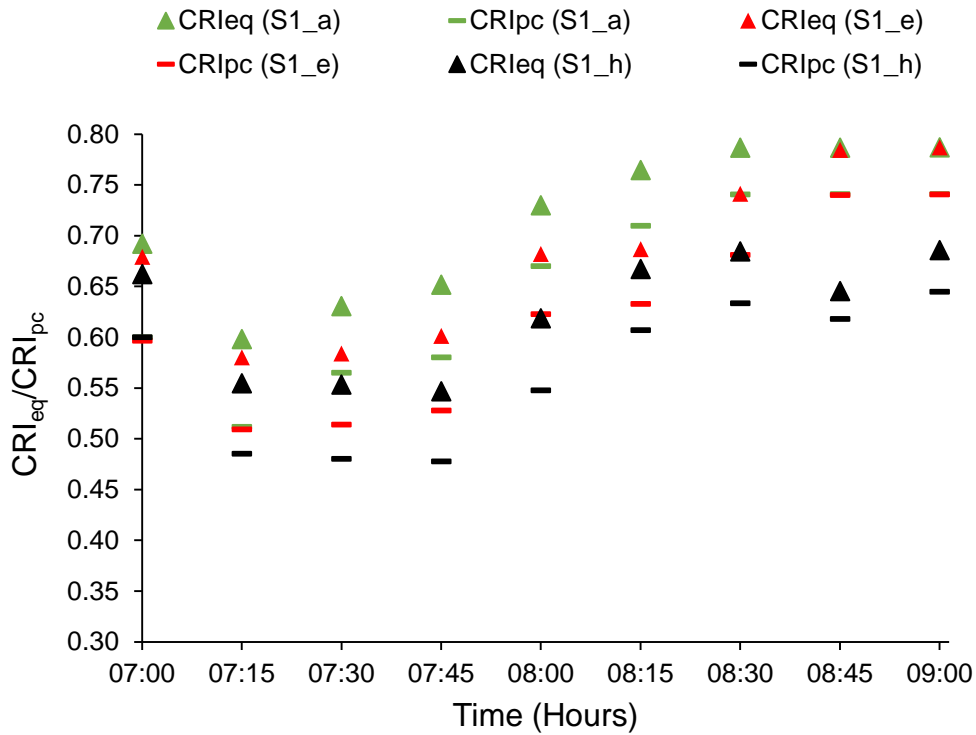


Figure 8.29 CRI_{eq} and CRI_{pc} for Delft road transport network case study under different scenarios.

8.7 Conclusions

In this chapter, the interdependence of the resilience characteristics has been explored using the influence of low level attributes such as link flow, capacity and speed on the characteristics. Each characteristic (i.e. redundancy, vulnerability or mobility), can be individually considered to reflect the level of resilience from a certain perspective. Moreover, two weighting methods have been used, namely equal weighting and principal component analysis, to obtain a composite resilience index for a road transport network based on the three characteristics.

Simplicity and transparency are the main advantages of the equal weighting method, leading to a recommendation for this approach when a quick assessment of the road transport network resilience is required. However, the values of the composite resilience index using equal weighting method are

always higher than these obtained from the principal component analysis technique, highlighting the probable influence of double counting effect. However, the sensitivity of principal component analysis to the data set should be taken into account when applying the method, as the weight allocated to each characteristic may change if further data is added.

The case studies introduced in this chapter show that the use of real-time travel information under a disruptive event (such an accident in case study 1 or an event leading to demand increase such as in case study 2) has much more impact on resilience characteristics than in normal conditions (such as all links operating or normal demand). The trend variation in each resilience characteristic may be different from the other characteristics, emphasizing the importance of considering all three characteristics to obtain the aggregated influence of the three characteristics. For example, real-time travel information has improved the redundancy and mobility indicators and, also, increased vulnerability as the travellers share the best route information causing more congested network. The synthetic road transport network of Delft city case study showed that the redundancy characteristic has the lowest influence on the first principal indicator compared with the other two characteristics for the scenarios investigated.

