# Optimal urban goods movement planning taking independent retailer restocking activities into consideration

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

The University of Leeds

Institute for Transport Studies

2019

The candidate confirms that the work submitted is his own, except where work which has formed part of jointly authored publications has been included. The contribution of the candidate and 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.

Some of the work in Chapter 6, 7, and 8 forms the basis of the following jointly authored papers:

**Nugroho, T.S.**, Whiteing, A.E., Balijepalli, N.C., (Under review). 'Independent retailer restocking choices in urban goods movement and interaction effects with traditional markets', *Networks and Spatial Economics.*

I developed the main idea for this work, under the guidance of A.E. Whiteing and N.C. Balijepalli. I performed the data collection process, the data analysis, the modelling work and wrote the manuscript. A.E Whiteing, and N.C Balijepalli provided recommendations on the modelling and comments on the results. The manuscript was improved by comments from all the co-authors.

**Nugroho, T.S.**, Balijepalli, N.C., Whiteing, A.E. (Under review). 'Optimal road pricing policies for city logistics planning considering retailer restocking choices in congested road networks', *Transportation Research Part E: Logistics and Transportation Review*

I developed the main idea for this work, under the guidance of N.C. Balijepalli. I performed the data analysis, the modelling work and wrote the manuscript. N.C Balijepalli provided recommendations on the modelling and comments on the results. The manuscript was improved by comments from all the co-authors.

# Acknowledgements

Completing a PhD has been a very lonesome journey for the past four years, and the author realises that the work would not have been successful without advice, help, and support from numerous people whom I wish to thank.

Firstly, the author would like to thank his two supervisors: Dr Anthony Whiteing and Dr Chandra Balijepalli, for their valuable insights and support during the research process. The encouragement I received from both of them is very much appreciated. The author also wants to thank Prof Ronghui Liu, and Prof Yusak Susilo for their advice during the transfer and viva examinations.

The author would like to express his special appreciation to Mr. Andrean Maulana, from Institut Teknologi Nasional (ITENAS) Bandung, for helping the author during the data collection process. He also wants to thank all the surveyors and all the respondents who helped with this research. The author also wants to say thanks to all his ITS and Indonesian fellows some of whom deserve to be mentioned here: Haruko, Anna, Qiyang, Rizal, Zihou, Thamas, Jeff, David, Dr Munajat Tri Nugroho, Dr Aswin Siregar, and Muhammad Farda M.Sc. Thank you for your friendship and continuous support during the last four years.

The author is indebted to the Republic Indonesia Endowment Fund for Education (LPDP Republic Indonesia) for the opportunity to pursue PhD study and sponsoring the research.

Last but not least, the author wants to express gratitude and thanks to his lovely wife, Sri Krisyanti, who always supported him during his study. He is also very touched and grateful to his two daughters, Naya and Rana, who become the incredible source of motivation to finish this PhD. Finally, he offers sincerest apologies to anyone who helped during the study but is not acknowledged here.

*"All praise be to Allah, the Lord of the worlds"*

# Abstract

The main aim of this research is to help the local authorities to better manage the urban goods movements (UGM) in cities. Particularly this research develops an integrated framework to analyse the impact of local authority policies by linking retailer logistic decisions as well as passenger movements with traffic conditions on the road network. The particular aim of this modelling approach is to identify the city logistics policies that meet local authority objectives to optimise urban road networks as well as incorporating retailers and other road user behaviour in response to traffic congestion.

The modelling framework is formulated as a bilevel optimisation problem in which the upper level problem represents the local authority objective, while the lower level problem constitutes the user equilibrium traffic assignment problem incorporating the traffic demand from UGM activities as well as passenger movement.

An analysis of independent retailers' restocking activities is done to represent the demand for UGM activities in the cities. Independent retailers, prevalent in developing countries, have different decision-making processes compared to the more studied chained retailers. In particular, independent retailers usually rely on their own vehicles to run their businesses and are strongly influenced by the presence of traditional markets. This thesis utilises regression methods and a discrete choice model to quantify the factors affecting the independent retailers' restocking trips and their subsequent logistic decisions.

The current study extends the state of the art of UGM model in the literature in two areas: (i) the bilevel model explicitly considers the interest of the three actors involved in the UGM activities viz. local authorities, retailers and road users, by setting up an optimisation problem to maximise the overall welfare; (ii) the demand models investigate deeper insights into independent retailer restocking activities.

The results for the demand modelling estimation for retailers in Bandung city centre show that vehicle ownership and the presence of traditional markets play an important role in shaping independent retailer decisions.

The application of the bilevel modelling framework for Bandung city centre reveals that restricting commercial vehicles and applying toll charges for commercial vehicles could increase the overall welfare of all road users. However, the policy must be carefully applied since it could produce an unwanted result. For example, applying a sub-optimal toll produces sub-optimal welfare gain for all road users or even disbenefit for particular road users

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## List of Abbreviation

| | |
|---|---|
| AC | : Average Cost |
| CCA | : Cutting Constraint Algorithm |
| MC | : Marginal Cost |
| CV | : Commercial Vehicle |
| IDR | : Indonesian Rupiah |
| IIA | : Independent and Irrelevant Alternative |
| IID | : Identically independently Distributed |
| MNL | : Multinomial Logit |
| MXL | : Mixed Logit |
| NL | : Nested Logit |
| OD | : Origin Destination |
| OLS | : Ordinary Least Square |
| PV | : Private Vehicle |
| TAZ | : Traffic Analysis Zone |
| UB | : User benefit |
| UE | : User Equilibrium |
| DUE | : Deterministic User Equilibrium |
| SC | : Social Cost |
| SUE | : Stochastic User Equilibrium |
| UGM | : Urban Goods Movements |
| VI | : Variational Inequality |

# Chapter 1 Introduction

This chapter begins by introducing the research background and the importance of addressing the research problems in Section 1.1. Next, in Section 1.2., we state the research aims and objectives and the tasks required. Section 1.3. states the new contributions of this thesis and the main contribution to the literature. This chapter closes by giving the thesis structure in Section 1.4.

## 1.1 Research background

Sustainability of the city depends on the activities of its citizens, whose lifestyles involve consumption of many goods and services that are produced outside the city's area. Activities such as offices, retailers, hotels, restaurants and cafés depend for their activities on goods and services that are delivered to their location regularly. Delivering goods and services to support these activities in a city involves many vehicle movements. In transport planning, these movements are often referred to as Urban Goods Movements (UGM).

UGM are important to city life for many reasons (Anderson et al., 2005). They are fundamental to sustaining the citizen and their lifestyle as well as to supporting trading activities that are generally generating activities and wealth. UGM also impact cities' and regions' competitiveness in the sense that efficient goods and service movements will impact overall logistics cost and therefore, the cost of commodities in the cities. On the other hand, UGM also bring negative externalities to the city's life. UGM are the activities that connect supply chains in national and regional areas to the supply chain within the cities. These last mile delivery activities, often solely rely on road transport, generate negative externalities to the city such as congestion, inefficient deliveries, resource waste and emissions (McDermott, 1980; Ogden, 1992). Given the importance of UGM and the problems they bring to the quality of the city, it is essential to plan and manage this activity effectively.

Managing UGM is a challenging and complex task since it involves many actors such as the authorities, logistics industry (for e.g. retailers/wholesalers/carriers), and the end consumers/other road users. In terms of managing UGM activities, the view held by the authorities towards the UGM actors greatly shapes the UGM measures applied by the authorities. Previous studies reveal that logistics decisions by actors from the logistics industry are often neglected by the local authorities which lead to less effective policies (Ballantyne et al., 2013). Some local authorities even view the logistics industry as an obstacle to policy implementation rather than core participants (Anderson et al., 2005; Vidal Vieira and Fransoo, 2015). This condition often makes transport policies result in a contrary outcome. For example, weight and time restrictions that are widespread in city logistics schemes could lead to more traffic congestion and worse environmental impacts (Quak and de Koster, 2006a).

Therefore, it is important to conduct a study that considered the three-sided interaction between local authorities, wholesalers/retailers, and other road users in a single modelling framework including the possibility of assessing city logistics measures in the model. By providing the modelling framework, local authorities need to think of UGM activities as an integral part of cities' lives and activities and not see them as a hindrance to city mobility. Instead, local authorities need to aim for city logistics policies that will lessen the congestion to other road users while still preserving the economic advantages of UGM activities.

One of the most significant activities related to UGM is retailing. Retailing activities are the outcomes of decisions made by the retailers which depend on whether they are independent businesses or chain retailers. Independent retailers are typically small sized businesses in which individual owners make their own logistic decisions - *where to procure the goods from* and *how to move the goods procured*. On the other hand, chain retailers do not take local decisions, but logistics decisions are taken centrally. Thus, independent retailer logistics decisions tend to be less consolidated than those taken by chain retailers.

Independent retailer restocking activities can be handled independently, i.e. the transport is done by retailers using their own employees and fleet, or by a third party operator, i.e. a professional carrier is paid to undertake the transport (Russo and Comi, 2010). The split between transport services varies significantly. Typically in North American and European cities, the shares may be around half each (Dell'Olio *et al.*, 2017), but in developing countries, independent transport is more dominant. For instance, a study carried out in 2004 in Medan, Indonesia, reveals that 90% of companies use their own vehicles to restock their shops (Kato and Sato, 2006).

Independent retailers, having less consolidated deliveries, often contribute more than chain retailers to traffic congestion and pollution. Independent retailers may produce a worse impact on the traffic congestion compared to the chain retailers given that their restocking activities are less consolidated. They often use their own vehicles and thus may increase the number of delivery trips with less efficient vehicle loading. The frequent use of their own vehicles and the limited capital triggers "just in time" restocking activities in which they have a flexible schedule for restocking their shop based on their actual demand and restricted capital (usually on day-by-day basis).

The authorities need to understand the diverse nature of restocking activities of independent retailers in order to be able to conceive effective city logistics policies. The diversity of retailing activities between cities around the globe results in variations in how local authorities should approach this problem (Dablanc, 2007; Visser and van Binsbergen, 1999). For instance, in many cities, particularly in the developed world, the development of an urban distribution centre is appealing since it is viewed as a way to consolidate the goods and improve the efficiency of delivery operations (Morganti and Gonzalez-feliu, 2015; Paddeu, 2017). Other cities may implement different measures such as off-peak hour delivery, weight and size restrictions, and low emission zones (Taniguchi *et al.*, 2003; Holguín-Veras *et al.*, 2008). The lack of knowledge on how restocking activities are undertaken by retailers can result in inefficient policy-making that not only hinders the economy but also worsens congestion and pollution (Quak and de Koster, 2006b).

## 1.2 Research objectives and tasks

The main aim of this research is to aid local authorities to find an optimal city logistics measure taking the interaction between retailers' restocking activities and other traffic into consideration. In order to achieve the aims, two research objectives are developed:

- to build a modelling framework that can adopt the local authority objective while considering the interaction between local authorities, wholesalers/retailers and other road users in a single framework;
- to understand independent retailers' restocking activities decision-making process.

Based on the research objectives, several research tasks are addressed as follows:

a. To carry out literature reviews on UGM activities. The literature reviews address two areas:
    - Overview of UGM activities and their city logistics policies. This task addresses the nature of UGM activities and the impact they bring to the cities and argues why these activities should be addressed separately from passenger movements and thus needs different approaches and policies from the local authorities (presented in Chapter 2).
    - Review previous UGM modelling approaches and their methods. The area of the reviews is based on the problems this thesis wants to address and divided into three aspects: (i) review of the methodologies to build the independent retailers' trips demand model; (ii) review of the role of a traffic assignment model to assess UGM activities; (iii) review

of the optimisation problem addressing UGM activities (presented in Chapter 3).

b. To propose an appropriate modelling framework and the subsequent methodologies that can be used to reach the research aim. The methodologies need to have a strong theoretical background and be applicable to dealing with our problem (presented in Chapter 4).
c. To develop an independent retailer restocking trips demand model. The objective of this research task is to build a model that can formulate the explanatory factors behind the logistical decisions by independent retailers. The model then is used as the behavioural representation of the independent retailers in the next task. This task is done through the sub-tasks below:
    - Conduct a revealed preference (RP) survey to collect preference data of independent retailers regarding their restocking activities. Independent retailers at Bandung, Indonesia, are used as the case study (presented in Chapter 5).
    - Build a demand model by estimating the relevant parameters for identifying and quantifying the factors that influence the decision of independent retailers in their restocking activities (presented in Chapter 6).
d. To formulate an optimisation problem that defines the local authority objective to optimise road network performance as well as the independent retailers' behaviour. The aim of this task is to find a combination of transport policy instruments that meet the objective by the local authorities to maximise social welfare for all road users. This research task is done through the sub-tasks below (all of these subtasks are presented in Chapter 7):
    - Formulate the optimisation problem incorporating the three-sided interaction between local authorities, retailers/wholesalers, and others
    - Use the available algorithm from the literature to solve the optimisation problem
    - Solve the problem in a small network scale to test the working of the bilevel programming problem.
e. To apply the demand model and the optimisation formulation to the real-world case of Bandung city centre (Presented in Chapter 8).

## 1.3 Novelty and contribution of the research

The main novelty of this study is in the area of city logistics / UGM planning. From a theoretical point of view, this study fills the gap in the literature by developing a new model of city logistics using an optimisation technique to explicitly model the local authority objective of improving the overall welfare and retailers' decision responses together with private vehicle routing in response to congestion on roads. The novelty of this approach is that both the behaviour of the retailers and that of the other road users are embedded in a single modelling framework that took into account the effect of congestion on the road network. By embedding the responses of all road users into a single framework, the local authorities can aim to improve the situation not just for a particular user but for overall road users in the road network.

From a methodological point of view, our proposed model utilizes bilevel programming to address urban goods movement problems. The bilevel programming approach is used to model the three sided interaction between the local authority, commercial vehicles, and private vehicles in one single framework. Further, we develop a traffic assignment formulation for *multiuser class* with *variable demand* as a variational inequality (VI) in the lower level problem within the bilevel program. The VI considers the behaviour of multiuser class traffic whilst incorporating the user decisions of route choice for commercial vehicles and private vehicles on two counts: user class specific choice, and route choice.

Another contribution of this research is investigating independent retailers' logistics decision regarding their restocking activities. Independent retailers have different logistics characteristics compared to chain retailers due to their dependence on more than one supply channel and they also primarily use their own vehicles to restock their shops. The logistics decisions mostly depend on their owner and are not centralised like for chain retailers. Furthermore, independent retailers rely heavily on the traditional supply chains in which the traditional market plays a significant role in those supply chains. Previous UGM studies mostly address chain retailers, thus by investigating the case of independent retailers, we can get a better understanding of transport demands derived by these particular retailing activities. In particular we explore the case of independent retailers in the developing countries context by using Bandung Indonesia as a study case.

## 1.4 Thesis structure

This report is divided into nine chapters, including this one to address the research tasks and the subsequent objectives. The thesis is organised as follows:

**Chapter 1: Introduction**. The first chapter of this report contains an overview of the problem that is to be addressed in this research, the aim and objective of the research, the research contribution and novelty as well as the structure of the written thesis.

**Chapter 2: Overview of Urban Goods Movement (UGM) activities**. The second chapter reviews the literature on UGM activities and their impacts on urban road networks. Several relevant transport policies to address the problem of UGM are also reviewed in this chapter.

**Chapter 3: Review of the methodologies.** This chapter reviews the existing methodologies that lay out the previous attempt at UGM activity modelling. The review can be classified into three categories: (i) methods related to restocking demand modelling; (ii) methods related to user equilibrium traffic assignment; and finally (iii) methods related to optimal city logistics policies and the solution techniques. Based on previous modelling attempts to aid local authorities to manage UGM activities, the gap in terms of modelling approach is then stated in the chapter summary.

**Chapter 4: Modelling framework and research methods**. In this chapter, the modelling framework to depict the local authority objective and retailers' behaviour is explained. This chapter also addresses the theoretical frameworks behind the proposed methods. Regression model and Random Utility Modelling (RUM) is used to model the independent retailer demand model. Meanwhile, to depict the optimisation process, this thesis adopts the well-known bilevel programming approach. The welfare economy objective is used to calculate the authority objectives as the upper level problem, while user equilibrium (UE) traffic assignment is used to depict both the behaviour of independent retailers and other road users in the lower level problem.

**Chapter 5: Data collection.** This chapter elaborates the process of data collection. The process includes the survey questionnaire design, the pilot survey and the actual main survey. This chapter also gives a descriptive summary of the data collected.

**Chapter 6: Demand modelling for independent retailers.** The main issue addressed in this chapter is the demand model estimation of restocking activities by independent retailers. The demand model reveals the important factors that affect the logistical decisions of independent retailers. The demand model produced in this chapter will be used in Chapter 8 to formulate the behaviour of independent retailers.

**Chapter 7: Bilevel programming formulation considering independent retailers' restocking activity.** This chapter elaborates on bilevel programming as a way to depict the interaction between local authorities' objectives and independent retailers' / other road users' behaviour. The model formulation, solution technique and the small network example are explained in this chapter.

**Chapter 8: Road pricing policies considering independent retailers' restocking activities.** In this chapter, the proposed modelling framework is tested in the real case of Bandung city centre area. It is based on the demand model estimation in Chapter 6 and optimisation formulation in Chapter 7. The test of several city logistics policies to optimise social welfare in the network is explored. Further, the policy implications of each policy are also explained in this chapter.

**Chapter 9: Summary and conclusions.** This chapter presents the conclusions of the research carried out, its limitation and points out recommendations for future studies.

# Chapter 2 Overview of Urban Goods Movement (UGM) activities

To achieve the objective of this research, a review on the subject of urban goods movement (UGM) is necessary. We begin this chapter by providing the definition of UGM and the various actors involving in UGM activities in section 2.1. Next, the importance of UGM to support a city, and yet the adverse problem and impact of these activities to the congestion and emissions level of the city are discussed in section 2.2. More importantly, section 2.3. discusses the role of public authorities to address the problem due to the inherence conflict between actors in UGM activities and the public authorities are seen as the only actor interested in finding an optimal solution.

This chapter also reviews selected urban goods transport policies that aim to improve delivery efficiency within the city in section 2.4. The case of optimal policies that consider UGM actor interests as well as the inhabitant of the cities is argued. Finally, section 2.5. reviews specific cases of independent retailer activities since this research address specifically on these activities. The review involves the difference between independent and chain retailers.

## 2.1 Goods movements in an urban area

Urban goods movement (UGM) is usually synonymous with urban freight distributions/city logistics and thus has many general definitions in the literature. Generally, UGM is defined as "*the movement of things (as distinct from people) to, from, within, and through urban areas"* (Ogden, 1992, p. 14). These activities are essential for cities' dynamics and lives; thus, it is essential to manage them effectively. Despite the above, in the context of this thesis, we will limit the UGM definition as "*the transport of goods carried out by or for professionals in an urban environment*" (Lindholm, 2013, p. 7). This definition is appropriate in our case since we concentrate our problem specifically on goods delivery activities in the urban area. It is recognised that this definition excludes considerable traffic generated by activities such as building and demolition traffic, waste collection and other hidden logistics activities that support urban lives. Saying this, a recent report on UGM activities around the world reveals that goods delivery activities are still the highest contributors to goods vehicle traffic (Dablanc, 2009).

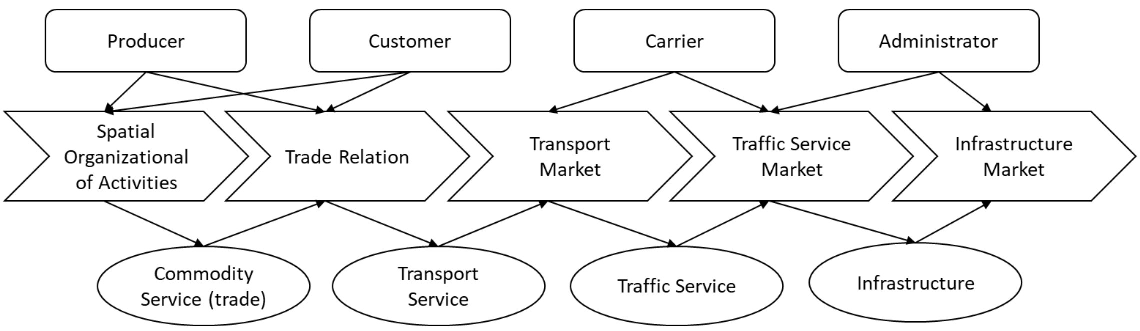
The needs of UGM activities are derived from the needs of cities to sustain themselves. As the world economy and population move towards cities, UGM activities play more important roles by sustaining citizens' lifestyles by providing the goods that are needed. It is on this note that Anderson et al. (2005) highlight a number of reasons why urban freight transport is essential. These include:

- UGM plays a significant role in sustaining citizen lifestyle
- UGM service industrial and trading activities are the significant economic activities generating wealth and prosperity
- An efficient freight sector increases the competitiveness of the regional economy. There will be a negative effect if industries in that region are hindered due to poor freight services.
- The effect of freight sectors and logistics costs on the cost of the commodities in the region.
- The environmental effect of UGM (e.g. emissions, noise, and in terms of energy used) is significant to the inhabitants of the cities.

Considering that the UGM activities are crucial to ensure people's quality of life and cities' economic development, many authorities have recognised the needs to tackle the problems associated with it. Only long-term planning and policies on urban transport can ensure the sustainability of UGM activities. Therefore, UGM activities should be included in the local authority agenda and need to be considered carefully in the planning stage.

### 2.1.1 The nature of urban goods transport

UGM activities are historically driven by private actors. Although the local authorities and city inhabitants play a vital role in UGM transport policies, the UGM itself is driven by private actors. Boerkamps et al. (2000) explain this by deriving and defining several different markets involved in UGM activities (see Figure 2-1).




(Source: derived from Boerkamps et al., 2000)

**Figure 2-1. Conceptual Framework for Urban Goods Movement (UGM) activities**

The demand for goods arises from the economic process of production and consumption. In this sense, demand for UGM activities arises when shippers and receivers create a trade relationship involving activities to transport the goods from shipper location to receiver location. The trade relationship implies that the demand to move the goods is not necessarily for transport per se; instead they are moved if there is a value gained by transporting the goods to some location other than the present one. Therefore, in more formal terms, the demand for moving the goods can be seen as derived demand.

Further, the movement of goods has unique requirements that differ from passenger transport. For example, while passenger transport in urban areas follows the behaviour to minimize the transport cost, urban goods movement does not necessarily try to minimize the transport cost alone. The reason is that industry seeks to have a reliable supply chain and sees traffic congestion as a lost production if it causes the delay of 'just in time' deliveries.

The just in time concept deals with the reduction or even elimination of inventories. Since the shop size in a typical urban area is typically small, the practice of just in time deliveries becomes important. The main difference between just in time deliveries and the traditional supply chain is that the goods are less characterized by their physical properties but more in terms of logistical requirements. From a transport point of view, this is an important change in which the transport-logistics of goods movement will change from one which tries to minimize the transport cost alone to one which minimize the overall logistics cost.