Despite these caveats, the composite resilience indices developed are able to capture some of the complex relationships between the resilience characteristics of road transport networks and the variation in demand in addition to the availability of real-time travel information. The behavior of both indices for the scenarios investigated has shown to be in line with the related literature. They can be used to investigate the overall impact of disruptive events and as a communication tool to support decision makers and stakeholders.

Chapter 9: Conclusions and Recommendations for Future Work

9.1 Introduction

This concluding chapter summarises the main findings of the current research in relation to the research aims and objects, as well as suggesting a number of potential investigations for future work.

9.2 Research summary

Road transport networks are increasingly exposed to a wide range of disruptive events including manmade and natural events, which have a great impact on their functionality. This thesis is concerned with measuring the road transport network resilience. It has employed three main characteristics, namely redundancy, vulnerability and mobility, measuring resilience at road transport network junction, link and origin-destination levels, respectively. The proposed resilience characteristics are able to evaluate the changes in transport network performance under disruptive events and could be adopted and quantified to reflect different types of transport networks and each disruptive event unique impact. A composite resilience index was also developed. Furthermore, the thesis investigated the role of real-time travel information systems on the resilience characteristics and the composite resilience index of road transport networks. Compared with previous literature, the proposed resilience index is based on more than one characteristic, enhancing its ability to capture different types of disruptive event impacts. Furthermore, each proposed characteristic indicator includes more than one performance measure, improving its ability to capture the impact of the interaction between the supply and demand variations. For example, the network mobility indicator developed based on

physical connectivity (i.e. supply side impact) and traffic condition attributes (i.e. demand side impact).

Various methodologies have been adopted to quantify each resilience characteristic and a composite resilience index. The redundancy indicator for various junctions in road transport networks has been developed using the entropy concept as it can measure the network configuration in addition to being able to model the inherent uncertainty in road transport network conditions (see Chapter 5). The link vulnerability indicator of road transport networks has been developed by combining vulnerability attributes (e.g. link capacity, flow, length, free flow and traffic congestion density) with different weights using a new methodology based on fuzzy logic and exhaustive search optimisation techniques (see Chapter 6). Fuzzy logic approach was also adopted to combine two mobility attributes that reflect the physical connectivity and level of service of road transport networks into a single mobility indicator (see Chapter 7). Finally, the aggregation of the three characteristics indicators was achieved using two different approaches, namely equal weighting and principal component analysis (see Chapter 8).

The synthetic road transport network of Delft city has been used to illustrate the applicability and validity of the three characteristics indicators developed, in addition to the composite resilience index. Moreover, it has been used to investigate the impact of real-time travel information on the proposed resilience characteristics and the composite resilience index. Traffic data of the synthetic road transport network of Delft city were generated by software simulation using OmniTRANS (Versions 6.022, 6.024, 6.026, 6.1.2). Additionally, real life case studies, namely Junction 3a in M42 motorway and different routes between 7 British cities, i.e. London, Bath, Leeds, Birmingham, Bradford, Brighton and Manchester, were used in redundancy and mobility investigations, respectively.

9.3 Main Findings

The current research presented a conceptual framework for resilience of road transport networks under disruptive events considering organizational and physical resilience. However, the project focused on the physical resilience side by investigating three resilience characteristics and composite resilience index of road transport networks. The main findings will be presented below for each aspect.

The main conclusions of the work presented in Chapter 5 on redundancy characteristic of road transport networks are summarised below:

- A number of redundancy indicators were developed from combinations of link characteristics to enhance their correlations with the junction delay and the volume capacity ratio. They also covered the static aspect of redundancy, i.e. alternative paths, and the dynamic feature of redundancy reflected by the availability of spare capacity under different network loading and service level.
- The entropy concept was successful in developing a redundancy indicator for various nodes in road transport networks that is able to cover both static and dynamic aspects of redundancy.
- The inbound redundancy indicators were able to reflect the variations in topology of the nodes (e.g. number of incident links) and the variation in link speed. However, none of the outbound redundancy indicators correlated well with the junction delay or junction volume capacity ratio.
- Two redundancy indicators developed from the combined relative link speed and relative link spare capacity showed strong correlation with junction delay and junction volume capacity ratio of a synthetic road transport network of Delft city. They were able to reflect the impact of the active traffic management scheme introduced at Junction 3a in M42 motorway near Birmingham in 2006.
- The developed redundancy indicators could be a potential tool to identify the design alternatives in addition to the best control and management

policies under disruptive events or for daily operation of road transport networks.