The goods demand may vary from city to city, from community to community. Therefore, the generation of the type of goods is also the reflection of the community needs and its culture. Depending on the different needs and inclination of the communities, a different type of goods may be sought and thus moved. As these goals and needs change, so the type and amount of the goods needed will change, and thus the demand for goods transport will also change. For example, the set-up of an urban delivery centre can be mainly initiated by private actors to meet their UGM needs. The city of Parma in Italy has the only urban distribution centre in the world that is dedicated to fresh products (Morganti and Gonzalez-feliu, 2015). It is the case since in Parma, the distribution centre is needed to consolidate the high demand for fresh product deliveries and therefore, the construction and operational cost of the distribution centre is financially feasible.

The demand for transporting the goods creates the transport market in which the transport supply provides services to move the goods from the shippers to the receivers. The nature of this transport supply characteristic is quite unique in the sense that there are no single private actors actually concerned with the overall process of moving goods. In such a supply chain, each actor might be concerned only with the task in hand. A carrier's activities may be determined by decisions such as the shipment size, vehicle fleet size, vehicle routing and other logistics related decision (Holguín-Veras et al., 2008), whereas the shipper as the owner of the goods may be quite unconcerned about the details of the transport service in which the goods are moved. They are more concerned about the cost of deliveries, and the reliability of the transport, and hence the decisions involving shippers usually related to transport service choice. The receivers are usually also not concerned about the process of goods transport. Their issues are more related to the time the goods arrived at their shop perimeters and the process of loading and unloading the goods from the delivery vehicles to their shops (Ogden, 1992).

Lastly, the administrator/public sector also has a significant role in shaping UGM activities. When the demand for transport goods emerges, commercial vehicle traffic appears and interacts with passenger demand traffic in traffic service markets. These problems appear particularly in urban road networks where commercial vehicles and private vehicles compete for space and priority on congested roads. Externalities such as congestion and pollution appear and become public issues. The local authorities' decisions to manage the traffic conditions through some city logistics measures can change the UGM activities quite significantly.

### 2.1.2 Identifying actors related to urban goods movement

UGM is naturally a more complex activity compared to passenger transport since there is a multitude of heterogeneity in UGM activities. Unlike in passenger transport where the primary decision-makers are the passengers and their aggregate decisions shapes passenger transport pattern, in UGM, there are several stakeholders involved and each of their decisions shapes how the goods are delivered and the subsequent trips and infrastructures required (Taniguchi et al., 2008). For example, the decision for a retailer to procure goods using personal vehicles will often produce more trips than if the goods are delivered by their supplier due to the less consolidated deliveries. A supplier may opt to use their own vehicles or choose to use third-party carriers to transport the goods. Each decision by the actors involved will impact how the goods are delivered, by whom, what vehicles are used, where the vehicles to transport the goods start their journey and the route taken by the vehicles.

As UGM is a complex activity with various actors, it is necessary to discuss the actors involved and their role in shaping the overall UGM activities. Generally, actors that are involved directly in UGM activities can be classified into two categories: public sector and private actors. Public sector includes cities authorities regulating UGM activities within a city boundary. Private stakeholders are usually private companies involved in the UGM industry. Such entities include producers, suppliers, wholesalers, freight forwarders, trucking firms, shop keepers etc. These private companies generally can be classified into three categories: suppliers, receivers and carriers (Muñuzuri et al., 2005).

The term suppliers often called shippers in the literature, is a generic term that describes companies, or entities, that generally produce the goods and where the origin of the goods is located. However, the suppliers do not need to necessarily produce their own products, since UGM is often the last mile distribution activities involving more extensive national or international supply chains. Thus, in the UGM context, shippers cover all economic activities involving goods procurements in the cities and distribution. In general, the responsibility for the consignment is with the shippers. They arrange the delivery and pay for the goods transport service. Therefore, it is reasonable to assume that the shipper seeks to minimise their logistical costs and the costs may or may not be the same as transport costs. Shippers may choose a more costly transport option if in the end they can save elsewhere in the distribution or manufacturing chain.

Receivers is also a generic term that describes people, companies or entities that receiving the goods, i.e. the destination of the consignment. Again, this may involve a wide area of economic activities including retailers, shop keepers, and eventually the end consumers. Receivers usually are less concerned about the transport costs of the goods since in most cases it is the shippers that actually pay the cost. Receivers generally are more concerned about the issues of delivery reliability and efficient handling when the goods arrive at their locations.

Carriers involve all trucking / delivery companies in which their main business is to deliver the consignment from the shipper to the receivers. Carriers may differ significantly from other carriers in terms of fleet size. In the deregulated market such as Egypt, China, and other developing countries, small size carriers are prevalent. These carriers can get work through word of mouth, or can be booked by the suppliers to serve them on a contractual basis (Herzog, 2009). However, in Europe, large carriers are more prevalent since a more regulated environment is in place and to ensure that the economies of scale of deliveries are met (Dablanc, 2009). The goals of carriers generally are to maximise their own profit. They can do it by different strategies such as varying scheduling and routing of their fleet to increase fleet utilisation.

Although in general private actors in UGM activities can be divided into these three categories, there are many cases in which we cannot adequately distinguish one entity as playing a single unique role. Many suppliers can opt to use their own fleets to deliver the goods; in the same manner, retailers may pick up goods from the suppliers and bring them back to their shop. In both cases, the entities may also be called carriers. Therefore, we should not think of the classification above as a rigid label for a particular establishment; instead the classifications help us to identify the activities involved in UGM activities.

Other stakeholders that are not involved directly in UGM activities yet are essential in terms of UGM planning: the city inhabitants i.e. the people living in the city. The city inhabitants are stakeholders who are not involved directly in UGM activities, yet, they are the ones who receive the negative externalities of UGM activities. Congestion, emissions, noise, visual intrusion etc. are externalities related to UGM activities that can degrade inhabitants' quality of life (Anderson et al., 2005). It is crucial to address the interest of these actors since, in the view of public policies, this group is usually more significant.

The last actor involved in UGM activities is the authorities/public sector. The authorities may be in any form depending on the city context and particular arrangements. However, since UGM refers to activities happening within the cities, we term the authorities in this thesis as local authorities. The literature reveals that regarding UGM activities, there are no single private entities nor the city inhabitants that are concerned with the overall efficiency of goods deliveries in the cities. Whilst private actors may be concerned to improve the efficiency of *their* deliveries, they have fewer concerns about the overall impact of deliveries on city congestion and pollution.  Therefore, it is the role of authorities to improve goods deliveries yet still consider the impact of the deliveries on the city inhabitants. The role of the authorities will be discussed in more detail in the next section (see Section 2.3.1).

### 2.1.3 Last mile deliveries and mode choices

Most UGM activities are last mile deliveries meaning the goods are transported to the location of the receiver to be consumed (Comi and Nuzzolo, 2014). In the last mile deliveries, road transport becomes the dominant mode or even the only mode that is able to provide door-to-door services. "Almost without exception freight generating and receiving locations (including households) are directly connected to the road network, so the road is the universally available option for moving goods between businesses and from businesses to consumers" (DfT, 2010, p. 3). Nevertheless, the inclusion of another type of transport such as rail and water transport to serve UGM activities is not impossible, though the importance of such movements depends on a range of factors within the particular city such as the location of the city and the type of industry and whether, for example, the city has a major port or airport (Browne, 1997).

Given the dominance of road freight in UGM activities, the question about alternative modes in last mile activities becomes less relevant. However, the issue arises regarding mode choice in UGM activities within the context of commercial vehicles types. Wang and Hu (2012) studied the choice of commercial vehicles in urban areas and found that automobiles, pick-up trucks, single unit trucks and combination trucks are the primary vehicles for commercial purposes. The research indicates that the choice for the type of commercial vehicle is cargo sensitive, travel specific and varies by the type of company. In terms of minimising the environmental impact of UGM activities, other possibilities are to choose low emission vehicles such as tri-cycle or electric vehicles (Arnold et al., 2018).

## 2.2 Problems associated with urban goods movement

One of the earliest studies on UGM provides insights into the problems incurred by UGM activities, viz. the under-utilisation of goods vehicles, traffic congestion and the lack of facilities for loading and unloading activities (Hicks, 1977). Within the studies, the major costs associated with UGM are also highlighted such as transport operating community costs, external costs, and urban infrastructure costs.

More recently, the combination of higher densities in urban areas and the trend for "just in time" replenishment have resulted in increased demand for reliable goods delivery (Visser et al., 2014) . "Just in time" delivery results in the overall delivery becoming less effective and more fragmented since the goods need to be delivered to one place at one time by one vehicle. The dichotomy of the demand and the limited resources of the urban environment have resulted in significant problems related to UGM activities. The most commonly mentioned are traffic congestion, pollution, safety, and noise (Behrends et al., 2008).

Quak (2008) summarises how UGM affects the three dimensions of society, economy, and environment in the city:

- Impact on society: physical consequence of pollution and emissions on general public health, road safety concerns, the intrusion of noise and reduction in overall air quality.

- Impact on economy: inefficiency and waste of resources, decrease in journey reliability and delivery punctuality, congestion and decreases in city accessibility.
- Impact on environment: pollutants, emissions, and waste products.

### 2.2.1 Impact of UGM activities in urban network congestion

One major problem related to UGM activities is congestion and delays caused by commercial vehicle traffic. The interaction between passenger and commercial vehicles commonly occurs on urban roads, where trucks, cars, buses and pedestrians compete for space and priority. Congestion thus harms in two ways: commercial vehicles responsible for the delay impact on other road users, and conversely, the high flow of other vehicles on the road can delay commercial vehicles and decrease their reliability.

Other road users and citizens in general see commercial vehicles as a disturbance on the roadway. Commercial vehicles are physically more enormous, occupy more road space and thus reduce road capacity. Due to their larger size and load weight, commercial vehicle vehicles generally have slower acceleration which slows overall traffic flow in an urban area. Further, loading and unloading activities often illegally occupy parking spaces creating resentment for other road users. Worst, in the case of parking curb absence, commercial vehicles tend to double park causing a bottleneck and reducing road capacity. These bottlenecks are challenging to predict and often affect not only the road section where the loading/unloading takes place but also the surrounding network.

On the other hand, commercial vehicles view the other road vehicles to increase their operation costs. Since goods deliveries rely heavily on the road-based modes, the reliability of goods delivery also depends on road network conditions. Industries often see road accidents and congestion as a problem in terms of lost production and a waste of resources.

Lindholm (2012) summarises the main problems incurred by UGM relating to congestion levels as follows: Truck traffic problems – caused by high traffic intensity, poor road conditions, insufficient road infrastructure. It also includes transport policy limiting access for trucks.  Parking and loading/unloading problems – insufficient loading bay at city centre area, handling problems, double / illegal parking. In conclusion, the impact of UGM activity on road performances can be divided into two categories: (i) truck flow related problems. This problem occurs because generally trucks are slower than other road users and other road users impede truck flow. (ii)

Parking/loading/unloading problems which can reduce road capacity severely if not well managed.

### 2.2.2 Problems related to citizens' quality of life

Other problems related to UGM activities mentioned in the literature is the way goods delivery affects the quality of life in cities. In many countries, UGM is increasingly becoming a disturbing factor for quality of life. In Europe, the externalities of freight transport are responsible for as high as one-third of the external cost of congestion (OECD, 2003). The unsustainable impact of UGM activities is numerous and multifaceted. It can be limited to the local area where the traffic is taking place (e.g. noise) or it can impact on wider society in terms of GHG emission.

Commercial vehicles are associated with slower acceleration and emit more emissions than passenger vehicles. As with most forms of motorisation of road transport, UGM produces significant GHG emissions particularly with diesel driven vehicles that produce most particulate matter emissions besides the regular carbon dioxide ($CO_2$). Particulate matters are a major problem since they are responsible for significant public health problems such as asthma and other respiratory illnesses. In Dijon, France, UGM activities are responsible for only 20% of $CO_2$ emissions, yet contribute to 60% of particulate matter emissions (Dablanc, 2009).

Another problem associated with quality of life is noise emissions (Russo and Comi, 2012). Studies on the effect of noise on human health give a clear warning. The noise may lead to stress and increased blood pressure. The noise emissions also are stated to be one of the reasons why local authorities are advised by urban planners to ban commercial vehicles from entering residential area and why the off-hour deliveries policy is not a widespread UGM policy. An off-hour deliveries policy departs from the idea of using the underutilised road network in the morning in order to increase delivery efficiency. However, the noise coming from commercial vehicles often makes this policy less favourable (Dell'Olio et al., 2017).

## 2.3 Public sector policies to address UGM activities

UGM activities are mainly industry driven and are the result of logistics decisions within goods distribution/ supply chain systems (Dablanc, 2009). Because of this nature as an industry driven activity, many people believe negative characteristics associated with UGM activities can be solved within the industry since there is an economic interest in doing so. Further, there is a notion that regardless of the measures put in place to organise UGM activities, the goods will still reach the final customers in a particular place and time since this has resulted from the logistics decision-making process. Nevertheless, evidence shows that due to the lack of any real incentive, private stakeholders in reality do not proactively work towards reducing the overall system cost; instead they usually work towards increasing their efficiency per se (Ogden, 1992). Therefore, a variety of factors driving the implementation of urban goods transport policies are given. Ogden (1992) identifies three issues influenced by UGM activities: (i) economic development; (ii) transport efficiency and (iii) minimisation of adverse impact.

Economic development needs a supportive freight system to be able to thrive. Therefore, poor accessibility, improving the reliability of deliveries, and other economic reasons also contribute to driving the implementation of urban goods policies. Although logistics operators are primarily concerned with achieving efficient deliveries to their customers, they are also largely interested in these policy objectives that are supportive of the realisation of this goal. However, the actual driving force for urban goods policy implementation lies in the minimisation of the adverse impact of UGM on urban areas. A study of UGM activities in European cities reveals that traffic congestion, air and noise pollution, and road safety are the most significant impacts that drive the implementation of urban goods policies.

### 2.3.1 The role of local authorities to manage urban freight

The sparse activities and decisions that define the relationship between supply and demand in UGM activities may infer different implications of how the private actors view the total UGM activities. There are few, if any, persons and organisations between private actors that are concerned with overall UGM process. The shippers, receivers, and carriers each have different activities and a different spectrum of interest and are not concerned with overall activities. In this case, planning objectives within the private sector are limited to the factors that concern them most. This is reflected in the research concerning UGM from the perspective of private actors. Most of them address problems such as: procurement decision problems (Russo and Comi, 2010), fleet optimisation (Qureshi et al., 2014), delivery/pick up problems (Figliozzi, 2007), and depot location optimisation (Taniguchi et al., 1999) and these have been well discussed in the literature.

Moreover, previous research argues that those in the private sector are not greatly concerned about the overall improvement in UGM activities (Ballantyne et al., 2013; Ogden, 1992). They might be concerned about improving efficiency in their respective action, e.g. carriers may want to increase delivery efficiency by improving the route choice taken by commercial vehicles (Figliozzi, 2007). However, as a whole activity, there is no single actor from UGM industry concerned about policies to improve overall activities by different actors and more importantly their externalities for other road users. The reason is that the suggested policies do not significantly improve their profit margins. Since UGM is in general a 'free market' sector and quite competitive, any decisions made within the systems are perceived to reach the equilibrium of the markets and thus already be 'optimum'. Another reason is that private actors do not want to draw attention to their activities for fear of unfavourable policies and publication (Ogden, 1992).

For these reasons, UGM activities run solely according to the decisions of private actors may be sub-optimal in a broader context because the UGM incurs negative externalities such as congestion and pollution; it is therefore the role of the government to remedy the situation. Yet it is important to note that policy interference should not target the day-to-day decisions of private actors, since the competition between firms in the market ensures that an efficient outcome is achieved. Instead, the policies should target a change of behaviour in strategic terms and thus shape the UGM activities in the long run.

In general, the goal of UGM policy by the authorities is to minimise the total social cost of goods distribution within the cities (Ogden 1992). The key phrase here is to minimise the social cost rather than logistics cost per se and this encompasses not only the cost incurred by private actors but by society as a whole. Since UGM incurs negative externalities such as congestion and pollution, the ideal role of policies is then to internalise this cost. However, this is not always the case. Given the nature of UGM activities, Ogden (1992) suggests that dealing with UGM activities is not a single approach solution and expects the solutions can address all the problems of UGM related activities. Instead, to deal with UGM activities, we need a range of strategies deployed for a particular place, in a particular time, for a particular issue (Holguín-Veras, 2010).

### 2.3.2 Policy aims and objectives

The general aims of the public sector towards UGM activities are to reduce the total social cost associated with it. Following the general aims, Ogden (1992) suggests more specific objectives which would help to achieve those goals (see Table 2-1).

These objectives, generally, comply with the objective of urban transport policies. However, the manifested solution for each objective might be complementary or, equally, may contrast with each other. For example, Visser and van Binsbergen (1999) state that economic and efficiency objectives are interdependent since improving UGM efficiency serves economic objectives such as improving regional competitiveness. In contrast, implementing speed limits or adding speed bumps whilst improving overall road safety may hinder the efficiency objective of the logistic operators due to slower traffic.

By implementing policies that improve and develop efficient UGM activities, a positive contribution to the regional and national economy can be made. UGM, as an industry, also contributes to the economies as a substantial employer (Visser and van Binsbergen, 1999). However, this thesis focuses on increasing efficiency objectives as they are seen as the most significant and have been studied intensively (Anand et al., 2015). Efficiency objectives are associated with the delivery cost of UGM activities. This cost includes all cost to transport goods from shippers to receivers such as direct transport cost, inventory cost, wage and labour cost, vehicle operating cost and depreciation as well as transhipment cost (if any) in the terminal.

**Table 2-1. Overview of the objective of UGM policy**

| Objective | Description |
|---|---|
| Economic | Improve goods movement within cities to improve local, regional and national economy. Usually focus on trade sector and port and intermodal facilities. |
| Efficiency | Minimisation of negative externalities such as congestion, delay and parking related issues within the city. Minimisation of transport costs related to goods transport that influence the overall logistics costs. |
| Road safety | Minimisation of damage, injury and fatality related accidents. |
| Environment | Mitigation of noise, air, and vibration pollution. |
| Infrastructure | Explore the role of government in providing infrastructure to manage goods flow. |
| Urban structure | Investigate the impact of freight transport facilities on city structure and city size and its effect on goods price. |

*Source:* (Ogden, 1992)

The economic gain from improving UGM activities is often not tangible (Ogden, 1992). Efficiency improvement by reducing the cost is merely transferred to other sectors of the economy i.e. there is no direct economy gain. However, this transfer is still considered necessary for two reasons: firstly, efficient UGM activities ensure they just consume the minimum necessary resources to move the goods in the most efficient way. Any resource that is freed thus will be available for other sectors (e.g. as UGM can minimise their fuel consumption, the available fuel can be used by other sectors). Secondly, the transfers within the national economy are crucial to improving equity within the people in that national objectives to income distribution can be achieved by managing resources allocated for each sector.

### 2.3.3 The current state of urban goods policies

Transport policies to improve UGM activities can be done by both public and private actors. Private actors may implement some improvement in deliveries operation and strategies, in a way that is able to make their delivery more efficient and thus enhance their economic advantages. The measures can be at strategic levels such as depot locations, tactical levels such as fleet management, or operational levels such as tour vehicle route optimisation (Koç *et al.*, 2016). These policies are usually implemented within private establishment operations. The objective mainly is to increase the establishments' delivery services efficiency.

**Table 2-2. Categorised list for UGM measures by the public sector**

| Categories | Policy instrument |
|---|---|
| Traffic management | - Commercial vehicles routes<br>- One way street<br>- Priority signal<br>- Truck lanes<br>- Intersection priority |
| Parking and loading | - Time windows for using parking curb<br>- Regulation to use curb for loading and unloading activities (e.g. maximum time to load/unload) |
| Regulation and licences | - Weight and vehicle dimension restriction<br>- Time window to enter a specific area<br>- Low emission zone<br>- Off-hour deliveries |
| Pricing | - Road pricing<br>- Area pass pricing<br>- Parking price |
| Land use and zoning | - Creation of communal storage in city centre<br>- Restriction of new developments<br>- Moving out industries that need heavy or harmful items from city centre<br>- Creation of distribution centre |

Nevertheless, this thesis focuses on measures implemented by the public sector. Public actors such as local authorities can introduce transport demand management measures that force commercial vehicles to change their operation and become more socially and environmentally efficient. Transport demand management has been defined as "*any action or set of actions aimed at influencing people's travel behaviours in such a way that alternative mobility options are presented and or congestion is reduced* " (Meyer, 1999, p. 576). The measures can be classified into: (1) Traffic management strategies; (2) Parking and loading strategies; (3) Regulation and licences strategies; (4) Pricing strategies; (5) Land use and zoning (Ogden, 1992). A list of policy instruments within these categories can be seen in Table 2-2.

Reducing traffic congestion through discouraging commercial vehicles from using the urban road network is not a realistic policy due to the lack of any alternative modes. However, local authorities can implement traffic demand management policies to specify the location and the time at which the travel occurs. In order to effectively implement the policies, the following are important factors to take into account: the city size and land use, the infrastructure condition, and the industrial and economic activities of the city.

### 2.3.4 Selected urban goods transport policies

The remaining of this section focuses on a handful of selected transport policies for UGM activities. The aim is to illustrate the impact of these transport policies in UGM activities and in congestion on urban roads. They have been chosen based on reasons that include: their suitability to be implemented in the congested urban area and the fact that they are currently operating in some cities or have been studied intensively.

#### 2.3.4.1 Parking policies

Generally parking charges are one of the main instruments for managing transport demand in the urban area. Parking charges can be used either as a transport demand policy to reduce traffic volume in particular zones or as a parking management policy to reduce parking problems or a combination of both objectives. In terms of passenger movements, higher parking charges are usually used in highly attractive zones in order to achieve a favourable modal split and to improve the quality of public transport services.

Regarding UGM activities, strategies for parking policies in the UGM context usually involve parking management policies rather than transport demand management (Taniguchi et al., 2016); e.g., problems related to the provision of on-street loading areas; time restrictions for using the facilities; the potential for using the space between private vehicles and commercial vehicles; enforcement issues and the requirement for the provision of off-street parking facilities have been discussed in the literature (de Abreu e Silva and Alho, 2017).

However, parking charges can also be used for a transport demand policy in the UGM context, particularly in the context where the prevalent retailers are independent retailers who usually use their own vehicles to restock their shop. A contemporary approach to parking problems is to reduce parking demand in a particular area to better match parking supply and other spatial characteristics of the city. In this study, parking charges are one of the possible policies to alter independent retailers' behaviour to reduce the traffic in the most attractive zones.