The main conclusions of the vulnerability characteristic of road transport networks (Chapter 6) are presented below.

- It was found that none of the vulnerability attributes on its own is able to justify the full impact of link closure on the vulnerability of road transport networks; therefore, it was imperative to combine many vulnerability attributes. The relative weights of these vulnerability attributes were identified using an exhaustive optimisation search.
- In case of closure of cut links, an additional term to subsidise the impact of unsatisfied demand has been introduced to model the decrease in the total travel time arising from the reduction of network loading.
- Attributes related to link length and shortest paths yielded a low contribution to the link vulnerability indicator, as they are heavily dependent on the network configuration and infrastructure characteristics.
- The calculated relative weights of vulnerability attributes are not universal but network dependent. However, for a particular network, the weights calculated can be implemented to study the impact of different scenarios on road transport network vulnerability, for example to test the effectiveness of different policies or the impact of introducing new technology.
- Overall, the network physical and operational vulnerability indicators developed showed a good correlation with variations in both supply and demand.

The mobility of road transport networks was investigated in Chapter 7 and the main findings from this chapter are summarised below.

- The developed mobility indicator based on two attributes, namely physical connectivity and traffic condition attributes was able to identify the causes of low mobility under different scenarios. For example, individual link closures have different impacts on physical connectivity and traffic condition attributes in the case study considered, i.e. the closure of some links had

more impact on physical connectivity attribute whereas other link closures resulted in greater reductions in traffic condition attribute. This emphasises the importance of considering both attributes in assessing the level of mobility in contrast to the case of a single mobility attribute that may refer to the level of mobility without providing insight to the cause.

- The estimated mobility indicator exhibited strong correlation with travel distance per minute for real traffic data between seven British cities.
- The network mobility indicator decreases with demand increase (departure rate) for a synthetic road transport network for Delft city. It also changes with supply side variations (i.e. network capacity reduction and link closure). These findings confirm that the network mobility indicator developed behaves in an intuitively correct way.
- The fuzzy logic approach proved to be simple but yet powerful tool due to its ability to model experience and knowledge of human operator. It has been successfully used to combine mobility attributes and vulnerability attributes in a single indicator, reflecting good relationships with relevant road transport network parameters.

The three characteristics indicators represent a potential tool that could be used to gauge the total network resilience under different scenarios. They can also be used to assess the effectiveness of different management policies or technologies to improve the overall network resilience. The main conclusions drawn from the development of a single composite resilience index presented in Chapter 8 are summarised below.

- Each individual characteristic is able to reflect the level of resilience from a certain perspective. The redundancy indicators can identify the ability of road transport networks to redistribute the traffic among different junctions whereas the vulnerability indicators measure the ability of the network links to accommodate the allocated traffic. Furthermore, the mobility indicator is able to assess the overall functionality of the network based on origin-destination level.

- Both proposed composite resilience indices based on equal weighting and principal component analysis are able to capture the complex relationship among the resilience characteristics of road transport networks and to reflect the impact of demand increase in addition to the level of real-time travel information. The trend of both indices for the investigated scenarios in Chapter 8 has shown to be in line with the relevant literature.
- The composite resilience index based on equal weight was always higher than that obtained from the principal component method for the case studies considered in Chapter 8, highlighting the influence of double counting effect in the equal weight allocation among the resilience characteristics.
- The main features of the equal weight method is the simplicity and transparency, making it recommended when a quick assessment of the road transport network resilience is needed. However, the principal component method for estimating the composite resilience index is more accurate as it eliminates the impact of double counting effect.
- The principal component method shows sensitivity to the dataset used for calculating the composite resilience index; i.e. the weight of each characteristics obtained from the principal component method may change when more data considered.