#### 2.3.4.2 Road pricing

Road pricing is a measure for allocating limited road space to be able to optimise the social benefit for all users. Road pricing is predicated on the urban road under the assumption that the best route choice for the urban road system is reached by matching the individual driver cost to the marginal cost in order to minimise the deadweight loss.

The road pricing idea started with Pigou (1920) who argues that congestion causes negative externalities and therefore can be charged. The main theoretical background emerges from the road pricing problem being a first-best pricing problem. The problem states that in order to maximise the social welfare of road users, using congested roads should be charged a toll equal to the difference between the marginal cost and the marginal private cost (Verhoef, 1996). Nevertheless, despite its theoretical basis, the first-best pricing problem gains little interest in practice due to operating costs and public acceptance issues. In this situation second-best pricing problems emerge as an interesting area of research. The key questions for second-best pricing generally include: where to apply the toll and how much? And what is the effect of the toll on different vehicles on the road network? This research deals with such questions and formulating the model to answer this question. The underlying theoretical framework for road pricing is discussed further in the next chapters.

Road pricing studies in the context of passenger travel demand are numerous. Nevertheless, to put it into a practical context, even in advanced cities in European countries, road pricing has just been applied in a handful of cities.  Even more, only about a third of European countries allow complex road pricing that incorporates different pricing for passenger and freight transport (Ruesch, 2004). In this case, studies about how to set up a road pricing policy and the impact it gives to freight transport become important studies.

Previous studies reveal the impact of road pricing in the UGM context and primarily address the change of behaviour among carriers since it is the case that the carriers are the most affected by road pricing measures. Studies focusing on how to set up road pricing in the UGM context are minimal. The aim to accommodate all stakeholders' interests is limited. To be able to do that, the behavioural changes among the stakeholders should be incorporated into the model (Holguín-Veras and Cetin, 2009).

#### 2.3.4.3 Land use strategies

It is well known in urban transportation that traffic is derived through demands for different activities and needs. These different activities are generated by various land use and the locations of particular land use could affect traffic patterns. Therefore, the amount of travel can be minimised and unwanted traffic can be removed by proper planning of land use.

Unfortunately, the land use planning for cities pays little attention to these opportunities with respect to UGM activities. As a result, logistics sprawl becomes the trend in most cities (Dablanc et al., 2014). Logistics sprawl refers to the trend for logistic related infrastructures to move from inner city areas to more suburban areas of the metropolitan area. Logistics sprawls can increase the distance needed to deliver the goods and cause more congestion and emissions to the people living in the inner city area.

There are several strategies related to land use for reducing UGM cost through land use planning. Zoning is the practice of planning a particular land for a designated purpose and prescribing the activities allowed to be undertaken. In the past decades, a land use planning trend has been to specify a zone by a particular activity and thus develop a massive and sustained goods flow into the cities.  By locating complementary land use in close proximity to each other, UGM costs can be reduced, e.g. by locating container repair and storage activities near the container depot area. This would not only reduce the distance to transport the containers, but also encourage a truck to go back to the depot while carrying empty containers.

Other strategies include relocation and urban renewal. Cities change over time. Industry or manufacturing activities that were traditionally located near the city centre area may consider relocation since they cannot expand and their market is no longer in the city centre area. By relocating the old activities, local authorities may assist in UGM problem-related activities too, since to relocate the activities means to relocate goods movement associated with them. On the other hand, local authorities have to decide what is the most suitable land use in the inner-city area. There is a trend towards greater non-manufacturing land use around the city centre area and a suggestion that warehousing and distribution facilities can be suitable activities in the inner-city area. These activities can not only serve the city centre area, but also make truck travel patterns follow counter-peak direction, outbound in the morning, and inbound in the evening.

#### 2.3.4.4 Vehicle restriction

Faced with UGM problems such as congestion and pollution, many local authorities view commercial vehicle traffic as something they should ban or at least strictly regulate (Lindholm, 2013). These restrictions could involve time windows, weight and dimension restrictions or be in the shape of environmental based restriction zones. Literature shows that the restrictions can be applied in different forms. Restrictions can be applied based on weight, dimensions, or environmental criteria (Visser and van Binsbergen, 1999). In a spatial sense, commercial vehicle restriction can occur both in time and space, e.g. Rome applied a Freight Limited Traffic Zone (LTZ) where the access and parking for commercial vehicles are subject to regulations and two time windows (Nuzzolo and Comi, 2014a). According to the regulations, access and parking for commercial vehicles are limited to an 8pm – 7am window for vehicles of more than 3.5 T weight. Other vehicles (less than 3.5 T weight) are granted access and parking in two windows, 8pm – 10 am, and 2pm – 4pm. Exemptions from the regulations are vehicles transporting perishable foods, pharmaceuticals, and maintenance vehicles. Currently, the regulations include an option for access outside the time windows with some charges. Further, to promote environmentally friendly freight vehicles, i.e. vehicles with CNG, LPG, hybrid and electric, these vehicles have a reduced charge.

Local area bans need to be introduced with a great deal of caution and thorough analysis of the likely consequences, because it is not certain that they will have an overall beneficial effect. The bans could likely increase the cost of goods deliveries and would not substantially reduce the nuisance caused by commercial vehicles e.g. a ban for large vehicles in the city centre area may lead to an increasing number of smaller vehicles and may cause worse congestion since smaller trucks produce more trips.

## 2.4 Optimal urban goods planning and policies

Transport planning literature reveals that the public sector (e.g. local authorities) is a critical player foreseeing UGM planning and its policies. The local authorities act both as proactive facilitators to efficient UGM activities, as well as an intermediary for the adverse impact of UGM on city inhabitants. Therefore, it is vital for local authorities to seek the balance between these two roles and implement the policies that will bring an optimal output.

### 2.4.1 The importance of optimal planning and policies

Previous research in the UGM area has highlighted the importance of addressing optimal policies compromising actors with different interests (Ballantyne et al., 2013). Two reasons are given why optimal policies should be addressed by the public sector: (1) UGM activities involve many stakeholders with different objectives that often conflict; (2) UGM and its policies are seen differently from various stakeholders' points of view.

Although in general the objective of UGM activities is to deliver goods as efficiently as possible, each actor has an individual interest that may be conflicting. UGM private actors in general are concerned about the total cost of delivery; therefore, they want to do UGM as efficiently as possible. However, in order to achieve that, the decisions they take often do not match what the others seek to achieve, e.g. the commercial vehicles often cause congestion particularly in dense city centre areas due to their slower acceleration and loading/unloading activities. Therefore, the selfishness of goods transport operators by using the road space for loading/unloading activities often conflicts with passenger transportation that shares the same road network. Further, in general, the inhabitants' objectives are to reduce or completely eliminate commercial vehicle traffics from their neighbourhood. They see UGM activities the commercial vehicle traffics to be a factor that can cause deterioration of their neighbourhood. In that way, many local authorities opt to apply city logistics measures to generally restrict commercial vehicles (Visser and van Binsbergen, 1999) to lessen the negative impacts such as congestion and emission.

Nevertheless, local authorities should be aware that policies that are harmful to the UGM operations may not work. Private actors are not willing to accept policies that are not profitable for them regardless of the positive impact on society. Stathopoulos et al. (2012) investigate how various stakeholders react to various city logistics policies. The research considers the interaction between policies and private stakeholders and found that acceptance towards policy implementation significantly differs among private stakeholders. It means the introduction of such policies can be seen as beneficial or a hindrance by different private stakeholders, e.g. private stakeholders tend to prefer policies that do not directly influence their behaviours such as increasing loading/unloading bays or a subsidy for operating eco-friendly vehicles. However, they are hugely reluctant about restriction policies such as time windows and entrance fee because of increasing costs related to the restrictions. In that sense, the authorities need to be careful in planning and implementing the policies. Even general transport policies such as the introduction of a bike lane will have a consequence for UGM operations due to reduced road capacity.

Moreover, inconsistent urban goods policies may worsen the condition rather than fix it, e.g. the inconsistency between two areas such as different times for time windows may complicate delivery operations. Banning larger vehicles in favour of smaller ones can have counter-intuitive results due to more vehicles being on the road, and the deliveries becoming less consolidated. Nevertheless, if local authorities successfully implement city logistics policies to manage the UGM industry the impact to overall society will be higher since typically logistics operators have a fleet of commercial vehicles as opposed to car owners who only have cars.

### 2.4.2 Integrating private actors' interest in the planning process

There is a tendency for public sectors to ignore freight operator participation, and view them as an obstacle to policy implementation rather than a core participant (Anderson et al., 2005; Vidal Vieira and Fransoo, 2015). This means policies are often result in a contrary way. Even more so, the private sector can always pass on the costs caused by the local authorities' city logistics measures to their consumers and therefore rather than altering the behaviour of commercial vehicles, the city logistics measures miss out on their real purpose and even hinder the economy.

The key area to be able to plan optimal UGM policies is to involve private actors in transport policy decisions (Ballantyne et al., 2013). Since the behaviour of private stakeholders is greatly influenced by such policies, the motivation behind their behaviour should be assessed before policy implementation. Therefore, it is crucial to have a tool that can assess UGM policies that can find the optimal compromise between the interests of the actors involved. This thesis addresses this problem specifically by investigating two issues: (1) private actors' decision-making processes and the factors influencing the logistical decisions. By investigating the private actors' decision-making processes, the result of *ex-ante* policies can be measured; (2) building a model that directly measures the response of private actors to the UGM policies as well as the response of other actors. By taking into account the response of the actors, the implications of the policies from a different perspective can be weighed and optimal policies can be implemented.

## 2.5 Review of independent retailer activities

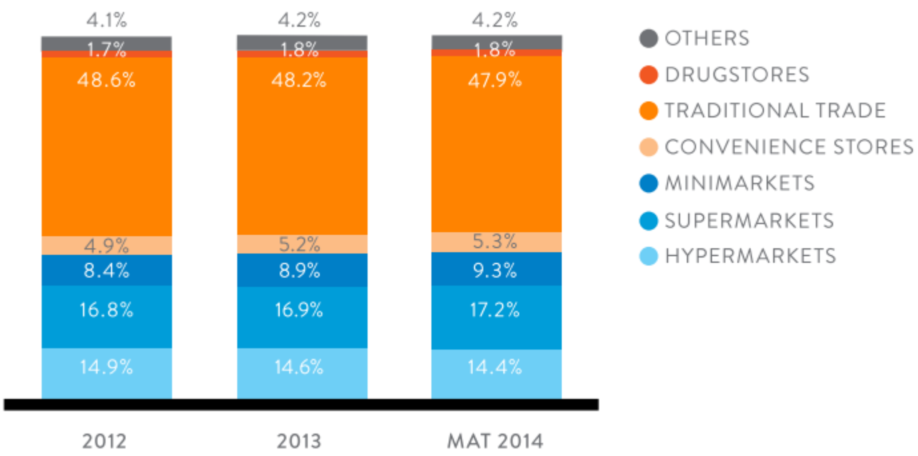
After reviewing UGM in general, the remaining sections of this chapter explain independent retailer activities that will be the subject of the thesis. Independent retailers refer to small businesses that sell everyday essential goods to end consumers. They are usually owned by a family, small sized, with only a small number of employees, often including the owners. As opposed to independent retailers, a chain retailer is a retailer that usually has many outlets within cities and works with a modern supply chain.

The study of retailer restocking activities in cities of developing countries is interesting because of the differences in the balance of retailer types compared to developed cities (De Magalhães, 2010). Cities in developed countries tend to have many larger retailers who are *chain retailers* while in developing cities, smaller *independent retailers* are the most prevalent. Previous studies suggest that independent retailers will act differently from chain retailers in terms of operating their shops (Shaw and Gibbs, 1999). They notably differ in selecting supplier channels and in the factors that determine how and when the restocking is done (Comi and Nuzzolo, 2014). Chain retailers comprise the big-name retailers whose restocking activities are managed centrally through distribution centres (Fernie *et al.* 2010) or through professional supply chain managers (Golhar and Banerjee, 2013). In this sense, each outlet of a chain retailers does not decide its restocking activities, instead decisions are taken centrally. In contrast, an independent retailer is a business usually owned by a single person or a family and thus decisions are mostly made by the owners. These retailers usually face multiple supplier channel options to procure their stocks, such as going to wholesalers in *traditional markets* or buying directly from local producers. The dimension of traditional markets makes it even more interesting as these may adopt a quite informal style of operation commonly observed in independent retailers. In terms of transporting goods, independent retailers often rely heavily on their own vehicles (Dablanc, 2009).

In addition, the limited number of studies on UGM in developing countries highlight the lack of city logistics measures to manage UGM, particularly to manage independent retailer restocking activities. The measures that are exercised in cities in developed countries often simply cannot be applied directly to cities in developing countries. This is because the supply chain characteristics, urban planning and political contexts between the cities are significantly different. For instance, surveys carried out on an Italian urban area reveals that restocking is done in which the primary decision makers are retailers using their own vehicles to restock from nearby warehouses (Russo et al., 2008). Meanwhile, models for restocking activities in the Japanese and US contexts suggest that the transport decisions are mainly done by carriers/shippers (Mei, 2013; Wisetjindawat et al., 2007). Therefore, a solution such as an urban distribution centre that works mostly in the context of chain retailers and their logistics partners may not be suitable for independent retailer restocking activities which are less consolidated and often rely heavily on their own vehicles.

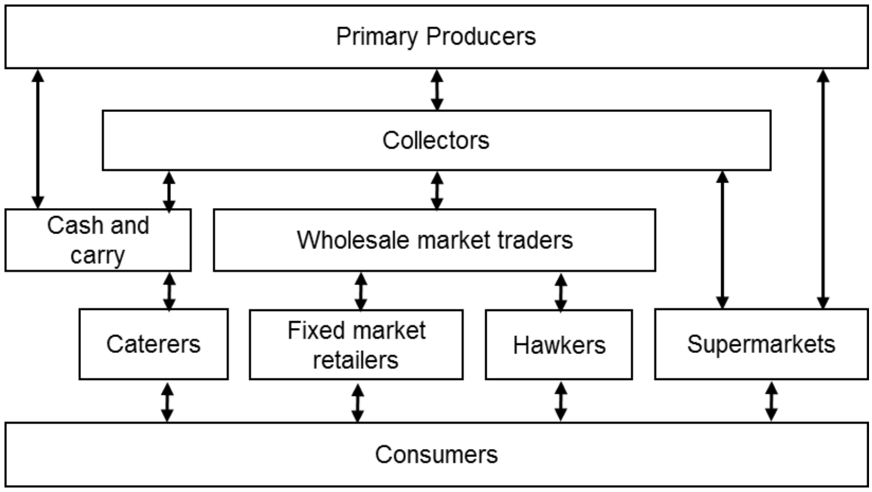
### 2.5.1 Traditional supply chain in developing countries

The conditions in terms of how goods are transported in developing countries show higher diversity than the developed countries. Several unique characteristics make UGM activities in cities in developing countries differ from the ones in developed countries. Independent retailers are the most prevalent providers of goods to the residents of the city. It is true that several activities in the cities in developing countries have a high level of integration in the global economic process and their related goods distributions. However, retail shares for Asian data demonstrate that traditional trade involving independent retailers and traditional markets still hold the majority of shares (see Figure 2-2)




(Source: Nielsen, 2015)

**Figure 2-2. Retail channel shares in Asia**




(Source: Cadilhon *et al.*, 2006)

**Figure 2-3. Fresh food supply chain in Ho Chi Min City**

Traditional trades have developed organically out of private sector initiatives and usually take many shapes. For example, in Vietnam, fresh food supply chains have traditionally taken several shapes involving independent retailers and wholesale market merchants across the cities. Producers and collectors are mainly located in the production area whereas wholesale traders, and retailers are urban based. The modern trades in the supply chain are represented by cash and carry businesses and supermarkets (see Figure 2-3). They are usually located in the city centre area where the people living are generally more educated and have a higher economic status. The traditional trades are represented mostly by the wholesale market (i.e. traditional markets).

The wholesale markets are typically spread across cities and serve the local area. To supplement the wholesaler markets' operations, independent shops also distribute goods from the wholesale markets to the nearby neighbourhoods. Further, the hawkers also deliver the products from the wholesale market directly to households in need of convenience and lacking time. Given the current supply chain condition in Ho Chi Min city, modern trade only has two percent of the total market share for a typical fresh product (e.g. tomatoes). Ninety-eight percent of the goods are supplied through traditional trade in which traditional markets play a prominent role. The wholesale markets are the main entry points for the supply of fresh products to the city.

### 2.5.2 The role of traditional markets in the distribution of goods

A traditional market, prevalent in developing countries, is a place where hundreds of establishments are located, and trade between suppliers and retailers typically takes place. In general, traditional markets constitute the lifeblood of economics and social activities in the city. In many countries, asides from the trade function, the traditional markets are focal points for health delivery, local administration, political campaigns, and other social activities. These are the politics and socio-cultural functions which enrich traditional markets' functional status and define their importance in urban life (Ofori, 2013).

Traditional markets have a typical supply chain role as shown in Figure 2-4. Establishments in traditional markets can involve both retailers and suppliers depending on who is buying goods from whom, but in many cases, they perform an essential wholesaling function whereby suppliers, usually from outside the city, go to the traditional markets to sell the goods to the establishments there, and urban retailers buy the goods and then sell them on to final consumers in their locality. In this respect, traditional markets act as places where supply chains meet, and goods are consolidated. To summarise a traditional market performs three basic functions for the cities (Gromsen, 1981) :

- The import of goods to the city and their retail distribution
- The export of goods from the city to the outer region
- The exchange of goods within the city.

With such a logistical role, in many cities, traditional markets function as a logistics hub for goods distributions within the cities.

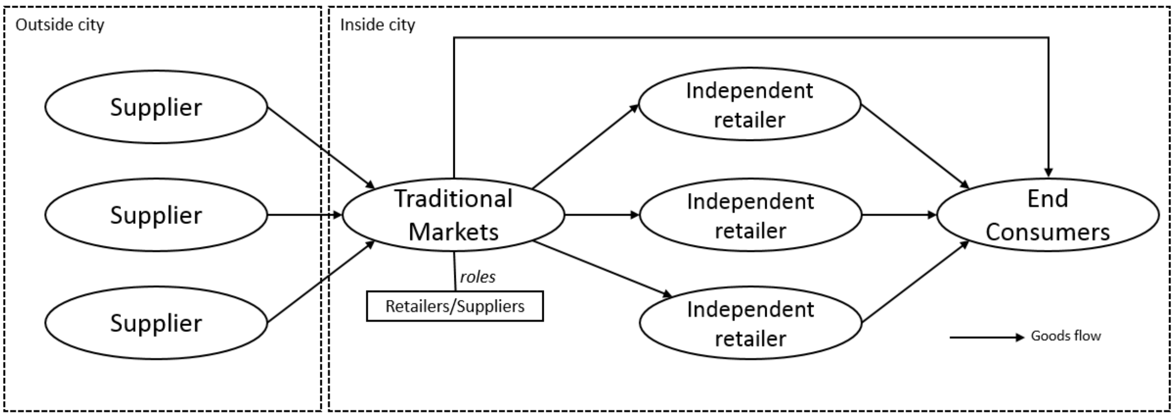



**Figure 2-4. The role of traditional markets in the supply chain**

It is common in cities in developing countries to have more than one major traditional market. For example, Jakarta in Indonesia has two major traditional markets that act as wholesale places for other traditional markets as well as retailers in the cities (Saragih et al., 2015). It is also the case in Ho Chi Min city in Vietnam that it has at least two major traditional markets (Cadilhon et al., 2006). The role of major markets is different from that of others, a major traditional market acts as a hub for the other markets in the cities.

It appears that the location of the traditional market serves to distinguish the role of traditional markets in the distribution process. Previous studies suggest the logistics facility locations tend to be either in the core of the city or sprawling out into the outskirts of the city (Giuliano and Kang, 2018), partly dependent on the purpose of the logistics facilities and the service they provide. Logistics facilities tend to concentrate in the city's core area if they serve the local economy activities (Dablanc *et al*., 2014). In this way, major traditional markets that act as a hub to the other markets in the city are usually located in the outskirt of the city, whilst traditional markets that serve the local establishments (i.e. the retailers) are usually located in the core of the city.

### 2.5.3 Independent retailers' restocking activities

Retailer restocking activity, as an important generator of UGM, has attracted researchers to study the activity and its impact on the urban environment. The size of the problem relating to retailer restocking activities varies considerably between different cities and has been studied extensively in developed cities. The studies include extensive survey methods related to retailer activities (Alho and de Abreu e Silva, 2015; Toilier et al., 2016); modelling and forecasting of the demand (Nuzzolo and Comi, 2014b; Russo and Comi, 2011; Wisetjindawat et al., 2007) and reviews of policies and their implementation (Cherrett et al., 2012; Visser and van Binsbergen, 1999) as well as the spatial problem of urban logistics facilities (Sakai *et al.*, 2015; Heitz *et al.* 2018). However, most of these studies are done in the context of cities in the developed world and studies in the context of cities in developing countries are somewhat limited.

The study of retailer restocking activities in cities of developing countries is interesting because of the differences in the balance of retailer types compared to developed cities (De Magalhães, 2010; Dharmowijoyo *et al.* 2017). Cities in developed countries tend to have many larger retailers who are *chain retailers* while in developing cities, smaller *independent retailers* are the most prevalent.

Studies suggest that independent retailers act differently from chain retailers in terms of selecting supplier channels to procure their goods. Chain retailers usually manage their supply chain centrally through a supply chain manager (Golhar and Banerjee, 2013) or a distribution centre (Fernie et al., 2010). The suppliers usually have a trading contract with chain retailers. The distribution to the chain retailer outlets is not the responsibility of each outlet. Hence, the outlets do not have the responsibility to decide on how and when the goods are transported. The chain's central management or the suppliers are the ones deciding when and how the goods are transported.

Unlike chain retailers, independent retailers make their own decisions on restocking activities. Generally, independent retailers have two main decisions regarding restocking their shop: (i) they need to decide the supply chain for their goods, and (ii) to decide the transport service to acquire the goods. They usually retain the flexibility to choose between multiple supply chain options. The most common supplier channel options to procure their goods include: (i) going to the traditional wholesaler market; (ii) buying from wholesalers outside their city area; (iii) joining wholesaler-retailer procurement agreements; (iv) buying directly from local producers (Shaw & Gibbs 1999). In the case of developing countries, one major supply chain is traditional trade.

Typically, independent retailers choose more than one supply chain depending on the goods type. The decision usually depends on the goods price, the cost to acquire them, and the trading relationship between retailers and suppliers.

The differences in restocking activity decisions effects the trips generated by each activity. As chain retailers manage their supply chain to their outlet centrally, the trips usually involve chain trips where the commercial vehicles from the suppliers visit several chain outlets to deliver the goods. In that sense, one outlet can generate multiple trips within a week. On the other hand, independent retailers may choose various supply channels so that the trip generation for each shop can differ. Independent retailers may also choose to go with their own vehicles and in that sense the restocking trips are similar to shopping trips.

One major difference of independent retailers compared to chain retailers is the way they acquire their goods. As retailers are typically characterized by selling multiple goods / commodities, the independent retailers face decisions to choose the supplier and the methods to bring the goods to their shops. From the transport point of view, independent retailers' restocking activities are very similar to the shopping activities done by the end consumers. In this case, the independent retailers restocking decisions comprise of *where* to procure the goods they are needed for their shops and *how* they acquire the goods.

### 2.5.4 Challenge to manage independent retailers' activities

As the population of cities grows and the business activities change, the pressure to implement efficient UGM activities increases. In cities in developed countries, major business change is taking place. The size of the inventory in a typical shop in the city centre has shrunk, demanding the delivery of goods to be on a just in time basis. The number of products and their variation have increased resulting in soaring demand for deliveries. Roughly, UGM activities can constitute as high as 30% of total traffic (Dablanc, 2009). This change is not the case of cities in the developed countries alone. Businesses in developing countries have also evolved in recent decades to cause different challenges for managing UGM activities.

In developing countries, independent retailers are still prevalent and can constitute 70% of goods distribution within the cities (Nielsen, 2015). It is a tough challenge to manage since these activities are sparse around the cities and more difficult to consolidate. Though the rise of chain retailers in recent years needs to be noted, managing independent retailer activities is still the key area to successfully managing UGM activities in developing countries. Given the nature of the supply chain and distribution process, the UGM activities that involve independent retailers provide more challenges in order to be managed appropriately.

The first challenge is related to the issue of less consolidated deliveries since each retailer operates as an individual business entity. Each retailer can then produce or attracts trips to their location. The sheer number of retailers scattered across the cities and the trips generated or attracted by these activities impose a significant impact on the level of traffic across the cities. A large portion of goods are then usually moved via independent vehicles (Russo and Comi, 2010). This means that commercial vehicles are owned and operated either by shippers or receivers. Own account or independent vehicles tend to be logistically less efficient due to generally smaller vehicles, lower load factors, and the issue of the necessity of ‘empty trips’. The latter means the vehicles are only loaded with goods on the way to deliver the goods but totally empty on the return trips.

Another challenge is the issue of informal sectors that involve non-motorised transport (NMT) for moving goods. Non-motorised transport in cities can be seen from a negative and positive viewpoint. On the negative side, NMT often causes more congestion due to less speed and the impact of NMT in a mixed traffic road. However, on the positive side, NMT is not producing emissions and helps to keep city air clean. However, a recent international report shows that the “motorisation process” happened rapidly in cities like Mexico City and New Delhi (UN-Habitat, 2013). In Mexico cities, annually 400 million tonnes of goods are distributed within cities areas and the main growing mode is small to medium sized trucking. While in New Delhi 60% of goods movements within the city is done using the same modes. Both cities face acute congestion problems and it can take up to four hours for a truck to cross the cities.

## 2.6 Chapter summary

This chapter has introduced the nature and roles of urban goods movement. UGM plays an important role in providing goods and services to maintain the city inhabitants' lifestyles. As the city population grows, so does the demand for UGM. As a last mile delivery activity, UGM relies heavily on road transport. In fact, road transport is universally taken as the dominant mode in UGM activities due to the fact that it is the only mode that offers a door-to-door service; however, this can lead to negative impacts such as congestion and environmental damage. Despite the importance of efficient delivery for the city economy, it is the adverse damage of UGM activities (i.e. congestion and pollution) to the cities that prompt local authorities to begin considering UGM activities in their transport planning.

UGM deals with activities involving several stakeholders thus creating a complex activity. Public actors, private actors and city inhabitants are three key elements shaping UGM and its policies. Transport planning literature reveals that public sector (e.g. local authorities) are critical players in the field of UGM. The local authority needs to address optimal policies concerning different actors in UGM activities. The reasons are twofold: (i) UGM actors and city inhabitant have different objectives regarding the activities; (ii) each actor has a different view on UGM and the subsequent city logistics policies.

Literature reveals that implementing UGM policies can be difficult. Private actors obviously have high resistance to UGM policies that hinder their activities such as restrictions on commercial vehicles. On the other hand, city inhabitants feel that commercial vehicles worsen the congestion and air quality in the city and thus need to be regulated. Therefore, it is important to address this seemingly conflicting objective into one single framework. The key to being able to do that is to involve private actors in the transport planning process.

Good understanding of the behaviours of private actors is needed in order to ensure that the UGM policies will reach expectations. This thesis investigates the interaction between transport policies and private actor behaviour. Furthermore, the importance of local authorities to address optimal transport policies is also a key element of current studies. Although studies with a similar direction have been conducted, to the best of the author's knowledge, a study that approaches the problem using a quantitative modelling approach has not yet been done. This study aims to fill the gap in this area.

In addition, this thesis addresses explicitly the cities in which independent retailers are dominant. It is important since previous research has looked at the context of UGM activities by chain retailers. Independent retailers are less studied compared to chain retailers although their importance in distributing goods in an urban area in developing countries is huge. By incorporating the independent retailer as private stakeholders, this research aims to investigate their logistics decisions and expand the literature by understanding UGM activities particularly in developing countries.

The review also reveals that independent retailers operate differently compared to chain retailers and this causes different problems. Concepts which have proved useful in cities to manage chain retailer activities do not necessarily work in cities in developing countries, e.g. the solution to build a public urban distribution centre might not be appealing in the context of independent retailer activities since a single independent retailer relies on multiple supply chains to restock their shops. Therefore, this study aims to investigate the UGM activities of independent retailers and build a corresponding demand model.

Given the problems of addressing the interaction between UGM policies and private actors as well as the importance of seeking optimal UGM policies, the next chapter deals with a review of modelling approaches to plan and evaluate UGM.

# Chapter 3 Review of methodologies

As Chapter 2 reviews UGM activities, this chapter reviews the methodologies to capture UGM activities in mathematical models. The literature shows various aims and perspectives from which UGM models have been built. Some studies put their effort into implementing innovative solutions such as vehicle routing problems in deliveries; others put their effort into examining the impact of government policies by building modelling frameworks. In some cases, the solutions have already been established, and the researcher tries to optimise their efficiency. It depends on the aims of the study and the aspect of UGM activities the analyst wants to address.

The rest of the chapter is written as follows: This chapter begins with a general review of previous UGM modelling research in section 3.1. To make it structured, in this section, the previous research is discussed according to stakeholder involvement in the model; the objective of the model; and the unit analysis of the model. The nature of UGM activities and the implication of that nature to the modelling effort is highlighted. This section also discusses the relevance of previous research regarding our attempt to model independent retailer activity. Next, Section 3.2. reviews methods for modelling UGM form the demand side. Here the primary aim of the model is to understand the factor contributed to the UGM transport demand and how policies could affect it.

Section 3.3. addresses the model related to the traffic assignment problem. The focus is on the interaction between commercial vehicles by retailers and private vehicles by city inhabitants. The role of traffic assignment to assess UGM related policies is discussed. Lastly, section 3.4. addresses the issue of optimization in UGM planning. A selection of paper using a bilevel programming method and the solution techniques are reviewed since this thesis adapt the particular method. Finally, this chapter is closed by a summary of the methodological reviews. This chapter is closed by the chapter summary that concluded the gap this study wants to fill

## 3.1 Urban goods movements modelling attempt

Goods transport models have been around in transport research since the early 1960s and appear alongside passenger transport. However, compared to the passenger transport model, the goods transport model did not receive much attention and progress was relatively slow. This was due to a lack of data, or appropriate behavioural economy that could distinguish goods movements from those of passenger movements. Goods movement were mostly treated in simplistic ways, as a different class of passenger movement, and still having the same theoretical framework as passenger movements.

Regarding urban goods movements modelling attempts, no significant research is notable until 1990 when researchers and policy-makers begin to pay attention to the impact of UGM in the urban area. One reason mentioned is the development of goods movements related studies such as logistics and supply chain management trying to improve firm logistics performance. These studies open up the possibility of using a set of data from private actors to understand UGM activities, hence a whole new generation of new UGM modelling developed in the early 1980s and 1990s.

### 3.1.1 General UGM modelling framework

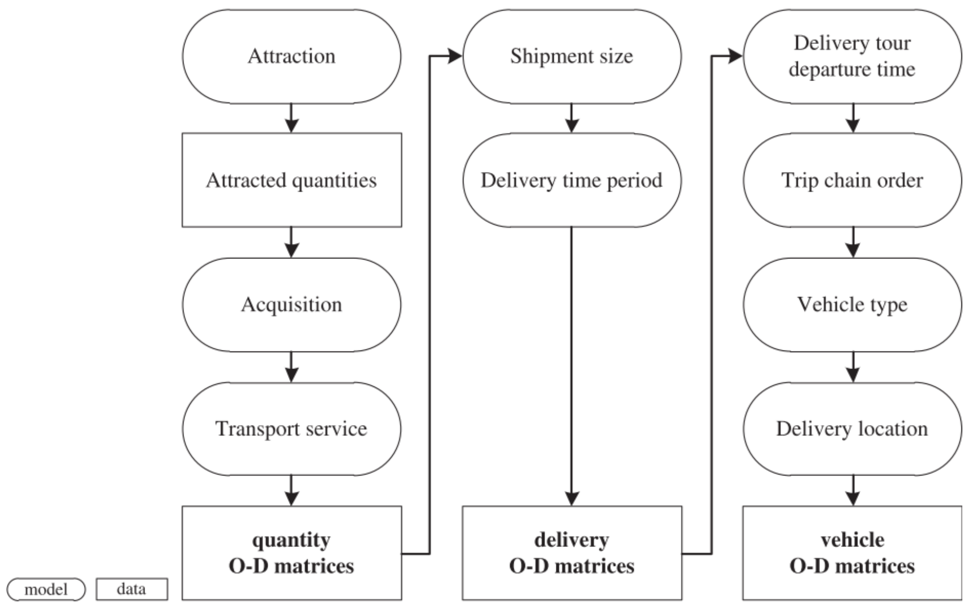
The role of the model in UGM studies and what characteristics the modelling framework should have been discussed by the early researchers. Hedges (1971) suggests a few characteristics for UGM modelling frameworks:

- Behavioural. The model should account for the behaviour of the decision makers that connects specific transport service demands and the key factors influencing the demand.
- Multimodal. The modelling framework should be able to address the variations of vehicle types associated with the delivery process.
- Multiuser. The model should be able to include passenger movement and show the interactions between those two.
- Policy sensitive. The model should be able to show the response to a change in policies variable.
- General applicability. The model could be applied in urban areas with similar characteristics.

There are also some fundamental differences in the movement of goods and the movement of peoples. These differences should be taken into account when one tries to build the UGM model.

The significant difference between people and goods movements firstly lies in the *decision maker*. With people movements, the main decision-makers mostly will be the person making the trips. In contrast, the decision-making process on the goods movement is more complicated since various actors are involved, influencing each other's decisions. In a UGM model, it is clear that the primary decision maker is a firm / establishment that generates a goods transport demand. However, an establishment can be a supplier, a carrier, or a receiver and each of these actors deals with a different set of decisions that need to be considered in the model. Wisetjindawat et al. (2007) show complex decision interactions between shippers, carriers, and receivers that actually constituted UGM activities. A shipper/receiver may decide the destination of the goods; however, the way the goods are transported usually depends on carriers' decisions. In other words, the decision regarding mode and route choice are usually made by the carriers. In this regard, a receiver may be interested in the time of delivery, and the shipment size but receivers are not interested in the actual transportation process since the decisions regarding the transportation of the goods are not theirs. Note that the shippers and the carriers can be a single firm or entity depending on the supply chain.

Other differences are in *the unit of analysis*. In people movements, the unit of transport does not change throughout the decision-making process, i.e. the individual trips unit move from origin to destination using a given mode and route. This is not the case with goods movements. The unit is changing throughout the decision-making process. Nuzzolo et al. (2010) divide the unit of delivery into three different units, according to the decision-making process and the level of planning involved (see Figure 3-1). At a strategic level, the models should be able to address the mechanism underlying demand for goods. Thus, the quantity unit should be pointed out. In the same way, on a tactical and operational level, the models should be able to point out the delivery trips and tours as well as the vehicles types; hence the delivery unit and vehicle unit are highlighted.




source: (Nuzzolo et al., 2010)

**Figure 3-1. The modelling system for freight vehicle OD estimation**

Another aspect that should be considered in modelling UGM activities is the various types of trips that occur in the deliveries. Figure 3-2.a depicts a direct trip in which the goods are transported from *suppliers* to *retailers*. The goods are transported by delivery trips in which after delivering the goods, the commercial vehicle goes back to the original location. In this case, the flow of goods and vehicle trips can be considered as the same. Figure 3-2.b depicts a situation where the retailers procure the goods by performing chain trips. In this case, the retailers conduct three trips to acquire the goods. The figure indicates that the start and the end of the commodities flow is not necessarily the same as the start and the end of that of the commercial vehicle trips (Holguín-Veras et al., 2014a). Therefore, the UGM analyst faces a major challenge to find a way to estimate zone to zone commodity flows and the equivalent in truck trips.

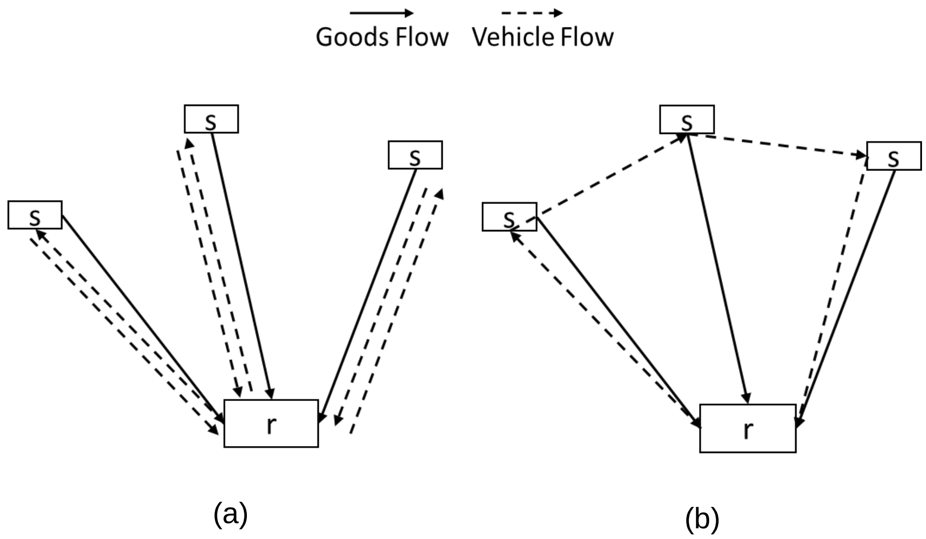



**Figure 3-2. Goods flow vs vehicle flows in UGM activities**

Given the characteristics of the UGM model, the following sub-sections review the previous UGM modelling attempts found in the literature. We classify the previous modelling attempt according to:

- The objectives of UGM models: define the problem the model wants to solve. Since UGM involves complex activities, rarely is there a model that aims to solve all the problem associated with UGM.
- Actors' involvements: defines the scope of the model by assessing the type of actor considered in the model.
- System descriptors: define the types activities and consequently, the unit in the UGM models.

### 3.1.2 The objective of UGM models

The ultimate objective of UGM management is to minimise the total social cost implied by UGM activities for all road users (Ogden, 1992). The total social cost can be derived into six objectives area: economic, efficiency, road-safety, environment, infrastructure and management; and urban structure. Intuitively, we can tell each objective is intermingled, thus improving one objective most likely would improve the others as well.

UGM models deal with issues such as minimising the environmental impact of UGM; infrastructure management (e.g. consolidation centre management); and the impact of UGM towards urban structure and all these have been done before. Eriksson (1995) built a trips-based model for UGM activities to investigate the impact of transport policies on air pollution level. Regarding infrastructure management objectives, Morganti and Gonzalez-feliu's (2015) research investigated the role of the urban distribution centre to shape the supply chain in foods and other perishable goods. Studies related to the location of a goods distribution centre also emerge in the literature. For example, the problem of logistic sprawl where the goods distribution centre has undergone spatial decentralisation and the impact of this decentralisation has been investigated in the literature (Dablanc *et al.*, 2014; Heitz *et al.*, 2018).

The specific objectives of research aiming to improve UGM activities to improve urban, regional, and national economy are varied. There is previous research aimed directly at measuring the impact of UGM activities on the local and regional economy. An efficient urban freight system can contribute to regional and national economic development and employment, mainly to assist different sectors of the economy to be more competitive, e.g., Harris and Liu, (1998) use input-output modelling of the urban and regional economy to deal with the impact of improving freight systems in the city and regional economy.

Another way to look at the economic objective is to measure system-wide effects, which reflect the interaction between freight and passenger transport and denote the effect of congested road networks on both passenger travel cost and freight cost. Hensher and Puckett (2005) built a model based on discrete choice modelling to investigate the behavioural response of private stakeholders and explore local authorities' measures such as congestion pricing as a way to improve the urban economy. Routhier and Toilier (2007) built the Freturb model with the aim of helping local authorities to understand UGM activities and assess different city logistics measures. The overall objective is not to improve deliveries and pick up activities per se, but to improve overall road performance for all road users.

Though various objectives of UGM modelling have been studied before, the literature shows that most of the previous research on modelling UGM activity considers the efficiency of UGM activity to be its primary objective (Cui et al., 2015). It is understandable since the scope of the efficiency objective is often intermingled with other objectives. For example, Crainic et al. (2004) investigate the role of satellites outside an urban area to improve the effectiveness of goods distribution as well as improve the air condition in the city centre area. The satellite platforms perform as urban distribution centres which manage goods delivery inside the city centre area.

The efficiency objective from the local authority point of view is well reflected in terms of how they manage the traffic generated by UGM activities. Thus, exploring administrator influence on traffic management through regulations, pricing and other measures are found in the literature as the objective of UGM models. For example, Hensher and Puckett (2005) set a modelling framework to investigate the behaviour of stakeholders in response to congestion prices. Russo and Comi (2010) and Nuzzolo and Comi (2014) built a modelling framework to describe the variables that affect retailers' behaviour and thus can be used to assess ex-ante policies measurement.

### 3.1.3 Actors' involvement in UGM models

Although UGM activities have been studied from many different perspectives, in terms of the modelling effort, previous studies mostly are an attempt to understand UGM activities, and their respective transport demands to meet local authorities' objective to reduce total social cost. There are UGM models that have been developed to meet administrators' objective to minimise congestion and emissions (Eriksson, 1995; Gentile and Vigo, 2013). Other models try to depict stakeholders influencing retailers and shopping activities in an effort to assist local authorities to understand UGM movement. Local authorities which lack UGM specific data are also addressed by a model that uses limited data availability (Gonzalez-Feliu et al., 2012; Holguín-Veras et al., 2014a; Muñuzuri et al., 2012). The role of administrators to provide and manage infrastructures such as a distribution centre are also incorporated (Crainic et al., 2004). Overall, these models assess the impact of UGM activities upon urban road network performance as viewed from a local administrator's objective.

Private stakeholder UGM modelling also emerges as an exciting research area. Most of the models covering private stakeholders' interest emerges from the sort of urge to optimise the private stakeholder's operation. Problems like finding the best route for the deliveries and its scheduling using the advance of the intelligent transport system (ITS) has the most advanced list in the literature (Crainic et al., 2009a; Taniguchi and Shimamoto, 2004). Other problems like increasing the efficiency of deliveries by deciding the fleet composition and depot locations (Koç *et al.*, 2016) can also be found in the literature.

Previous studies address the importance of involving private stakeholder behaviour in local authority planning (Elspeth and Ballantyne, 2013; Gatta and Marcucci, 2016). The nature of multi-stakeholders in UGM activities emphasises that the UGM modelling framework should predict the behaviour of stakeholders, and the consequences of city logistics measures to the stakeholders involved; e.g. Wisetjindawat et al. (2007) used microsimulation to model retailers' restocking behaviour. A utility function is used to describe the interaction between suppliers' characteristics and retailers' behaviour. Some data are generated through microsimulation, thus the model is not purely behavioural in terms of the actual decisions from the retailers. Russo & Comi (2010) and Nuzzolo & Comi (2014) build a modelling framework to describe the variables affecting retailers' behaviour towards restocking activities. Interaction between end consumer shopping activities and retailers' restocking activities are described using a multi-step discrete choice model.

Private stakeholder involvement in the model is crucial because the objective of private stakeholders and local authorities often conflicts. The local authority is the only stakeholder interested in achieving the overall objective, that is, minimising the total cost of urban road networks (Ogden, 1992), whereas, the main objective of retailers is to increase their efficiency per se and often at the cost of the overall system cost. Further, by incorporating them into the model, the demand estimation process becomes more realistic and by including them, the behavioural models can assess the impact of local authority measures in a better and more natural way (Anand *et al.*, 2015).

### 3.1.4 Unit analysis of UGM models

There exist in UGM literature two different unit analyses that gives rise to two families of UGM model: *commodity-based model*, and *vehicles trips-based model*.

Both categories have their place in UGM studies. The commodity-based model recognises that fundamentally the demand of UGM is the movement of commodities, not the movement of vehicles. Shippers and receivers are making a trade out of moving the goods and these activities generate demand for goods movements. The commercial vehicle movements are only the supply-side responding to the demand.

However, the local authorities are more concerned with commercial vehicle trips since many of the costs and problems associated with UGM are the result of the presence of commercial vehicles on the road network. Therefore, the various points of view on policy and planning issues cause the differences in modelling approach.

Selection of the unit of analysis has a significant impact on the objective and the ability of the model as well as the data requirement to build the model. In terms of the level of detail, commodity based models are superior to vehicle trip based models since the latter cannot explicitly consider the commodity types in the models (Holguín-Veras et al., 2014a).

Previous UGM studies highlight the fact that the type of commodity has been a significant variable that influences UGM actors' behaviour. The reason is commodities may have different economic value and also different operational constraints. For example, the modelling framework for hazardous items might be different from daily items due to their specific demand and infrastructure requirements. Hence the model needs to incorporate stakeholder specific behaviour in terms of handling such items and the risks following the activities should be considered (Corde*iro et al.*, 2016).