The main advantage of the proposed composite resilience index is its ability to take into account attributes such as network configuration in representing redundancy and vulnerability. It also reflects the effect of demand amplification during and after the event by the use of mobility characteristic

As the very recent version of the OmniTRANS software (Version 6.1.2, May 2014) has included route choice models in DTA framework, it was possible to investigate the impact of real-time travel information on the three resilience characteristics using two case studies. Furthermore, the use of real-time travel information has different impacts on each resilience characteristics highlighting the need to develop a composite resilience index to obtain the aggregated influence of the three characteristics as presented in Chapter 8. The main findings of this investigation are presented below.

- Under low demand, the real-time travel information has very low impact on the mobility and redundancy characteristics of road transport networks as intuitively expected. However, the network vulnerability indicator was higher for full network capacity than for link closure but this may be attributed to the demand allocation by OmniTRANS software.
- The importance of the percentage of travellers using the real-time travel information increases with the demand increase.
- The impact of real-time travel information on resilience characteristics is significantly affected by the number of travellers having access to the real-time travel information in addition to the percentage of traveller complying with the real-time travel information.
- The use of real-time travel information in case of a disruptive event (such an accident or an event leading to demand increase) has much more effect on resilience characteristics, consequently on the composite resilience index, than in normal conditions.
- Overall, the variation trend in each resilience characteristic due to the availability of the real-time travel information to travellers may be different from the other characteristics, emphasizing the importance of considering all three characteristics together.

9.4 Suggestions for Further Research

Based on the overall findings of this research, further work may be carried out in a number of areas as discussed below.

- The current research briefly explored the importance of management under organizational resilience dimension. However, more research is essential to quantify its role and how it could be integrated with the physical resilience.
- The current investigation focuses on the resilience of road transport networks; however, it is recommended to investigate the resilience of the whole transport system. Therefore, other characteristics, such as diversity,

could be included to consider the availability of different transport modes, including trains, aeroplanes and ferries.

- The proposed characteristic indicators and the composite resilience index have been applied to a synthetic Delft city road transport network in addition to few other real life case studies, such as junction 3a in M42 motorway and routes among 7 British cities. With data available for other road transport networks, further research could apply the indicators developed here to these data to further the understanding of the performance of road transport networks under climate related events and various management schemes implemented.
- In developing the composite resilience index from the three characteristics indicators, which were also obtained from respective, attributes, various theoretical methodologies were adopted. It would also be useful to investigate the formulation of these indicators from expert opinions.
- The current investigation has focused on the impact of real-time travel information on the resilience of road transport networks. However, it would be interesting to explore the impact of other ITS, e.g. in-vehicle intelligent transport systems, on the resilience of road transport networks.
- Further research is suggested to investigate the impact of the outbound links on the junction redundancy indicator, as they did not show strong correlation with the junction delay or volume capacity ratio for the case studies considered. Another suggestion is to investigate a combined redundancy indicator covering both the inbound and outbound links.

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Appendix A: A Four Steps Traffic Model

A.1 Introduction

This appendix introduces a brief summary about trip generation, trip distribution and mode choice steps, as they have to be carried out prior to the fourth step, traffic assignment. However, the traffic assignment stage has been presented in Chapter 4.

A.2 Trip Generation

The first stage of this approach is outlining a zoning and network system, and the collection and coding of planning, calibration and validation data. The data could be classified into two main groups, namely the population for each zone and their economic activity including employment data, shopping areas, educational facilities and leisure facilities. There are several techniques that have been developed to predict the number of trips generated by or attracted to a certain zone, for instance the multi regression approach and category analysis. The multi regression analysis is used in the trip generation model to estimate the number of generated or attracted trips in a zone level (aggregated regression analysis model) or the household or individual level (disaggregated regression analysis model).