However, a vehicle trips-based model is also fairly important remembering that at the commodity level, the model would need higher data requirements. In this case, the availability and more importantly the reliability of the data are the issues to be addressed (Muñuzuri et al., 2010). Further, the calibration and validation of the commodity-based model would be more painful and expensive since the data are enormous. Key features and the differences between commodity and vehicle level UGM model can be seen in Table 3-1 below:

**Table 3-1. Key features of commodity level and vehicle level UGM model**

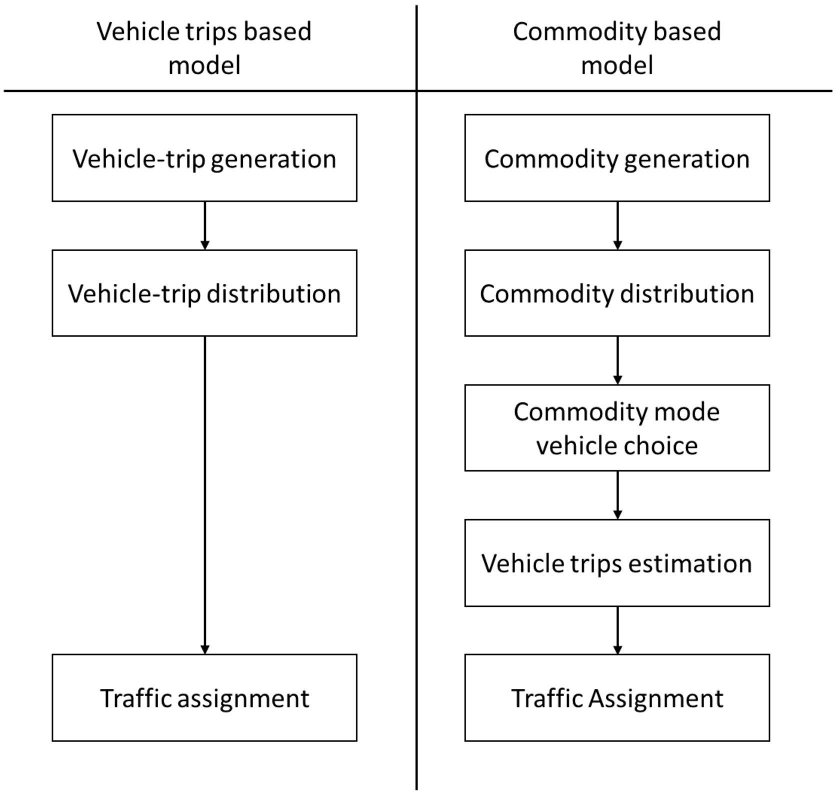
| **Features** | **Commodity Level** | **Vehicle Level** |
|---|---|---|
| Ability to consider commodity type | High | None |
| Ability to replicate real-life process | High | Low |
| Ability to consider mode choice | High | None |
| Ability to consider intermodal aspect | High | Low |
| Data Requirements | High | Medium-Low |
| Calibration data cost | High-Medium | Low |

(Source: Holguín-Veras et al., (2014a))

## 3.2 Modelling urban goods movement demand

The conventional modelling framework to predict UGM transport demand relies on defining the activities in a multi-stage manner. In practice, one way to do that is by accommodating the four-step models. Consistent with the practice in passenger transport, the four-step model consists of the generation model, distribution model, mode choice model, and traffic assignment model. Despite many criticisms, four-step derived models are the most used methodologies for UGM modelling (Gonzalez-Feliu et al., 2012).

Generally, the first three modelling steps from the four-step model, i.e. generation, distribution and mode choice models are stated as a demand model. By applying these three steps, the analyst can quantify the demand of trips in the study area. In the passenger movement model, the unit of each step will not be different. However, this is not the case in goods movements. The existence of the change of the unit along with the UGM actor decisions has given rise to a commodity-based model and vehicles trips-based model (see Figure 3-3).




(Source: Holguín-Veras et al., (2014a))

**Figure 3-3. Model components of vehicle trips-based model and commodity-based model**

Commodity based models are developed based upon the movements of the commodities and the notion that these movements should be modelled directly. The state-of-the-art feature of this model is to use an equivalent of the four-step model of the passenger model, i.e. commodity generation, commodity distribution, mode choice, and traffic assignment. The difference is in the additional step of vehicle trips estimation models once the commodity flows have been estimated (see, for example, models developed by Nuzzolo and Comi (2014); Russo and Comi (2010) and Wisetjindawat et al. (2007).

On the other hand, the vehicles trips-based model estimates directly the vehicle trips that are needed to move the commodities. The models usually include the trips generation model and trips distribution model (Muñuzuri et al., 2012). In this model, the focus is on predicting the amount of commercial vehicles traffic. There are also vehicle trips based models based solely on the vehicle movement in the road. These models usually use secondary data such as traffic counting data (Eriksson, 1995; Holguín-Veras and Patil, 2008).

In order to give a more comprehensive understanding, next we review each modelling step, i.e. the generation model the distribution model, and the mode choice model in more detail, in the following sub-sections.

### 3.2.1 Review of generation modelling

As indicated by two different types of UGM model, to build a UGM generation model, it is important to distinguish commodity based models and vehicle  trips models (Holguín-Veras et al., 2014b). Commodity generations refer to production and attraction of actual goods usually measured in terms of weight (e.g. tonnage) or volume (e.g. $m^3$) units. Meanwhile, vehicle trips generation refers to the number of commercial vehicle trips generated by the demand for urban goods transport.

Generally, commodities generation models are based on the function of establishment size, as a larger establishment usually generates more goods to their premises. However, the issue of vehicles trips generated by the establishment is a separate issue. The reason is the number of vehicle trips is not only impacted by the number of goods but also the shipment size of the goods and, to a lesser extent, the vehicle type and size (Holguín-Veras et al., 2011). The role of shipment size is quite significant because the establishment can increase commodity generation without increasing the number of trips simply by increasing shipment size or changing the type of vehicle or mode.

Regarding the modelling techniques, two main approaches are found in the literature: regression model and cross-classification analysis. Like the cross-classification analysis conducted for passenger demand, the advantages of the model lies in the fact that the model can be carried out using disaggregate data and no prior assumption is needed to build the model. However, the cross-classification analysis needs large data samples compared to regression analysis.

**Table 3-2. Summary of selected UGM generation models**

| Researchers | Study area | Modelling approach | Level of aggregation | Dependent variable | Independent variables |
|---|---|---|---|---|---|
| Ade Ogunsanya (1984) | Lagos, Nigeria | R | A | Commodities weight | Population, size of the zone, land use, volume of export in the zone |
| Bastida and Holguín-Veras (2009) | New York, Manhattan, Brooklyn | R; CA | D | Commodities weight | Commodity type, industry sector, employment |
| Gentile and Vigo (2013) | Emilia Rog, Italy | CA | D | Commodities weight | Industry category |
| Alho and de Abreu e Silva (2015) | Lisbon Portugal | R; CA | D | Vehicle trips | Industry category, number of employees, retail area |
| Pani et al. (2018) | Seven cities in India | R | D | Commodities weight | Employment, gross floor area |

R: Regression, CA: Cross analysis; D: Disaggregate; A: Aggregate

Models can be classified into two main groups based on the type of data used, namely aggregate and disaggregate models. Aggregate models use an average of individual data level to provide the average estimates over a group, while disaggregate models use individual data points to explain the behaviour of individuals. Disaggregate models are more advantageous, with an ability to use the inherent variability in the data, and lower changes to achieve multicollinearity between the variables (Ortuzar and Willumsen, 2011). However, disaggregate models need a correct aggregation procedure to produce a respectable aggregate demand. A handful of studies regarding UGM generation models are summarised in Table 3-2.

### 3.2.2 Review of distribution model

Next we discuss the distribution model. The distribution and mode choice involve complex modelling since they involve multiple actors and their decisions. Parallel with three groups of private actors described in Chapter 2, the role of these private actors and their associated decisions in goods deliveries can be stated as follow:

- Suppliers are often responsible for planning and managing the distribution of goods. This actor decides the transport type service, time of delivery, as well as delivery tour if any.
- Carriers include all actors responsible for providing a transport service to the shippers. In term of modelling, the carriers decide the routes taken to reach the location of the receiver.
- Receivers decide how much and where to restock. In some cases, retailers also decide how the restocking activities are done that includes decisions such as what time, which vehicles, and which delivery tour has to be used.

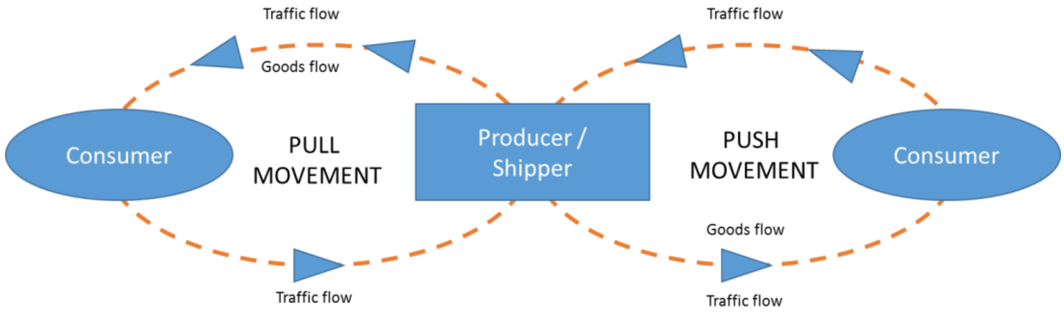
Since it involves multiple actors with different decisions, generally, the distribution models consist of consecutive discrete choice models. They may comprise multiple decisions by multiple actors depending on the supply chain structure. Referring to the choices involved in UGM activities, Comi and Nuzzolo (2014) identify that there are two main choices: one related to the demand of the goods, and one related to the supply/logistics choice. The demand sides of choice include decisions such as: how many goods to procure, and where to procure the goods from. Meanwhile, the supply side of choice includes decisions such as: which type of transport service is used (e.g. using own vehicles, or using third party logistics), what time is taken to make the trips, which type of vehicles to be used, and which delivery tour type (e.g. direct trips or round trips).

*Supplier location choice* is the first step in the distribution model. This decision is mainly made by retailers. The supplier location choice model indicates the origin of the goods; however, it is not necessarily where the commercial vehicle trips begin. Supplier location choice model can be an aggregate model using the gravity model or a disaggregate model using a destination choice model. Gravity model usually formulates the demand distribution in the unit of trips. While it is practical to use the gravity model when the availability of data is limited (Muñuzuri et al., 2010), the gravity model does not usually include the behaviour of stakeholders involved in moving the goods. This limitation is addressed by using a choice modelling approach to investigate the factors affecting the decisions.

The next step is to model the *transport service choice*. Transport service choice (i.e. the distribution channel choice) is important for decisions in UGM since it describes how the goods are transported from the shipper locations to the receiver locations. Two macro behaviours related to receiver behaviours are presented to organise a reader framework.

> Pull-type behaviour: "*the end consumer arrives at purchasing place, performs the transaction and purchases the commodity, then the user transports the good to consumption zone, both in going from consumption zone to purchase zone or vice versa, the user may make other stops.*"(Comi et al., 2014, p. 164)

> Push type behaviour: "*the end consumer may and may not go to purchasing place, perform a transaction and purchase the commodity, the commodity transported to the consumption site by actors other than the user*."(Comi et al., 2014, p. 164)




(Source: Comi et al., 2014)

**Figure 3-4. Receivers push and pull movement**

In this framework, the pull movements emphasise the retailers as the main decision-makers in the transport service decisions. In other words, the pull movements assume retailers also act as the carriers since they procure the goods using their own vehicles. The leading decision maker in the pull movement is the retailers them self, and the consecutive decisions by retailers may include route choice, type of journey (either single trips or routing trips), number of stops ,number of goods acquired per stop (if they choose routing trips), and mode/type of vehicle choice (Russo and Comi, 2010).

Meanwhile, in the push movements, the decisions are on the actor besides the retailers i.e. shippers or carriers. The main decisions here are made not by retailers and thus each model should be modelled independently. The decisions may involve shipper related decisions, viz. carrier choice and shipment size, as well as decisions involving carriers, viz. route choice (in another case it may involve a tour optimisation problem), and mode / type of vehicle choice.

### 3.2.3 Review of mode choice model

UGM traditionally does not involve mode choice since UGM is involved in *last mile* delivery in the sense of goods deliveries. Unlike international, national and regional goods movements that may involve modes such as railway and maritime modes (Arencibia et al., 2015), UGM is mostly associated with road-based vehicles.

However, there are variations in the size of the commercial vehicle that can be considered. For instance Wang and Hu (2012) classified commercial vehicles into: automobiles, pick-up trucks, sports utility vehicles (SUVs), single axle trucks, and combination trucks. Their research suggests that travel time, number of stops, the type of cargo, consignment size, as well as establishment attributes are among the significant attributes affecting the mode choice.

Further, recently, bike delivery systems can be considered an option to deliver parcels in a dense city centre area (Arnold et al., 2018). All mode choice methodology found in the literature mostly uses a random utility model as the theoretical basis.

We summarise several choice models regarding UGM activities in Table 3-3. Supplier location, transport service and mode choice models have been studied previously and the table shows methods as well as the attributes affecting each decision.

**Table 3-3. Previous studies on modelling the choice from private actors' perspectives**

| References | Alternatives | Decisions | Decision maker | Attributes | Methodology | Location |
|---|---|---|---|---|---|---|
| Wisetjindawat *et al.* (2006; 2007) | Traffic zone inside the study area | Destination choice | Retailers | Number of establishments; total area; total goods generated; population; number of employees; distance | MNL | Tokyo (Japan) |
| | Private; rental; share; delivery service (small and large truck) | Carriers and vehicle choice | Shippers | Type of firm (e.g. retailer, wholesaler, or manufacturer); number of employees; commodity type; delivery lot size; frequency | NL | |
| Russo and Comi (2010) | Pull; push transport service | Transport service | Retailer | Deliveries per week; shipment size; travel cost; travel time | MNL | Rome (Italy) |
| | Traffic zone inside or outside the study area | Destination choice | Retailer | Travel time | BL | |
| | All traffic zone inside the study area | Zone choice | Retailer | Travel time; number of establishments; number of employees; commodity type; CDB dummy | MNL | |
| | A vehicle with capacity less than 10 $m^3$ or the others | Vehicle choice model | Retailer | No of employees; depot area; deliveries per week; the distance between depot and shop | BL | |

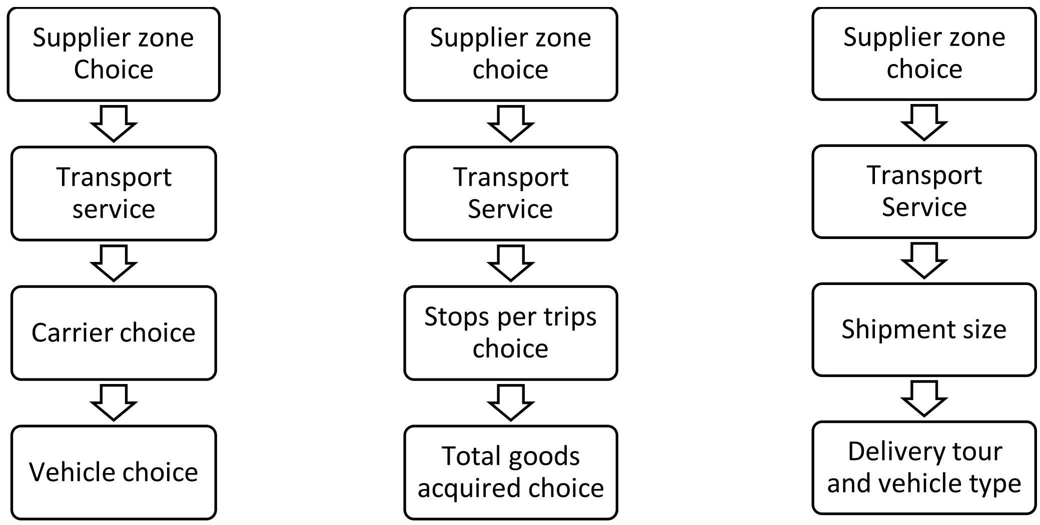
| References | Alternatives | Decisions | Decision maker | Attributes | Methodology | Location |
|---|---|---|---|---|---|---|
| Wang and Hu (2012) | Cars; SUVs; pick-ups; single trucks; multi trucks | Mode choice | Carrier | Tour travel time; total travel time in a day; number of tours; number of stops; commodity type; company related attribute | NL | Colorado (US) |
| Nuzzolo and Comi (2014) | Pull; push transport service | Transport service choice | Retailer | Number of employees; average shipment size; type of retailers | BL | Rome (Italy) |
| | One trip; two trips; three trips; more than three | Tour type choice | Shipper | Dummy related to LGV; retailer accessibility index; average shipments; dummy related to food commodity | MNL | |
| | Cars; LGVs; MGVs | Mode choice | Retailer | Number of employees; average shipment size; store area | MNL | |
| Mei (2013) | Traffic zone inside and outside the study area | Destination choice | Retailers/shipper | Travel time, number of stops within tour trips; dummy specific variable | MNL | The triangle (USA) |
| Ellison *et al* (2017) | Numbers of stops within tours;<br>traffic zone within the study area | Tour type choice<br>Number of stops | Retailers/shipper<br>Retailers/shipper | Occupation of the decision makers<br>Total travel time within tour; type of industry | MNL<br>NL | Sydney (Australia) |

Note: MNL = multinomial logit; NL = nested logit; BL= binomial logit

### 3.2.4 Modelling retailer logistics decisions as discrete choices

After discussing the UGM modelling effort in general, we now jump to the cases of independent retailer demand modelling.

Previous studies reveal independent retailers' decisions as a series of consecutive decisions (see for example Wiset*jindawat et al.*, 2007; Russo and Comi, 2010; Nuzzolo and Comi, 2014). However, there are significant differences in the approach regarding the decisions taken by the retailers (see Figure 3-5). With a closer look at the model and the paper, this difference emerges because of the different contexts for the supply chain which is modelled based on the situation in a particular country.




(Wisetjindawat *et al.*, 2007) (Russo and Comi, 2010) (Nuzzolo and Comi, 2014b)

**Figure 3-5. Restocking sequential decision made by independent retailer**

Metropolitan Tokyo was used to build a simulation model of goods procurement across the city (Wisetjindawat et al., 2007). The model is based on the assumption that each retailer procures goods according to push movements in which goods are delivered by the suppliers. In this case, the carrier and vehicle choices are explicitly modelled as the supplier's decision. Meanwhile, Russo & Comi (2010) and Nuzzolo & Comi (2014) build models for independent retailers in cities in the Italian setting. They categorise the restocking movements into pull and push movements which mean retailers in the respective study have an option to restock their shop using their own vehicles. Hence, in these models, the type of movement, the amount of quantity acquired per trip, and the possible number of stops per trip are included in the decision models.

## 3.3 Traffic assignment to address UGM problem

The assignment model can be separated from the other three models of the four-step model. While the other three models deal with the demand side of UGM activities as discussed in the previous section, the traffic assignment model is where the result of the UGM demand modelling (i.e. commercial vehicle trips) together with the demand from other road users interacting with the supply side of UGM activities. It is also the step where the problems associated with UGM is analysed and where most policies of UGM related to traffic management and demand management are measured.

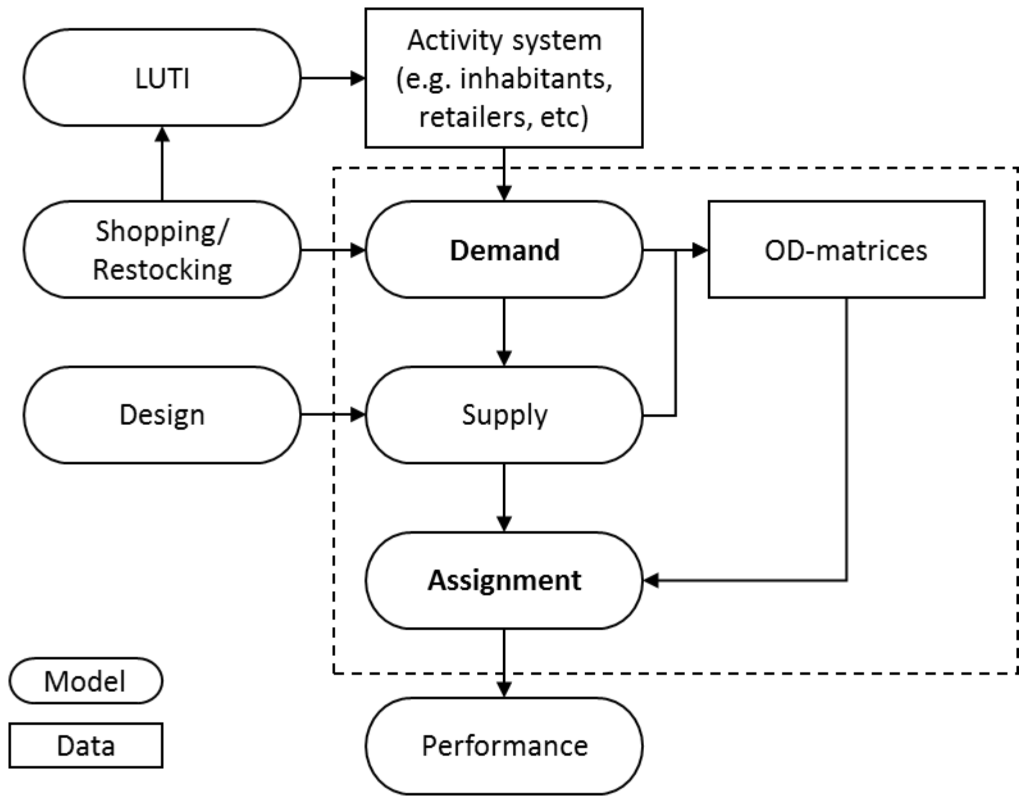



**Figure 3-6. Urban freight transport modelling structure**

According to Comi et al. (2012), the general model of UGM should consist of a set of models depicted in Figure 3-6.. Following the modelling structure, all aspects of UGM related decisions and the impact of policies can be modelled. The modelling set up allows the analyst to:

- Forecast how the key land use activities may be expected to change, taking into account the transport infrastructure performance (Land-Use Transport Interaction –LUTI – model).
- Forecast goods quantities requested by the end-consumer through the simulation of shopping activities.
- Simulate the distribution of goods involving UGM private actors' decisions.

- Represent the supply side serving the UGM activities including their operational characteristics and how to modify supply in order to optimise given objectives whilst satisfying given constraints.
- Assign demand into the multi-mode (or in the case of road transport, multi-user class) through assignment models. The interaction between the demand and supply model in the assignment model allows analysis to evaluate the performance of the UGM activities and the impacts of a given city logistics scenario.

Given the demand side of UGM activities mostly involves private actors' decisions and the impact of local authorities in that process can be considered minimum, the commonly applied city logistics policies traditionally appear in the form of traffic management (e.g. traffic limitations for commercial vehicles; truck lanes, or tolling for commercial vehicles). Surprisingly, traffic assignment problems represent the area where, as far as the author knows, the UGM research is lacking since most of the previous UGM models deal with the demand aspect of UGM (Comi et al., 2012).

Further, the previous research tends to ignore the nature of mixed traffic involving urban goods delivery and prefer to depict vehicle movements for vehicle routing problems (Russo and Comi, 2010; Wisetjindawat et al., 2006) or by simply including commercial vehicles as part of passenger demands, and using available commercial traffic assignment software to test their model (Grosso et al., 2012; Muñuzuri et al., 2012). The disadvantage of the latter approach is the model cannot consider the distinctive characteristics of commercial vehicles compared to private vehicles particularly in terms of congestion and emission effects in the urban area.

### 3.3.1 The role of traffic assignment model

The fundamental aim of a traffic assignment process is to reproduce the pattern of vehicular movements based on specific behavioural rules. Therefore, given the role of the traffic assignment model as a tool to analyse the interaction between UGM demand and supply, the traffic assignment model concerning UGM activities needs to:

- Incorporate the decisions of private actors that shape the demand side of UGM activities. In that case, unlike the standard traffic assignment for passenger movement, the decisions of UGM demand is not merely the route choice. For example, retailers that use their own vehicles may choose supplier location based on the transport cost directly associated with traffic conditions.

- Incorporate mixed traffic conditions. Since commercial vehicles and private vehicles impact the traffic differently, it is compulsory to include multi-user class problems into the traffic assignment that aims to analyse UGM activities.

Additionally, the traffic assignment model should be able to assess local authorities' policies regarding UGM activities. This means the modelling set up should be able to simulate the effect of exogenous scenarios on the private actor's decisions that shape UGM activities. In this paradigm, the model should be able to estimate the variability of the demand based on traffic conditions. In the end, the model allows us to obtain link flow for commercial vehicles, to then assess the impacts of given local administrators' policies.

In the next subsection, we discuss the two conditions that need to be met for the traffic assignment model to properly incorporate UGM activities.

### 3.3.2 Incorporating road user behaviour in the traffic assignment model

In the UGM model, the importance of including private actors' decisions have been highlighted and actually modelled (see Crainic et al., 2009b; Russo and Comi, 2010; Wisetjindawat et al., 2007). However, the previous UGM model does not assess the change in behaviour based on traffic conditions and traffic management measures in a single framework, making it difficult to assess whether the traffic management measures applied by the local authority result in a positive outcome. For example, a study by Barnard (1987) takes a decision for shopping decisions by using a multinomial logit model. Although the model includes travel time and travel cost as one of the attributes that influences the shopping destination, travel time and travel cost in their model are fixed and do not account for the real conditions of the traffic on the road network.

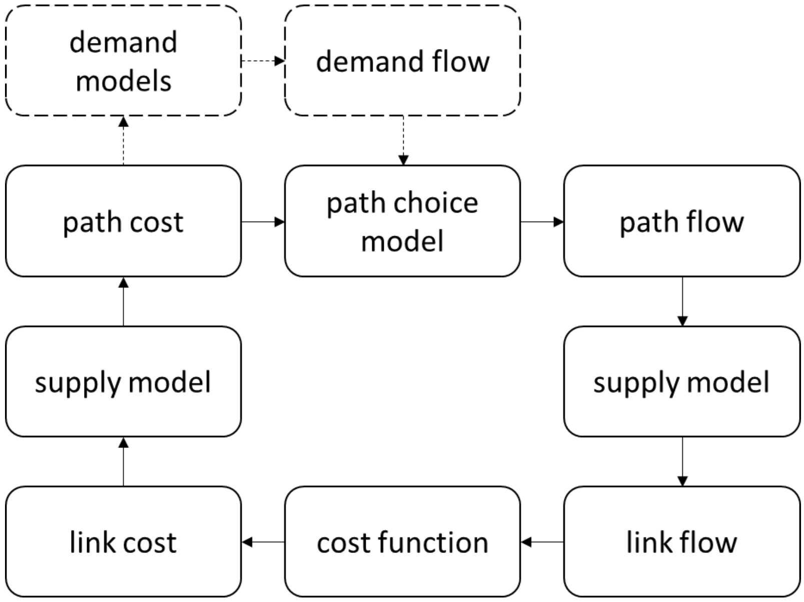
Therefore, there is a need to have a model that accounts for road user behaviours according to the level of service on the network. In the context of UGM activities, the model needs to incorporate private actors such as carrier/retailer behaviours into the model. One way to incorporate choice other than route choice into the model is by building a combined model. A combined model is a model that combines at least two stages of typical four stage modelling such as combining trips distribution and route choice or model spilt and route choice. Lam and Huang (1992) review three types of the combined model found in the literature:

1. The OD demand for each mode is known to the analyst and thus the objective then is to assign the traffic following the user equilibrium (UE) condition. In this case, it is not really a combined model-split assignment problem; rather the works are addressing the case of multi-user class / multimode traffic assignment problem (see, for example, paper by Dafermos, (1972); and Van Vliet et al. (1986)).
2. The sum of the OD demand is known for the analyst, yet the modal split of each mode is a function of travel time for a given mode in the network. In this case, the UE condition is extended to include mode choice. In the equilibrium condition, no user can lessen their travel cost by changing route or mode. The work by Abdulaal and LeBlanc (1979) falls into this category.
3. If only the trips production is known by the analyst, the problem then is how to predict the OD matrix and their link flow. This model falls into combined trips distribution and a route choice problem. In the equilibrium, no travellers can reduce their travel time / travel cost by changing the destination or route. The works by Lam and Huang (1992) and Oppenheim (1993a) fall into this category.

Another way to see the problem of incorporating road user behaviours into the traffic assignment model is through the variable demand concept. Early research in the traffic assignment model mostly formulates the user equilibrium condition with the assumption that the demand between the OD pair is fixed. This means that the traffic assignment with the UE condition only considers the route choice dimension for the given OD demand. Or in another words, the traffic assignment models do not consider the role of other choices such as trip destination choices, or time departure choices in the equilibrium configuration.

Nevertheless, more research includes variable demand in the model set up, since in the real world, the demand may actually fluctuate depending on the traffic conditions. In the case of variable demand, choices other than route choice are explicitly included in the traffic assignment formulation. For example, as congestion increases, the travellers may decide to use different modes, shift the time of travel, or not travel at all.

Many local authorities and transport modellers point out the urgency and the need for demand variability to be included in the equilibrium configuration since the demand elasticity may be relevant over a medium-long term horizon. From an operational point of view, variable demand modelling is needed to imagine the impact of policies that will cause substantial changes in mobility characteristics besides path choice. From a methodological point of view, the variable demand is necessary when the demand is unknown and needs to be estimated by a set of models (Cantarella et al., 2013).




(Source: Cantarella *et al.*, 2013)

**Figure 3-7. Scheme of variable demand approach**

In order to take the phenomenon of demand variability into account, the demand between OD pairs in the network is then assumed to follow a specific demand function. The demand function is usually a function of traffic condition between the OD pairs and depicts the choice dimension of travellers besides the path choice model (see Figure 3-7). Sheffi, (1985) proposes two standard demand functions depending on how the analyst formulate the choice decisions of the travellers.

The first demand function reflects the traveller's decision such as shifting the time of travel or deciding not to travel at all. In this setup, all OD pairs have the same demand function, yet each OD pair may produce different trip rates depending on the traffic conditions between the OD pair. The demand function, however, may include specific parameters reflecting population size, income distribution, vehicle ownership, and retail activities for each destination zone. An example of this demand function in the literature is a power function (Clark et al., 2009; Koh et al., 2009) as follows:

$$D_w = \breve{D}_w \left(\frac{\mu_w}{\breve{\mu}_w}\right)^{-0.57} \qquad 3\text{-}1$$

where, $\breve{D}_w$ and $\breve{\mu}_w$ are the initial demand and cost respectively. $\mu_w$ is minimal travel cost between the OD pair *w* after the traffic assignment process.

The second demand function reflects the combination of distribution and traffic assignment models. Here, the focus is on the distribution of trips or in other words, the total trips originating from each zone is considered fixed and the question then becomes how these trips are distributed among possible destinations. In this case, the analyst only knows the sum of trips originating from the origin zones but does not know the trips distribution. Then the traffic assignment model is extended to include the distribution model and in equilibrium, no user can change his route or destination to lessen his travel cost. An example of the distribution function is a logit function (Lam and Huang, 1992; Oppenheim, 1993b) as formulated as follows:

$$D_w = D_r \frac{e^{-\beta(u_S)}}{\sum_{s \in S} e^{-\beta(u_S)}}; \quad w \in W \qquad 3\text{-}2$$

$$u_s = \beta * \mu_w^1 + \alpha_{s_n} * z_{s_n} + \delta \qquad 3\text{-}3$$

Equation 3-3 specifies the utility function for destination (supplier) zones, which is dependent on the shortest travel time between the OD pair, $\mu_w^1$, and $n^{th}$ character of the supplier zone *s* such as the number of establishments in the destination zone, the presence of wholesalers/traditional markets in the supplier zone etc. and $\delta$ is a Gumbel distributed IID random term.

### 3.3.3 Commercial vehicle flow in traffic assignment model

The traffic assignment model in the UGM context involves the case in which more than one user class should be considered in the model. In the literature, this problem is called a multiple user class traffic assignment problem. A user class refers to a unique set of trips which are identical in respect to vehicle type, their criteria for route choice and network restriction (Van Vliet et al., 1986). This case is particularly true in the UGM context, in which there are at least two user classes that can be defined: commercial vehicle transporting goods, and private vehicles transporting passengers.

The consideration of commercial vehicles in a joint manner with private vehicles is required given the different characteristics of the trips. These characteristics may include the different behaviours that shape their trip patterns; the different perspective towards *value of time* (VOT); and a different contribution to congestion i.e. each user class has a different impedance factor towards link performance function (Dafermos, 1972).

Generally, there are two ways to address the traffic assignment problem concerning different user class. The first one is assuming the cost function of different user classes to be a symmetric function. This means that one class of vehicle impacts other classes as much as the others impact one particular class. Van Vliet et al. (1986) show this approach by assuming only the time component of each of the user classes is flow dependent and the cost to transverse the link only depends on the total passenger car unit (PCU) on that link. These assumptions imply that a link cost can be modelled entirely as PCU values using the link respective to the user class for e.g. the delays caused by 10 PCU cars and 5 PCU trucks which are as much as the delays caused by 5 PCU cars and 10 PCU trucks. Note that this approach incorporates different delays between user classes by using PCU as a conversion factor.

The other way to approach the multiple user class assignment problem is by assuming the cost function of different user classes to be asymmetric cost functions. This approach is made possible since traffic equilibrium conditions can be stated as a variational inequality allowing the asymmetric cost function to be considered (Dafermos, 1980; Smith, 1979). In such a multi-user class approach, each user class has the individual cost function and at the same time contributes to its own cost and the other classes' costs differently (Dafermos, 1972). The model assumed that there is a single generalised cost associated with using a particular class (i.e. mode) on a particular link.

Nagurney (2000) proposes the concept of a *multi criteria* traffic network assignment model; this approach is different from the model proposed by Dafermos (1972) as the model explicitly identified direct travel cost and travel time as criteria for route selection. In this way, the multi criteria traffic user equilibrium model allows the analyst to weigh the criteria such as direct travel cost and travel time in an individual manner rather than assuming a single generalised cost. Moreover, the use of multiple criteria for the decision-making process also allows one to consider all factors that are considered important (e.g. emissions factor) to be included in the decision-making process.

## 3.4 Optimisation problems in UGM modelling attempt

The literature shows UGM modelling efforts are very diverse in terms of their motivation and approach and in general two approaching methodologies appear in the literature regarding the UGM model: the transport planning method and optimisation method. The first approach usually takes the perspective of local authorities to design and plan goods movements. The aim is mainly to help local administrators to understand the nature of UGM activities and the impact of these activities on urban lives and the economy. The methods are usually designed to support the assessment of transport policy whether it is on strategic, tactical or operational horizons (Gentile and Vigo, 2013; Muñuzuri et al., 2010).

Meanwhile, the optimisation approach is usually taken from the private sector / logistics company point of view. In this type of research, an operation research technique such as solving optimisation problem is used to model tactical and operational decisions related to UGM activities. The model can be related to delivery tour optimisation, delivery vehicle route optimisation, or fleet and depo location optimisation (Figliozzi, 2007; Crainic, et al., 2009; Qureshi et al., 2014) Nevertheless, it is vital to address the optimisation process from the local authority's perspective. Since UGM activities involve various stakeholders, the local authorities need to plan and design optimal policies that result in an optimal solution for everyone.

Currently, many local authorities view commercial vehicle traffic as something they should ban or at least strictly regulate (Lindholm, 2013). This restriction could involve time windows, weight and dimension restrictions or be in the shape of environmental based restriction zones (Visser and van Binsbergen, 1999). These city logistics measures obviously have a direct impact on the behaviour of the retailers regarding their decisions on where/how to procure their goods. However, retailer logistics decisions are often not sufficiently accounted for by the local authorities which leads to the formulation of sub-optimal policies (Ballantyne et al., 2013). Some local authorities even view them as obstacles to policy implementation rather than core participants (Vidal Vieira and Fransoo, 2015). This situation makes transport policies often result in a counter outcome to the intended objectives. For example, weight and time restrictions on a particular road link in a network could lead to more traffic congestion elsewhere and may worsen the environment (Quak and de Koster, 2006a). Such restrictions also impose a higher economic cost on the retailers and neglect the fact that efficient UGM activities are needed to maintain the economic vitality of cities. Even more, the retailers can always pass the cost caused by the local authority to their consumers and therefore rather than altering the behaviour of commercial vehicles, the city logistics measured can miss out on their real purpose and even hinder the economy.

### 3.4.1 Review of selected bilevel optimisation papers

To be able to design optimal UGM policies, the local authorities must include the possible response of both UGM private actors and city inhabitant in the analysis. The objective of the local authorities is to maximise / minimise an objective function taking into account the response of all road users. The local authorities may opt to design iterative responses whereby the policies are implemented depending on the current traffic situation, evaluate the benefit of the policies and redesign the policies towards the updated traffic situation. The process goes on and on until some form of convergence is met.

On the other hand, local authorities can opt to include the responses of road users in the design process. In this setting, the local authority is assumed to have the ability to anticipate the response of all road users to the policies imposed by creating leader and follower relationships between local authorities and the road users. In the literature, a bilevel optimisation problem is one effective tool for determining optimal city logistics in the case where a leader-follower relationship exists.

There has been an increasing amount of research conducted using a bilevel program in transportation studies. In the transport literature, the bilevel model is often used to describe a network design problem (NDP). In this research, a typical upper level problem is the objective of local authorities. The objective can have various policy dimensions included in the formulation. Wang et al. (2014) build an NDP problem in which the local authorities' objective is to find an optimal capacity expansion for the road network. Koh et al. (2009) build an NDP model that seeks a second-best optimal road pricing scheme. Ho et al. (2013) solves the first and second best toll for multiple user class cases in the case of designing cordon toll. In the models, the objective included decision factors that are continuous in nature. There is also a bilevel program problem that deals with discrete decisions such as designing one-way streets (Lee and Yang, 2005).

The lower level problems usually include follower behaviours and are typically assumed to follow user equilibrium conditions. Two conditions emerge in the literature where some research addresses the problem with a single user class (Koh et al., 2009), while the others highlight the importance of addressing multiple user classes in the model (Holguín-Veras and Cetin, 2009; Wang et al., 2014). The user equilibrium condition can be addressed as variational inequality (VI) and thus transforms the bilevel programming into a mathematical program with equilibrium constraint (MPEC).

The bilevel programming technique is also used in the field of business logistics and supply chain (Roghanian et al., 2007; Ryu et al., 2004). However, the inclusion of the method to study the problem of urban goods movements/city logistics is still limited. A few examples of bilevel modelling in city logistics include the optimal location of a logistics terminal (Taniguchi et al. 1999) and the optimal design of a freight transport network (Yamada et al., 2007). To the best of the author's knowledge, there is still no research in UGM studies that addresses the optimal policy from the local authority point of view using a bilevel programming technique. This thesis aims to address this gap in the literature.

### 3.4.2 Review of solution technique to solve the bilevel problem in a transport area

There are many solution techniques which have been developed to solve the bilevel optimisation problem. A review by Farahani *et al.* (2013) shows that a solution technique to solve NDP can be classified into three categories: (i) exact mathematical model; (ii) heuristics; and (iii) metaheuristics.

Exact methods, such as branch and bound, rely on mathematical properties to solve the problem. An example of the use of the exact methods includes Leblanc (1975) who solved the discrete NDP for the Sioux Falls network. However, exact methods are not applicable to tackling large network problems due to computational efficiency. The largest network being solved by exact methods is a network consisting of 40 nodes and 99 links (Drezner and Wesolowsky, 1997).

The second category is the heuristics method. Heuristic methods are mostly used to solve a continuous network design problem (CNDP). Heuristics develop a solution within the problem and use an iterative way to solve the problem. Heuristics may not converge but they are more efficient than exact methods. Before applying heuristics methods, some solution technique transforms the problem into a single level optimisation model and then solves the resultant problem with available algorithms. An example of the heuristics methods is an iterative optimisation approach, linearisation approach, and cutting constraint algorithm.

An iterative optimisation approach solves the problem by solving the upper level problem (optimisation problem) and lower level problem (UE traffic assignment) separately. Firstly, the method solves the upper level problem without a UE condition and then subsequently solves the lower level with a fixed solution for the upper level. The process will repeat until it reaches convergence. The first person to suggest the method was Steenbrink (1974) who proposed the Iterative Optimisation Assignment (IOA). Linearisation methods transform the problem of NDP into a linear bilevel problem and then solve it by using a standard algorithm to solve a linear bilevel problem. LeBlanc and Boyce (1986) developed a bilevel network design problem with linear approximation of travel time in the link. They then used a simplex based algorithm to solve the problem. Hearn et al (2001) propose an algorithm using a VI formulation for the UE condition to generate an extreme point from the feasible regions. The idea is to use the shortest path problem to generate the extreme point needed.

Further Lawphongpanich and Hearn (2004) propose a cutting constraint algorithm (CCA) to solve the second-best toll problem. This method generates an extreme point within a feasible solution iteratively until the solution is converged. The method was tested and shows encouraging results.

The third category is the metaheuristics approach. The metaheuristics approach does not rely on the mathematical structure or function that forms the NDP problem. Instead, the metaheuristics approach builds a mechanism driving the optimisation process inspired by different natural-based phenomena. For instance, a simulated annealing (SA) process is inspired by a metallic annealing process (Kirkpatrick et al., 1983) and the genetic algorithm (GA) is based on the evolution process in nature.

The main advantage of the metaheuristics technique is that the methods do not require the derivative or restrict the form of the objective function. The method involves a stochastic process during the search and thus is able to avoid the local optimal and seeking the global maximum. Indeed, the flexibility of the metaheuristics technique allows the direct application of this method to solve the NDP problem. For example Friesz et al. (1992) applied the SA process to solving NDP with a UE constraint. Recently, Mera and Balijepalli (2019) used SA to solve the NDP problem involving a network resilience attribute. Xiong and Schneider (1992) applied the GA technique to solving an NDP problem. Clegg et al. (2001) similarly solved the CNDP with the GA technique.

## 3.5 Chapter summary

This chapter has presented a review of previous UGM models and their specification. Local authorities represent the main perspective when the planner develops a UGM model. This is understandable since most models aim to improve the efficiency of UGM activities. In particular improving the UGM activities relating to the traffic conditions where most of the negative externalities from UGM activities occur such as delays, congestion and emissions. The efficiency objective can be seen from both public and private actor perspectives. From the local authority perspective, increasing UGM activities' efficiency aims to improve the overall system and try to reduce the social and environmental costs relating to UGM activities. Meanwhile, from a private actor perspective, improving the efficiency of deliveries does not necessarily work towards reducing system costs, rather it can work towards reducing their operational costs within the cost of the overall system.

One way to address this conflicting objective is by involving the behaviour of private actors in the model with the aim of aiding the local authority. By involving private stakeholder attributes and characteristics, the model can perform an analysis of UGM activities in a more realistic way. Further, the impact of an administrator's policies on the behaviour of private stakeholders can also be assessed.

In terms of methodology, the review reveals that in terms of demand modelling, the four-step model is the most common methods to depict UGM activities. The flexible nature of the four-step model means this approach can easily meet the objective based on the perspective that the modeller/analyst wants to point out. However, the traffic assignment model is the area where the previous model lacks integration. The previous research does not assess the change of behaviour based on traffic conditions and traffic management measures in a single framework, making it difficult to assess if the city logistics traffic management measures applied by local authorities resulted in a positive outcome.

To summarise, this thesis aims to propose a model to aid local authorities to find optimal city logistics measures by utilising a bilevel programming framework. The modelling framework assesses the objective of *the local authority* whilst simultaneously considering *private actors* logistics decisions and the *passenger movements*. As far as the author is aware, research specifically addressing this three-sided interaction simultaneously do not exist, and this thesis aims to fill this gap in the literature. The detail of the modelling framework and the underlying methodologies will be explained in Chapter 4.

The summary of previous modelling research and the current study's location within the modelling framework can be seen in Table 3-4 below:

**Table 3-4. Review of results of UGM modelling research and the current studies**

| Author | Perspective | | Stakeholder | | | | Objective | | | | | | Methods | | | | Assignment model | | Optimisation process |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Public | Private | Shipper | Carrier | Retailer | Local Authority | Economic | Efficiency | Road Safety | Environmental | Infrastructure Management | Urban Structure | Generation | Distribution | Mode Choice | Traffic Assignment | User Equilibrium | Vehicle Routing Problem | (Yes / No) |
| Current study | x | x | | | x | x | | x | | | | | x | x | | x | x | | yes |
| Alho and de Abreu e Silva (2017) | x | | | | x | | | x | | | | | x | | | | | | |
| Bastida and Holguín-Veras (2009) | x | | | x | | | | x | | | x | | x | | | | | | |
| Boerkamps et al. (2000) | x | x | x | x | x | x | | x | | | | | x | x | x | | | | |
| Ellison et al. (2017) | x | | | | x | x | | x | | | | | x | x | | x | | x | |
| Eriksson (1995) | x | | | x | | x | | x | | x | | | x | x | | | | | |

| Author | Perspective | | Stakeholder | | | | Objective | | | | | | Methods | | | | Assignment model | | Optimisation process |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Public | Private | Shipper | Carrier | Retailer | Local Authority | Economic | Efficiency | Road Safety | Environmental | Infrastructure Management | Urban Structure | Generation | Distribution | Mode Choice | Traffic Assignment | User Equilibrium | Vehicle Routing Problem | (Yes / No) |
| Figliozzi (2007) | | x | | x | | | | x | | | | | | | | x | | x | yes |
| Gentile and Vigo (2013) | x | | | | x | X | | x | | | x | | x | x | | | | | |
| Harris and Liu (1998) | x | | | | | | x | | | | | | x | | | | | | |
| Hensher and Puckett (2005) | x | | x | x | x | X | | x | | x | | | x | x | | | | | |
| Holguín-Veras and Cetin (2009) | x | | | | | | | x | | | | | x | | | | | | |
| Muñuzuri *et al.* (2012) | x | | | | | x | | | | | | | x | x | | x | x | | |
| Nuzzolo and Comi (2014) | x | | | x | x | x | | x | | | x | | | | | | | | |

| Author | Perspective | | Stakeholder | | | | Objective | | | | | | Methods | | | | Assignment model | | Optimisation process |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Public | Private | Shipper | Carrier | Retailer | Local Authority | Economic | Efficiency | Road Safety | Environmental | Infrastructure Management | Urban Structure | Generation | Distribution | Mode Choice | Traffic Assignment | User Equilibrium | Vehicle Routing Problem | (Yes / No) |
| Oppenheim (1993) | x | | | x | | | | x | | | | | | | | x | | x | |
| Routhier and Toilier (2007) | x | x | | x | x | x | x | | | x | | | x | x | | x | | x | |
| Russo and Comi (2010) | x | x | | | x | x | | x | | | x | | x | x | x | | | | |
| Taniguchi *et al.* (1999) | x | | | x | | x | x | | | | x | | | | | x | x | | yes |
| Wisetjindawat et al. (2007) | x | x | | x | x | x | | x | | | x | | x | x | x | | | | |

# Chapter 4 Research methodology and modelling framework

This chapter presents the primary research process to answer the research objectives presented in Chapter 1. It explains the research activities and the theoretical framework for the methods used in this thesis. This chapter also serves as signposting for the thesis, presenting the way this thesis is written.