In the current research, an aggregated regression model is used at the zone level, with the average number of trips per zone as the dependent variable and the average zone characteristics, e.g. number of residents, education and jobs (shown in Figure A.1), as the independent variable. This is due to the scope of this research being more related to the aggregated changes rather than the individual behaviour and choices that would be more critical in the case of the resilience of transport system as a whole. For example, for Delft city road transport network, the case study used in this research, the regression models adopted to estimate the number of produced and attracted trips are as follows:

$$P_i = 0.19 \text{ Residents}_i + 0.04 \text{ Jobs}_i + 0.02 \text{ Research}_i + 0.02 \text{ Education}_i \quad (\text{A.1})$$

$$A_i = 0.035 \text{ Residents}_i + 0.5 \text{ Jobs}_i + 0.2 \text{ Research}_i + 0.2 \text{ Education}_i \quad (\text{A.2})$$

where P_i is the number of trips produced from zone i , A_i is the number of trips attracted to zone i , Residents_i is the number of residents in zone i , Jobs_i is the number of jobs in zone i , Research_i is the research facility space in zone i and Education_i is the amount of educational services offered in zone i . The demographic data distribution for each zone is presented in Figure A.1. The coefficient values of demographic data inputs such as residents are implemented to aggregate the effect of all the demographic data inputs. The values available in the given example with OmniTRANS software are used here to provide a general example of variations, i.e. 0.19 and 0.035 are the coefficient values of residents used for production and attraction respectively. (Use the term 'generated')

Furthermore, a number of attracted and produced trips are added to adjust trip ends to account for external and through traffic. The total trip ends for each zone is shown in Figure A.2.

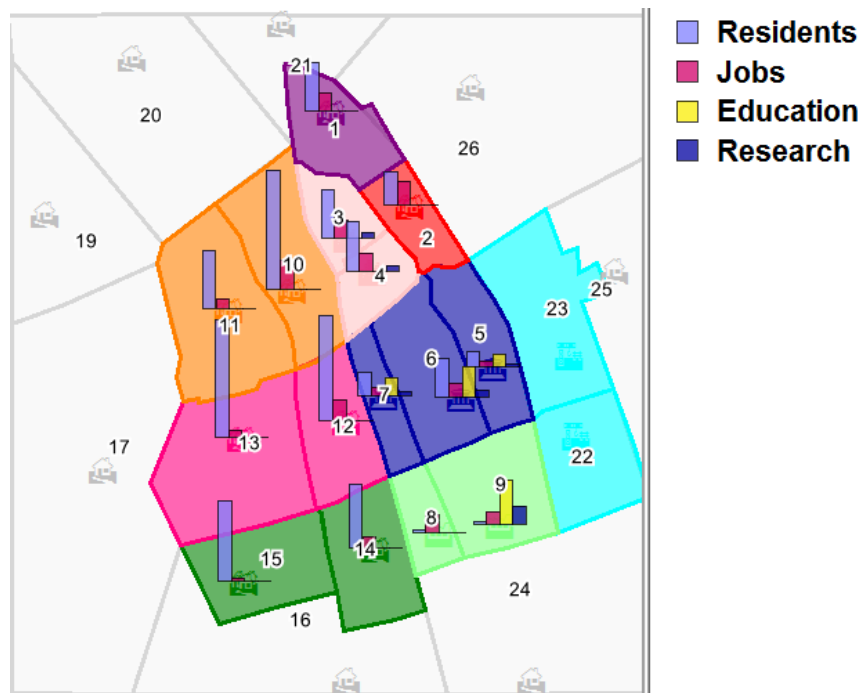


Figure A.1 Socio economic data per each zone in the study area.