The research process is divided into 4 stages: (i) a preliminary study; (ii) a data collection process; (iii) model estimation and formulation, and (iv) implementation of the modelling framework. The research activities begin with a preliminary study which is explained in Section 4.1. Then Section 4.2 describes the modelling framework and its theoretical framework based on the problem and research gap found in the preliminary study. The data collection method used in the study is then elaborated in Section 4.3. Given the proposed modelling framework, two activities need to be done: demand model estimation, and formulation of the bilevel optimisation problem. Section 4.4. outlines the theoretical background of the demand model estimation including several discrete choice models. Meanwhile, Section 4.5 explains the theoretical framework for the formulation of the bilevel optimisation problem. Activities revolving around modelling implementations are discussed in Section 4.6.

The research methodology framework is shown in Figure 4-1.

## 4.1 Preliminary study

The preliminary study is an attempt by the author to find the research questions in the area of study and formulate an appropriate research design to tackle these problems. Preliminary studies involve four main activities: (1) defining the research problem and objective; (2) exploring UGM practice and the problem incurred by UGM activities; (3) reviewing the literature on UGM modelling and the available methods; (4) designing research methods to answer the problem and fill the research gap found.

The research problem and objectives are firstly based on the actual context of the problem faced by the author. Then, the author deepens the understanding of the problem by doing the literature review. The research objectives are stated in Chapter 1.

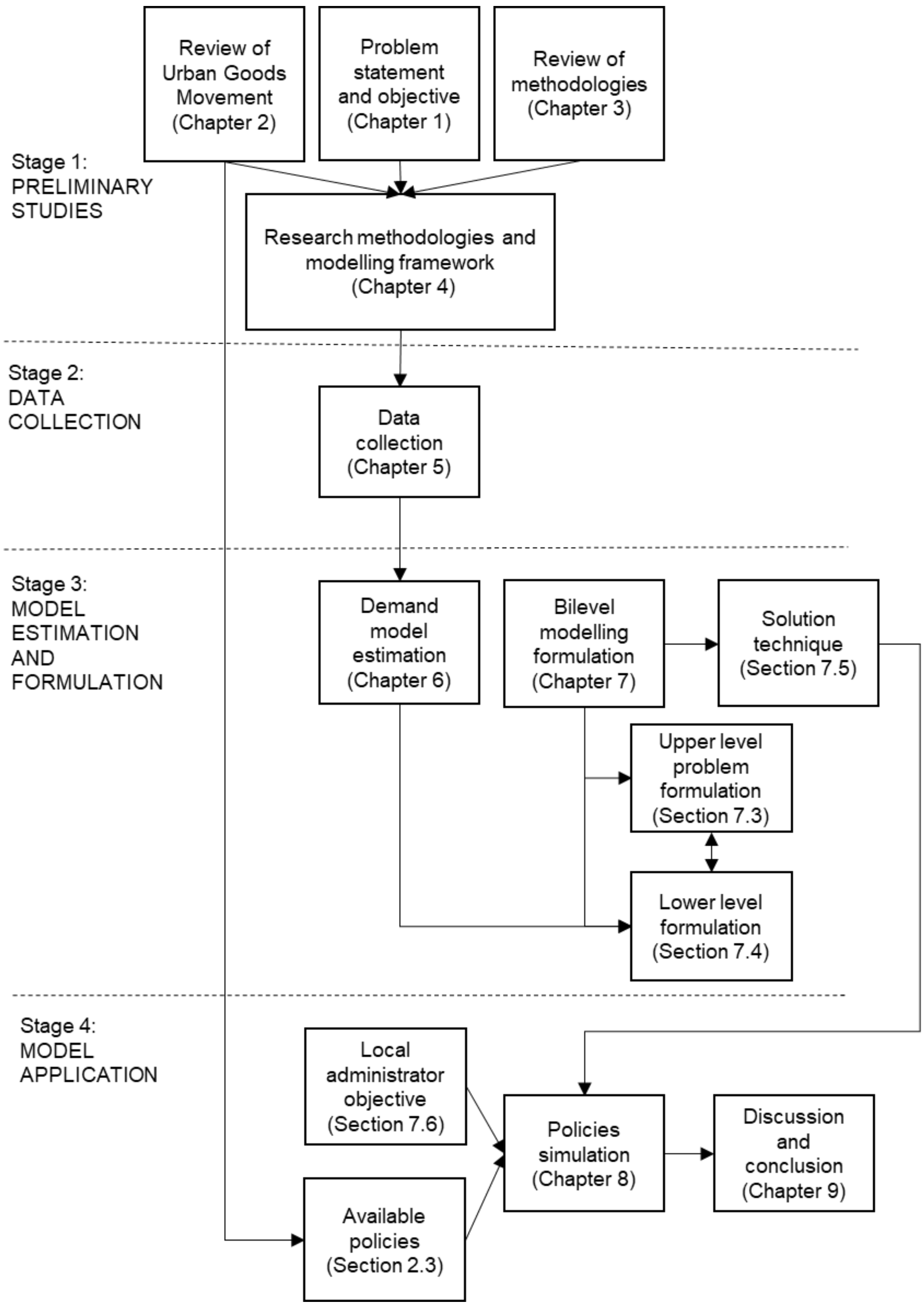



**Figure 4-1. Research methodology framework**

The literature review helps the author to understand the research field and helps the author to identify the gap in the literature and claim the novel element of the current research. This thesis deals with Urban Goods Movement (UGM) activities particularly in a developing country context. Therefore, as part of the literature review, the author reviews UGM in various area such as: the nature of UGM activities, the problems induced by such activities for the cities involved, and the current way authorities deal with UGM activities. The research particularly deals with independent retailer activities that are prevalent in developing countries in which literature reveals that such studies are very limited. The reason is that in many developing countries, UGM activities are often conducted in an informal way suggesting difficulties to obtain the data needed. Therefore, to enrich the reading materials besides relying on the typical literature provided by mainstream scientific journals, the author also reviewed international reports dealing specifically with these activities (see for example (Dablanc, 2009; Herzog, 2009)).

This study wishes to approach the problem in a quantitative way, i.e. by building a modelling framework that can capture the problems. Therefore, the author conducted a literature review on UGM modelling. The literature review helps the author to have a better understanding of the previous UGM model and identify the proposed originality of the current study. Firstly, the author reviews, in general, previous modelling attempts for UGM activities. The key difference between the modelling of goods transport and passenger transport is addressed in the review. The review then continues by reviewing the models that deal with the demand sides of UGM activities particularly from the perspective of local authorities. Subsequently, the literature review process also gives the author the idea of the parameters needed to build the demand model in the current research. Parameters found in the literature review are used to design the actual questionnaire used in the data collection process. As the current study addresses the UGM from the local authority point of view, the review then continues to address the role of a traffic assignment model to address UGM activities. Further, the optimisation problem in the area of UGM is also considered in the literature review. The results of the literature review process are presented in Chapter 2.

Next, designing the research methodology is an important part of the overall research process. The research methodologies should be able to answer the research questions presented in Chapter 1. Based on the preliminary study, the author then defines the methodology including the modelling framework of this study. This research methodology and modelling framework are presented in this chapter.

## 4.2 Modelling framework

As mentioned in Chapter 1, one of the objectives of this research is to approach the problem of UGM through a quantitative / modelling approach. The modelling framework is presented in this section.

### 4.2.1 Independent retailers demand model requirements

The first step in building a demand model is to identify the components of UGM activities that want to be modelled, seeking a link between private actor decisions and city logistics measures.

This thesis focuses on the case in which UGM activities are dominated by *restocking activities* by the retailers in a typical city centre area. Even if the proposed model can be applied to all restocking/shopping activities, this thesis focuses on the bold part of Figure 4-2. In this sense, the modelling system will be detailed for the case in which goods are generated by independent retailers' demands and not the end consumers' demand. Further, although restocking activities can be influenced by the decision maker besides the independent retailers (e.g. if the goods are transported by the carrier, the independent retailers do not have the influence to decide the route choice) this thesis focuses on trip demands that are generated and shaped by the decisions of independent retailers.

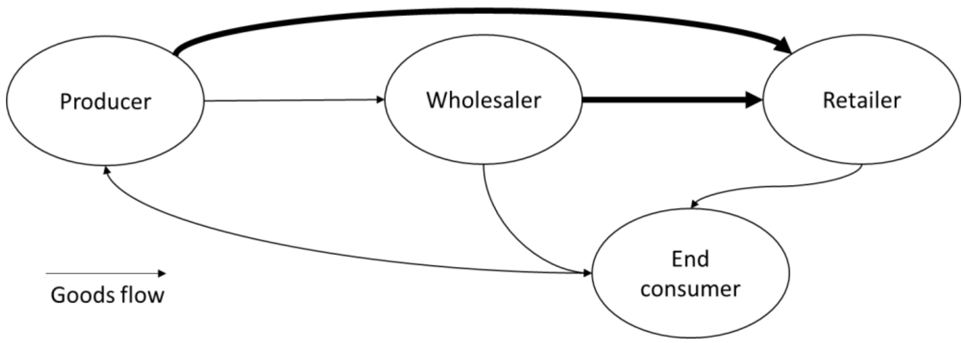



**Figure 4-2. Structure of UGM activities**

The proposed demand model is based on two steps out of the four-step model: *generation* and *distribution*. The generation model reproduces the trip demands on a zone-based level (TAZ). Characteristics of the retailers are then used to determine the demand for restocking trips in each zone.

As discussed in section 3.1.4, the unit of analysis in the UGM model can be divided into two categories: commodity based approach and vehicle based approach. The commodity based model takes into account the economics and characteristics of the goods type into the model. In contrast, a vehicle-trips based model attempts to directly forecast the commercial vehicle traffic generated by retailer activities. We must acknowledge that the commodity based model is the best in term of methods available. The reasons for this are that the commodities based model can consider commodity types, which has been found to be a key variable that influences freight behaviour (Holguín-Veras et al., 2014a)

However, in this thesis, we are proposing a model based on the trips based approach for the two reasons discussed below:

- Trips based approach has the advantage of the data requirements, in a sense that the data needed to build a trips based model is less extensive compared to a commodity based model. In this sense, building a UGM model using a commodity based model in a developing country context is inherently difficult as this requires a high quality and extensive data of establishments and their activities in which commonly unavailable.
- The trips based model is of direct interest in our thesis since we build a model that deals with the effect of commercial vehicles on the network, and for this, vehicle trips are far more important than the commodity being moved. Further, our model aims to investigate the three sided interaction between commercial vehicles, private vehicles, and the local authority in order to minimize the problems associated with UGM, and these interactions between the three actors are at a trips based level.

Having chosen the trips based analysis, we acknowledge that the model does not explicitly consider the influence of the various type of commodities, and thus the model cannot be used to predict any changes in demand that are related to any changes in the commodity types.

The distribution model is shaped by decisions by independent retailers. As we discussed in Chapter 3, independent retailer decisions regarding restocking activities can be considered as relating to two main decisions: *where to go, and how to procure the goods*. Or in other words, the independent retailers' main decisions are:

- Supplier location choice: an independent retailer may procure their goods from several suppliers, and hence decide which suppliers they want to procure the goods from. Supplier location choice is an independent retailer decision representing the attractiveness of a particular supplier location perceived by independent retailers compared to the other locations. The attractiveness of the supplier location is derived from the transport cost associated between the retailer location and supplier location and the inherent characteristics of supplier location that can increase their attractiveness (e.g. the number of establishments in the supplier location).
- Transport service: represents the way the goods are transported to the retailers' shop. In this thesis, the transport service choice represents the independent retailers' decisions on whether to use their own vehicles to procure the goods or opt to let the suppliers decide the transport services to deliver the goods to their shops. The former implies the vehicle trips will originate from the retailer

locations (*r* nodes) and end at the supplier location (*s* nodes), whilst the latter implies the other way around, i.e. vehicle trips will originate from the supplier location (*s* nodes) and end at the retailer locations (*r* nodes).

### 4.2.2 Addressing the optimal policies to manage independent retailers' restocking activities

As mentioned in the introduction, one of this study's objective is to aid local authorities to manage independent retailers' restocking activities. To be able to do that an optimisation problem needs to be considered in the research methodology. The literature review reveals that one way to address an optimisation problem in which there are two actors influencing each other's decisions is through a bilevel programming approach.

From a historical point of view, the bilevel programming approach is closely related to the economic problem of the Stackelberg game in the field of game theory (Stackelberg, 1952). In this game theory, two distinct players emerge: a group of players – called *leaders* – direct the other players – called *followers* – in the game. In the particular framework of the game, the leader is assumed to be able to anticipate the reactions of the followers; this ability allows him to choose his *optimal* strategy accordingly. The existence of a distinguished player who can anticipate other players' reactions is what makes the Stackelberg game different from the Nash game (Nash, 1951). In a Nash game, each player observes the actions of the others and then chooses the strategy optimal to them. The equilibrium is reached when no player can improve his objectives by changing the strategy. Or in another world, the player in the Nash game is homogenous.

In general, the bilevel programming problem can be divided into two problems: an upper level problem and a lower level problem. The upper level model represents the objective of the leader – in our case the local authorities. As discussed in Chapter 2, the local authority is the only actor in UGM activities that aims to search for an optimal solution for all actors involved in UGM.  Local authorities want to achieve their objective by implementing city logistics policies. Therefore, the upper level model needs to incorporate local authority objectives as well as the introduction of city logistics policies into the formulation.

The policy introduced can be in the form of discrete decisions or continuous decisions. Discrete policy decisions may include the selection of a suitable set of actions from a number of possible actions. For example, these actions may include constructing new roads, making particular links one-way streets, or restriction for specific links.

Meanwhile, continuous choices include decisions such as determining tolls for road pricing policies and road capacity enhancement.

The lower level problem represents the decisions taken by the players other than the leader – i.e. the followers. In the urban road networks, the followers are all road users using the road network to move from their origins to their destinations. As this thesis analyses UGM problems, this thesis explicitly address the decisions relating to independent retailer restocking activities.

As we discussed in the previous section, the restocking activities consist of two main decisions: *supplier location choice* and *transport service choice.* We propose a model that explicitly includes the *supplier location choice* as part of the lower level problem of bilevel programming.  We include the supplier location choice as this decision can be seen as the strategic decision by independent retailers. The supplier location choice act as a destination choice for commercial vehicle and therefore by including this decision into the lower level problem, we explicitly consider the retailer's behaviour into the optimization problem. The assumption of including *supplier location choice* as one of the decisions in lower level problem is limited to the independent retailers restocking activities that we are studying. Nevertheless, we believe, the concept of introducing the choice decision into the lower level problem of the bi-level programming problem can also be applied into different planning contexts. For example, the chain retailers may more interested in mode/shipment size choice (Pourabdollahi et al., 2013) than the supplier location choice, and such choice can be applied in the model.

By explicitly including the *supplier location* choice into the lower level problem, two issues need to be addressed: first, the issue of commercial vehicle flow interaction with private vehicles in the road network. This raises the issue of a *multi-user class traffic assignment problem*. The commercial vehicles and private vehicles are expected to bring different contributions to the cost to trasverse the links. The second issue involves the performance of the network affecting the behaviour of each user class. The problem involves the demand level of each user class that is the function of travel cost between the OD pairs. This problem raises the issue of a *combined traffic assignment problem* in which the traffic assignment is calculated simultaneously with decisions other than route choice decisions.  In our case, for private vehicle demand, the problem becomes traffic assignment with elastic demand, in which the choice for private vehicles includes the route choice and the choice to not travel. As for commercial vehicle demand, since we adopt the supplier location choice as the other decision besides the route choice, the problem becomes the user equilibrium traffic assignment combining route and destination choice.

### 4.2.3 Modelling framework

Next, we discuss the overall modelling framework. The modelling framework needs to take into account the three sided interaction between the local authority, retailers, and other road users. The modelling framework is comprised of two main steps: (1) building a demand model for restocking activities; (2) the bilevel optimisation model formulation and application (see figure 4.3.)

The first task of the modelling works is to build a demand model. The model aims to predict transport demands according to independent retailer activities by investigating their logistics processes. These demand models formulate the way the local authorities can alter the behaviour of independent retailers. The input of the model is the data gathered from the survey capturing the decisions made by independent retailers. The models involve a multi-stage model comprising a generation and a distribution model.

The generation model predicts the restocking trip demands by independent retailers considering the characteristics of retailers in a particular zone. The distribution model, comprised of supplier location choice and transport service choice, predicts the flow of restocking trips. By choosing a supplier, the origin and destination of the goods are known. However, the goods movements are not always equal to vehicle trips. It depends on the transport service the independent retailers choose. By choosing a particular transport service, the manner in which the goods are delivered is determined.

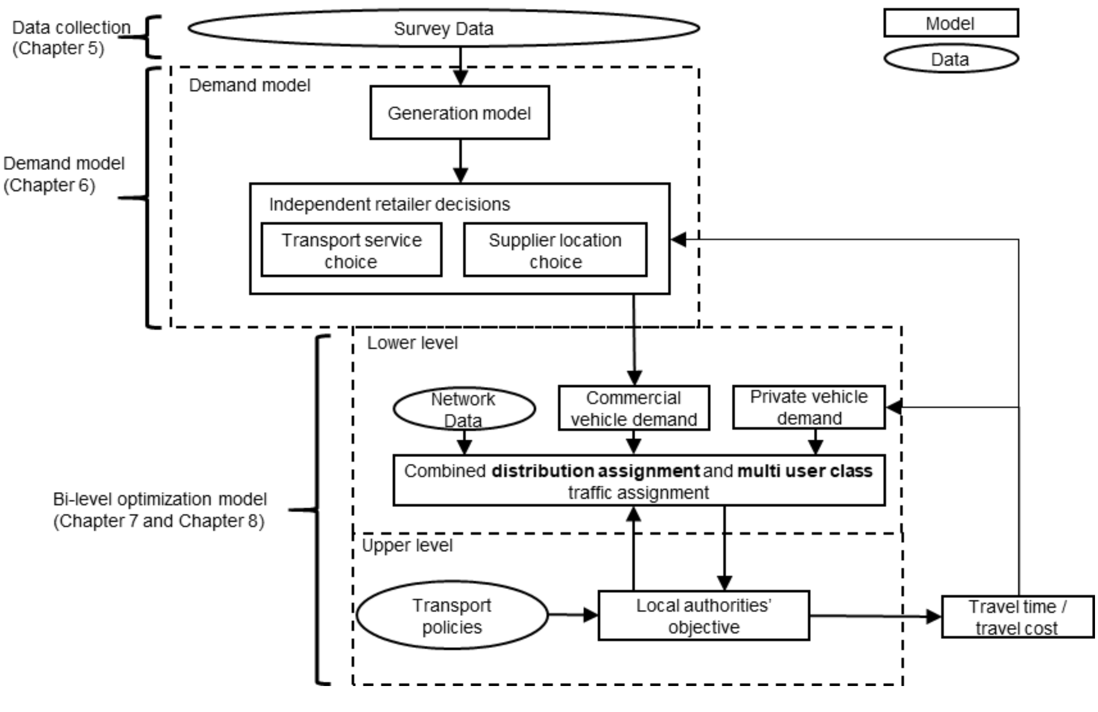



**Figure 4-3. Modelling system structure**

We then move to the next step to formulate the bilevel optimisation model. The aim is to assess optimal transport policies that meet local administrator objectives while considering independent retailers' restocking activities.

Our modelling system structure (figure 4.3) differs from any previous models found in the literature in several ways. Firstly, our proposed model provides an integrating framework to analyse the three-sided interaction between local authority, retailers/wholesalers, and the other road users by applying the bilevel programming into our problem. By applying the bilevel programming into our model, we can treat the problem as a leader and follower problem in which the local authority is a leader that can control the behaviour of the followers through applying policies. The aim of the leader is to optimize the system, which in our case is to maximise economic benefit. In the bilevel programming model, the aim of the leader is formulated as the upper level problem.

Secondly, our modelling system also explicitly incorporates the interaction between the local authorities and the road users through the formulation of the lower level problem in the bilevel programming. The lower level problem involves the formulation of *combined* and *multi-user class* user equilibrium traffic assignment. The combined term refers to the condition in which the demand is not static. The demand function consideration in the user equilibrium (UE) formulation depicts the condition in which the UE formulation considers decisions other than route choice.

This thesis considers two different demand models for two user classes. The retailer demand is depicted as commercial vehicle demand and we address the supplier location choice as the combined decision in our model. As discussed in a previous section (section 4.2.1.), we see supplier location choice as one of the strategic decisions taken by independent retailers. By incorporating the supplier location choice model that is estimated in previous modelling work, the distribution of restocking trips will be assessed simultaneously with the route choice problem. As for private vehicle demand, we consider the demand function in which the other decision is not to travel. Further, the traffic assignment needs to consider both commercial vehicle and private vehicle demands on the road network highlighting the need to consider multi-user class traffic assignment.

Note that by including the supplier location choice in the lower level problem, the result of the current traffic assignment will change the distribution of restocking trips since for each iteration, the traffic assignment will produce a new travel cost for each OD pair. In this manner, the iteration process of the model continues until the result of the retailer decisions and the network performance converge.

From a methodological point of view, the work of modelling the lower level problem becomes a complex problem since we need to consider two different choice decisions and two different user classes. Yet another novelty of this work is that these choice models are subsumed as a constraint in the lower level problem rather than being solved in an iterative manner. The lower level model formulation and the difference between these two approaches are discussed in the numerical example in Chapter 7.