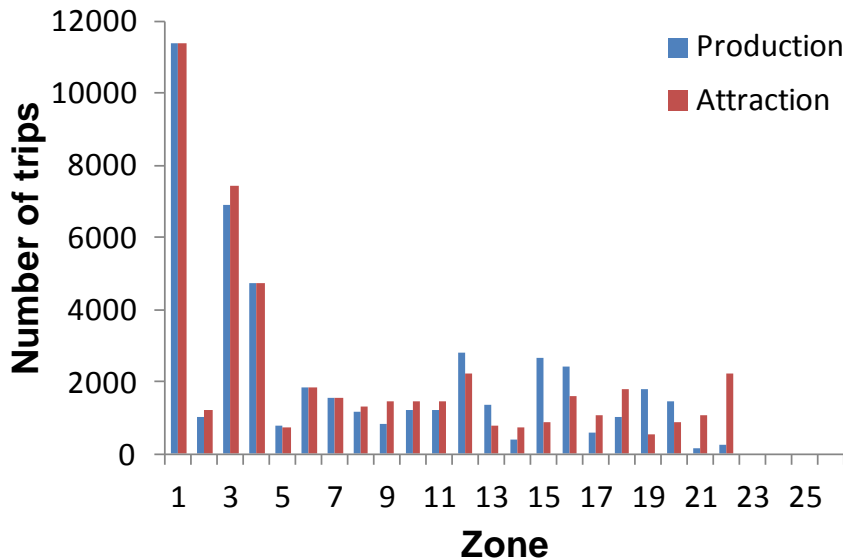


Figure A.2 Produced and attracted trips per each zone in the study area.

A.3 Trip distribution

Trip distribution modelling involves the allocation of generated trips between origin-destination pairs, i.e. forming an Origin-Destination matrix (OD) within the area under study. There are two main approaches used in the trip distribution modelling, namely the growth factor and the gravity distribution methods.

In the growth factor method, a basic trip matrix containing the current trips between each pair of zones, based on survey data, is multiplied by the estimated growth factor for a certain time period. There are various growth factor methods based on the used growth factor, e.g. uniform growth factor where each matrix cell is multiplied by the same growth factor, or using different growth factors for each zone. For example, developing areas are expected to have higher growth factor than developed ones. In such case, the calculations of attracted or produced trips are based on single or double constrained growth factor methods. The mathematical formulation of each method is explained in details in Ortuzar and Willumsen (2011).

A number of limitations to growth factor method have been highlighted by Ortuzar and Willumsen (2011). For example, the demand matrices developed are heavily dependent on the base-year trip matrix, which could lead to enlarged base-year trip matrix errors. In addition, these methods could be inapplicable for new areas or missing cells in the base-year trip matrix. This

approach also does not take into account the network changes; therefore, it could be more convenient for short term predictions rather than the long term where network changes are expected.

The second approach of trip distribution methods are gravity models which are comparable with Newton's gravity model. The hypothesis adopted is that the number of trips between zones is inversely proportional with their generalised cost. The generalized travel cost between a pair of zones is calculated in form of an impedance matrix reflecting the distance, time, or any other cost of travel. The generic form for the trip distribution model is as follows:

$$T_{ij} = a_i b_j P_i A_j f(c_{ij}) \quad (\text{A.3})$$

where, T_{ij} is a number of trips between zone i and zone j , a_i and b_j are scaling or balancing factors, P_i is the total number of trips produced from zone i , A_j is the total number of trips attracted to zone j , $f(c_{ij})$ is a generalised function of the travel costs and c_{ij} is the generalized travel cost between zones i and j .

The generalised function of the travel costs, known as the distribution function, could have a different form such as exponential, power and lognormal function, and discrete distribution functions.

A.4 Mode Choice

Mode choice involves splitting these trips by mode, e.g. cars, public transit or non-motorized such as walking based on several attributes. In general, mode choice models could be classified into two approaches, namely aggregated models that are based on zone information and disaggregate models that based on household and/or individual data. Aggregated models are adopted in this research due to their suitability to network performance analysis. Simultaneous trip distribution and Logit-based choice models are usually used to distribute the total travel demand for a given OD-pair over the available modes (Garber and Hoel, 2009). In simultaneous trip distribution and modal split, the portion of the OD matrix using a certain mode is estimated based on the mode skim matrix.

In this research, trip distribution and modal split are simultaneously performed using a lognormal function; more details about the mathematical formulation can be found in Ortuzar and Willumsen (2011).

Appendix B: Traffic Flow Modelling

The basic assumption of the traffic flow modelling was developed by Greenshields (1935) and becomes known as the “fundamental equation” that links traffic speed, density and flow as presented in Eq. 4.2.

$$q = kv \quad (\text{B.1})$$

where q = traffic flow (vehicles/time unit), k = density (vehicles/road length) and v = space mean speed (length/time unit).

Hoogendoorn and Bovy (2001) classified traffic flow models according to their level of detail, namely macroscopic, microscopic and mesoscopic modelling. A brief introduction on each technique is presented below.

B.1 Macroscopic Modelling

Macroscopic models deal with the traffic flow on aggregate base and utilise traffic characteristics such as speed, flow, density, and travel time to describe the collective vehicle behaviour (Kotsialos et al., 2002). A wide range of mathematical models have been developed to simulate the traffic flow as a stream based on the relationship between the traffic speed, density and flow (Hoogendoorn and Bovy, 2001). These mathematical models could be classified into two main regimes: single regime and multi regime models. In the single regime models, the same functional form is used under all traffic conditions; meanwhile multi regime models consider the effect of congestion on the driver behavior by introducing different relationships between density and velocity at different flow such as free-flow regime and congested regime. Tables B.1 and B.2 show some of the single regime models and multi regime models, respectively, developed in the literature. Macroscopic models are mainly utilized for planning applications, and operations control design of large road traffic networks over a long time period (Burghout et al. 2006).

Table B.1 Single regime models

Greenshield's macroscopic stream model (1935)	$v = v_f - \left[\frac{v_f}{k_j} \right] k$	v = mean speed at density k v_f = free speed k_j = jam density k_o = optimal traffic density
Greenberg's logarithmic model (1959)	$v = v_o \ln \frac{k_j}{k}$	
Underwood exponential model (1961)	$v = v_f \cdot e^{\frac{-k}{k_o}}$	
Pipes' generalized model	$v = v_f \left[1 - \left(\frac{k}{k_j} \right)^n \right]$	

Table B.2 Multi regime models

Edie's model (1965)	$v = \begin{cases} 54.9 \exp\left(\frac{-k}{163.5}\right) & \text{for } k \leq 50 \\ 26.8 \ln\left(\frac{162.5}{k}\right) & \text{for } k \geq 50 \end{cases}$	v = mean speed at density k k = density
Drake et al. model (1967)	$v = \begin{cases} 50 - 0.098k & \text{for } k \leq 40 \\ 81.4 - 0.913k & \text{for } 40 \leq k \leq 65 \\ 40 - 0.265 & \text{for } k \geq 65 \end{cases}$	

B.2 Microscopic Modelling

Microscopic models are dealing with the movement of individual vehicle and the interaction with their environment. The literature carried by Hoogendoorn and Bovy (2001) showed that the development of microscopic models started during 1960s with car following models. They discussed three of car following models namely safe-distance, stimulus-response and psycho-spacing models. Under each of the pervious concepts, a number of formulas had been introduced based on the understanding of the relationship between the dynamic of the vehicle and its precursor. For instance, Pipes (1953) claimed that the movements of the several vehicles are controlled by an idealized law of separation where each vehicle sustains a distance from the following vehicle. The proposed distance is the sum up of two parts, variable distance which is proportional to the velocity of the following vehicle and minimum distance of separation when the vehicles are at rest. Hoogendoorn and Bovy

(2001) also discussed other models developed by Leutzbach (1988) and Jepsen (1998) presented in Table B.3

Table B.3 Different safe-distance models

Pipes (1953)	$D_n(v) = L_n(1 + \frac{v}{16.1})$	D_n = required gross distance headway
Leutzbach (1988)	$D_n(v) = L_n + Tv + \frac{v^2}{2\mu g}$	L_n = length of the vehicle n
Jepsen (1998)	$D_n(v) = (L_n + d_{min}) + v(T + vF)$	v = velocity of vehicle T = overall reaction time μ = friction with the road surface g = acceleration gravity d_{min} = a constant minimal distance between vehicles F = a speed risk factor

B.3 Mesoscopic Modelling

Mesoscopic models utilize the main characteristics of both microscopic and macroscopic models. In these models individual vehicles are represented, but the description of their activities and interactions based on aggregate (macroscopic) relationships (Burghout et al., 2006). For instance, the location of each vehicle is determined based on microscopic concepts while the travel time is calculated from the average speed on network links estimated from a speed-flow relationship. The literature shows a wide range of mesoscopic models such as CONTRAM (Leonard et al., 1978; Taylor, 2003)