Providing the bilevel programming setup, the next step involves implementing the model to test city logistics policy simulation. Two examples are discussed in the next chapters in this thesis to discuss the fruitfulness of the formulation. The numerical example, using a small network, consists of 7 links and provides evidence of the working of the model. Further, this numerical example shows how the model can capture different retailer decisions based on various traffic conditions as well as incorporating cities logistics policies into the model. The second numerical example deals with the real-world network of Bandung city centre, in which several city logistics policies are simulated.

Regarding the time of the model, we are modelling peak-hour conditions particularly morning peak hour. Considering this study only models morning peak hour conditions, it is possible to neglect the complexity of trips that involve trip chains. The conditions in morning peak hour, when the passenger trips are high and the independent retailer shops are beginning to open, supports the assumption that the trips start from one zone and end at another zone. The time limit prevents the model from assessing multi-stop trips all around the city. Further, by concentrating our effort on morning peak hour, our model addresses crucial periods in the cities in which the interaction between passenger transport and goods transport are most severe.

### 4.2.4 The architecture of the model

In this subsection, the general architecture of the proposed modelling framework is explained. The aim is to give spatial meaning to the proposed model. This thesis, seeks to propose a modelling system to simulate goods movement at an urban scale combining urban passenger movements and commercial vehicle movements, given decisions made by retailers. The general architecture of the model is used for all models in the thesis and provides the spatial dimension for the model. The main purpose is to identify the geographical system within an urban environment involving independent retailer activities in the model.

The transport system surrounding the urban area can be expressed by two main themes: nodes and links. Nodes are a set of vertices of points in the urban area, usually interpreted as intersections, while links are the roads connecting the nodes.

Note that two-way streets would have two different links connecting each node. Links have an impedance factor which is affected by the actual flow. These impedances are a measurement of the link representing the time required to traverse the street. Typically, impedance on the link is represented by link performance function which draws a relation between link flow and link travel time.

We propose an urban area traffic model in which the sub-districts of the study area are treated as traffic analysis zones (TAZs). Thus, each TAZ is an administrative area defined by the local authority. Each TAZ is represented by a node known as a centroid. The centroid is the node that would be the start and the end of each trip in that zone. Once the set of centroids is defined, we can then derive the set of OD matrices. This matrix specifies the flow between every origin centroid and every destination centroid of the network. The representation of centroid in the network shows the model's level of detail. Because every trip would start and end on the centroid, it would imply the centroid as the aggregation of movement in the zone. Hence the movement within a zone which is represented by a single centroid is not modelled.

To represent independent retailer activity, each TAZ would then accommodate centroids. Two different sets of centroids are defined:

$$\{r\}, \{s\}$$

- {r} is the set of centroids representing the independent retailer shops in the study area. Independent retailers can either receive deliveries or procure goods to their shops using their own vehicles.
- {s} is the set of centroids representing supplier places in the study area. If the transport service is decided by the suppliers, the vehicle movements start from these centroids.

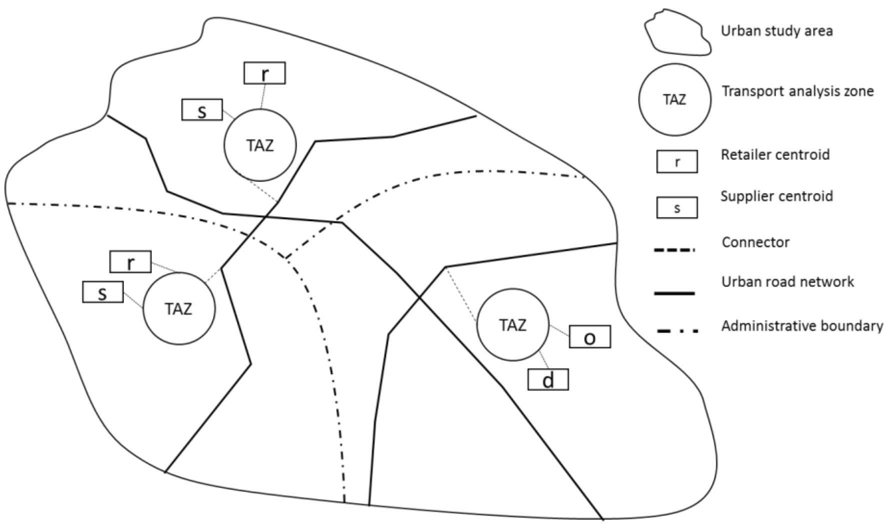



**Figure 4-4. General architecture for the model**

In general, {r} and {s} can be located in the same TAZ; however, they represent different entities and behaviour in the model, thus each of {r} and {s} are defined as separate centroids in each TAZ. It is important to note that {r} can be identified as several independent retailers in the same zone in the study area. Hence, each centroid in TAZ represents aggregate characteristics of the retailers or suppliers in the particular TAZ (see Figure 4-4).

For commercial vehicles, the origin nodes are the retailer nodes (*r*) and the destination nodes are the supplier nodes (*s*). Therefore, valid OD pairs are formed by combining retailer and supplier nodes for the commercial vehicle user class. Meanwhile the private vehicle user class does not distinguish zones between *r* and *s* nodes; hence each TAZ acts as an origin and a destination for private user vehicles. Therefore, in this setup, the path followed by a commercial vehicle and a private vehicle need not necessarily be the same for a pair of TAZs since we define origins in a different way for different user classes.

## 4.3 Data collection methods

This research exploited the survey method to collect the data required to model restocking activities by independent retailers. In particular, we concentrate our efforts on the establishment survey that reveals the logistics decisions within the restocking activities.

In the UGM literature, surveys related to UGM activities are part of UGM research. The purpose of these surveys is to gain an understanding of UGM activities through real-world data. Although there is no standard data requirement when studying UGM activities, previous studies reveal the type of data that have been collected via survey: (i) data related to goods/vehicle delivery and collection trips; (ii) trip details and patterns of vehicles; (iii) activity related to parking and loading/unloading. Allen et al. (2012) mentioned twelve survey techniques (e.g. drivers' survey, roadside survey, etc.) to capture restocking activities. Nevertheless, we are only concerned with an establishment survey since it is the most common technique and the one we would like to use in this study.

The establishment survey is the most common survey used for UGM studies because it can cover most of the information needed in UGM studies such as: data related to an establishment's supply chain, vehicle trip generation and vehicle trip purpose, as well as parking and loading/unloading activity at the establishment location. It is claimed that, although expensive, the accuracy of the survey is generally very good. Despite the usefulness of an establishment survey, there are no standards regarding their content and structure, sampling method, or survey technique due to the different and specific purpose of the study and the influence of local context (Alho and de Abreu e Silva, 2015).

### 4.3.1 Constructing the questionnaire

The questionnaire is designed to *reveal* the actual choice of independent retailers regarding their restocking activities. In order to do that we utilise the revealed preference technique (RP) when designing the questionnaire.

The limitations of the RP technique to describe decisions particularly transport decision compared to the stated preference (SP) technique are noted in the literature. The main limitations are summarised in Kroes and Sheldon (1988):

- It can be difficult to obtain sufficient variation in the RP data for all variables of interest
- There is often a strong correlation between variables of interest (e.g. travel cost and travel time) in RP data. This makes it difficult to properly estimate the variables reflecting the trade-off between variables from the RP data.
- RP data cannot simulate the situation where there is a new choice to be considered.
- RP data require that the explanatory variables can be described in an "objective / engineering" unit. E.g. RP is more useful for evaluating variables such as travel time and travel cost compared to the variables such as seat design/station facilities.

Knowing the limits of RP data, this study still uses the RP survey given the nature of the UGM problem we want to tackle. Considerations about choosing the RP technique include the following: (i) difficulty producing a choice of set particularly to model the *supplier location choice*. The nature of the supplier location choice is that there are too many choices of suppliers' location available so that it would be impossible to construct an experiment design necessary for SP studies; (ii) one of the advantages of an SP experiment is that it can test a new choice that is not already available to the decision makers. However, in this study, we are not testing anything for a new choice to emerge (e.g. a new alternative mode). We simply want to capture the current decisions of independent retailers regarding their restocking activities.

The questionnaire consists of five sections: (i) Independent retailer characteristics; (ii) goods and supplier choices; (iii) transport related decisions; (iv) questions related to parking / loading/ unloading activity; (v) optimal respondent identity. The full design process of the questionnaire is presented in Chapter 5.

### 4.3.2 Conducting the survey

There are three types of survey technique that are used to do an establishment survey: face-to-face survey, telephone survey, and self-completion survey. The decision to choose a particular technique is due to the type of data needed, the number of respondents, and resource limitations. The type of data needed depends on the study objective. A self-completion survey is commonly used to cover a large number of respondents in a wide geographic area. However, telephone calls and face-to-face are commonly more interactive and produce a better response rate than a self-completion survey, albeit they are more resource demanding. Both surveys can be conducted sequentially in which the phone call can be used to obtain permissions and to arrange face-to-face interviews.

This thesis exploits face-to-face interviews by trained surveyors to collect the data. Although more expensive and time consuming than telephone calls, face-to-face surveys can produce better data validity and a higher response rate. Moreover, an independent retailer is typically owned by a family and operates in an informal way. Thus, it would be easier to gain information from them by face-to-face interview to build trust and also get their consent directly. To make sure the survey will run smoothly, a pilot survey will be conducted to perfect the questionnaire design.

## 4.4 Demand model estimation

The demand modelling formulation and estimation steps involve multi stage modelling: generation and distribution models. The actual estimation will be presented in Chapter 6. In this subsection, we focus on the theoretical background for the estimation process.

For the generation model we use a regression estimation technique to investigate the relationships between the dependent variable (number of restocking trips) and independent variables (retailers' and restocking characteristics). As for the distribution model, we use a discrete choice modelling technique to model the retailer decisions.

The next several subsections elaborate the theoretical framework of the estimation for this model.

### 4.4.1 Generation model estimation technique

In this thesis, we use ordinary least squares (OLS) regression methods to estimate the generation model. The ordinary least square method works by measuring the squared residual (vertical distance between the point of a data set and the predicted line). The goal is to minimise the sum of these squared deviations. Before fitting the regression model, the data has to meet the following assumptions:

a) The relationship between the independent variables and dependent variable needs to be linear
b) Absence of influential data points i.e. outliers data
c) The data should meet the homoscedasticity condition meaning the probability distribution of all independent variables should have the same variance
d) All independent variables in the regression model should be normally distributed
e) In the case of multiple linear regression in which we deal with many variables, the multicollinearity conditions should not be met. The multicollinearity condition is defined as the condition where the independent variables have a linear relationship with each other

It is well known, in transportation research, that the regression model is used to model trip generation. However, in order to get the aggregate trips, there are two models that are widely used, namely zonal based multiple regression and individual / unit based regression (Ortuzar and Willumsen, 2011). It is well noted that the individual based regression is superior to the zonal based regression as argued below.

A zone-based model estimates the trips generation based on the variations in trip-making behaviour between zones. For this to be valid, a zone should have homogeneous socio-economic activities but represent an as wide as possible range of conditions. The major problem is that the main variations in the trip data usually occur in the intrazonal level. Intrazonal variations can be reduced by decreasing the size of the zones; however, smaller zones imply more expensive models in terms of data collection and larger sampling errors. For this reason, this thesis builds a model that is independent of the zone boundaries.

This generation model reported in this chapter adopts individual based regression analysis. As the trip generation model is based on retailer-level regression, each retailer's characteristics are taken as input data. Because the model is a linear model, the zonal level values can then be quantified simply by replacing the attribute values in the equation with the average zonal value and then multiplying them by the number of independent retailers in each zone. In this way, the trip generations are quantified by attributes of independent retailer characteristics.

#### 4.4.1.1 Choosing the dependent variables

In the case of a multiple linear regression problem, the number of dependent variables should we include to build a good regression model is an important question when building a model. To make this decision, several factors should be taken into consideration:

a. Are there strong theoretical reasons to include a particular variable in the model or it is important to include the variable for policy testing?
b. Does the estimated parameter for these variables have the correct sign based on theory or intuition? and;
c. Are the variables statistically significant?

If in doubt, one way forward is to eliminate the least significant variable (based on the theoretical background, the purpose of the model, and the statistic tests) and then re-estimate the regression in order to examine the effect of variables removal.

#### 4.4.1.2 Goodness fit of the model

Next, we discuss the goodness of fit of the model. The method to measure the goodness of fit of the regression model is through a *coefficient of determination ($R^2$)*. The test measures how close the data is to the regression line. It has limiting values of 1 (meaning the regression explains all the variabilities of the data around its means perfectly) and 0 (meaning the model does not explain the variability of the data).

Further, the goodness of each independent variable can also be measured. We achieve that by doing hypothesis testing on independent variables (t-test). The t-test is basically a statistical test to accept or reject a $H_0$ hypothesis stating that the parameter $b_i$ is equal to zero if the value of the t-test is below the critical value of student statistics for a given significance level and the appropriate degrees of freedom. The other test is the F-test that compares the fits of different independent variables. Unlike the t-test, the F-test measures the variance for the overall model, i.e. multiple variables simultaneously (F-test). We reject the $H_0$ hypothesis stating that all parameters are equal to zero if the value of the f-test is below the critical value of F distribution. The difference between the $R^2$ and F-test is, while $R^2$ provides the strength of the relationship between dependent variables and independent variables, the F-test determines whether this relationship is statistically significant or not.

### 4.4.2 Distribution model estimation technique

The distribution model is a discrete choice model based on utility and random utility theory (Ben-Akiva and Lerman, 1985) and will be explained in the next subsections.

#### 4.4.2.1 Basic utility theory and random utility model

Utility is a concept for measuring a choice or combination of choices using attributes attached to alternative or decision-maker characteristics. The specific manner in which various attributes are combined and defined for overall utility is called a utility function.

The underlying concept of this utility function allows the modeller to assess different alternatives and predict the choice made by the decision maker by assuming that they are rational and always choose to maximise their utility (Oppenheim, 1993b). The typical typology of a utility function can be seen as follow:

$$U_j = V_j + \varepsilon_j \qquad \text{4-1}$$

where $V_i$ is the deterministic term of the utility function, and $\varepsilon_j$ is the random term. These two terms define two models known in discrete choice modelling: deterministic utility model, and random utility model.

Translated into the probability of choice context, if the utility function just includes the deterministic term, the analyst then has accurate information about decision-making utilities for all decision makers. The modeller then can predict with certainty and deterministically the decision maker's choice. Although this sound goods and convenient, there are possibly three errors regarding the use of deterministic utility models. Firstly, the decision maker often has incomplete or incorrect information or a different perspective on some or all the attributes. As a result, a unique individual may take a different decision while facing the same alternatives. Secondly, it can be implied that the analyst never has a perfect understanding and information regarding attributes relative to every decision maker. For example: the analyst may not have a good understanding of the reliability of a specific service compared to the individual who uses the service on a daily basis. Thirdly, the modeller is unlikely to know precisely all the attributes related to the decision-making process made by every individual. Using a model which does not take account of all of this often incurs behavioural inconsistency describing the above.

The alternative of fixing the issue in deterministic utility models is introducing a random term which defines what we called random utility modelling. Based on random utility theory, we assume that:

- Each retailer is assumed to be a rational decision maker who maximises utility relative to their choice.
- The decision maker considers mutually exclusive alternatives which make up a choice set of $C$.
- Then the decision maker assesses each alternative $c$ from the choice set $C$ and selects the alternative that maximises his utility
- The utility function comprises measurable attributes. Two types of attributes can be classified as follows: (i) attributes related to alternative $C$ and (ii) attributes related to decision makers.

- Finally, the utility assigned by the decision makers is not known with certainty by the analyst due to a number of factors and therefore represented by the random error variable $\varepsilon_c$.

The random utility model (RUM) is a modelling technique which cooperates random term in the utility function. The function of this random term is to represent the differences, unknown to the analyst, between individual decision makers. The deterministic part is often called the perceived parts where the analyst can observe the behaviour of decision makers regarding alternatives, while the random part is where the analyst does not know for certain due to a number of factors. The deterministic part is usually assumed to be linear in parameters.

RUM is widely used in the area of transportation research, particularly to predict the behaviour of transportation related decisions. The decisions usually involve a choice set involving several alternatives with a different value for each attribute.

#### 4.4.2.2 Component of deterministic term of a utility function

Components of a deterministic part of utility function involve the set of attributes. These attributes can be related to the alternatives (i.e. the choice set faced by the decision maker), decision-maker characteristics, or both. Mathematically, the deterministic term of the utility function can be written as follows:

$$U_C = \beta\, a_c + \gamma_c\, b_t + ASC_c \qquad 4\text{-}2$$

where $U_c$ is a utility function representing alternative $c$; $a_c$ are the attributes related to alternative $c$; $b_t$ are attributes related to decision maker $t$ characteristics; $ASC_c$ is the alternative $c$ specifics constant ; and $\beta$ and $\gamma_c$ are constants that would be estimated. Note that $a_c$ and $b_t$ may include more than one significant attribute to form the utility function.

Attributes related to the alternatives (i.e. the set of choices faced by a decision maker) influence the utility of each alternative. The attributes included in this component are measurable attributes related to the service of alternative and expected to influence the decision of decision makers. E.g. in the context of supplier choice in UGM activities, the attributes related to the alternative can be total travel time, total travel cost, reliability, etc. These components differ for each alternative and can differ for each decision maker due to the differences in OD locations for each individual decision maker.

Meanwhile, attributes related to the decision maker influence utility for each decision maker. These attributes represent the different bias across the decision makers by incorporating personal attributes into the utility function. Income, sex, age and number of vehicles owned are some attributes related to decision makers. The attributes are important since, often in the decision-making process, personal characteristics play a major role. E.g. retailers who own their own vehicle are likely to choose to go to their supplier themselves.

Moreover, often it is difficult to quantify all the decision-maker characteristics, and therefore the other biases that cannot be quantified in the utility function are included in the alternative specific constant ($ASC$) in the utility function. Alternative specific constants work by putting a particular alternative as a reference. The reference alternative then normalises to the other alternatives. The selection of the reference alternative does not influence the model interpretation.

Sometimes it is useful to define the interaction between attributes related to the alternative and attributes related to decision makers. The aim is to consider how attributes related to the alternatives can be evaluated differently by a different group of decision makers. E.g. one might argue that independent retailers who have their own vehicles tend to go to the supplier location that has traditional markets given that they own a vehicle to do that. This can be represented in the model by representing retailers who have their own vehicles using a dummy variable and then in the utility function multiplying the dummy variables with the presence of traditional market attributes.

#### 4.4.2.3 Specification of the additive error term

As described before, the utility function has two major components, namely deterministic components and random components. Deterministic components represent measurable components in the utility function, while random components represent the limit of the analyst to completely and correctly specify all attributes related to decision makers' choice behaviour. By definition, the random components are unmeasured and unobserved. By including the error term, Equation 4-2 in the previous section can be rewritten as follows:

$$U_C = \beta \, a_c + \gamma_c \, b_t + ASC_c + \epsilon_c \qquad \text{4-3}$$

where the $\epsilon_c$ represents the error / random term of the utility. Because the random components ($\epsilon_c$) cannot be calculated, a wide range of distributions are used to represent the distribution of error terms over the decision maker and alternatives. E.g. if we assume the distribution of a random term follows a normal distribution, the model formulation becomes the multinomial probit model. However, this assumption leads to a complex mathematical form making it difficult to estimate and interpret the model. An alternative distribution, the Gumbel distribution, leads to the more well-known model of the multinomial logit model (MNL) as discussed below.

**The multinomial logit model (MNL model)**

The form of a discrete choice model is determined by the assumption of the random term of the utility function. In that way, two specific assumptions are needed to build the MNL model: (i) the random term of utility function follows extreme-value (Gumbel) distribution; (ii) the random term is identically and independently distributed (IID) across all alternatives and observations.

In the MNL model, the probability of the decision maker choosing alternative *c* is as follows:

$$P_c = \frac{e^{U_c}}{\sum_{c=1}^{C} e^{U_c}} \qquad \forall \quad c \in C \qquad 4\text{-}4$$

where $P_c$ is the probability of alternative *c* being chosen, $U_c$ is the utility of alternative *c*. The utility of $U_c$ is usually assumed to be linear in parameters as shown in Equation 4-2. Inserting Equation 4-2 into Equation 4-4, the probability becomes:

$$P_c = \frac{e^{\beta\, a_c + \gamma_c\, b_t + \, ASC_c}}{\sum_{c=1}^{C} e^{\beta\, a_c + \gamma_c\, b_t + \, ASC_c}} \qquad \forall \quad c \in C \qquad 4\text{-}5$$

The MNL modelling framework is very useful for describing the behaviour of decision makers by predicting the probability of particular alternatives using a simple closed equation.

**Nested logit model (NL model)**

The MNL model has been used widely in a transportation research context; however, it is widely criticised for *independent of irrelevant alternative* (IIA) properties. The IIA property implies equal competition between all pairs of alternatives. This assumption is not always correct in every choice decision. For example, in the case of mode choice within an urban area, the bus and light rail are likely to be similar to a car since they share the same attributes as public transport. Such similarities, if not included in the measured utility, can lead to a correlation between alternative. The correlation between alternative is a violation of IIA properties from which MNL are derived.

This limitation of MNL encouraged researchers to build different models that are not bound by the IIA assumption. Among them, the simplest and most widely used is nested logit (Koppelman and Bhat, 2006; Williams, 1977). The nested logit model works by grouping or nesting subsets of an alternative that are similar to each other into one group. The alternatives in the same groups will have the same competitiveness to the alternative in a different nest.

In an NL model, the probability of a decision maker choosing alternative *j* from nest *k* can be written as:

$$P_c = \frac{\theta \; e^{U_c}}{\sum_{c=1}^{C} e^{U_c}} \qquad \forall \quad c \in C \qquad 4\text{-}6$$

θ is the logsum parameter/nesting parameter that shows the correlation between the nest. To be consistent with RUM principles, the value of the parameter should be between 0 and 1. The interpretation of the different value of the nesting parameter is as follows:

- θ >1 or θ <0 not consistent with the theoretical derivation, reject the NL model.
- θ = 1 implies zero correlation between the nest, and thus the NL model is the same as the MNL.
- θ > 0 and θ < 1 implies non zero correlation between the nests, and it is the appropriate value of the NL model.
- θ = 0 implies the perfect correlation between nests meaning the choice between the nested alternative, conditional on the nest, is deterministic.

**Mixed Logit Model (MXL Model)**

The mixed logit is the most generalized model of choice model that obviates the limitations of the standard MNL model. In the case of addressing the repeated choice of panel data, the emphasis has been on extending the model to include a random parameter that address the correlation between the observations.

The mixed logit implementation can be done in two ways: (1) by including the random coefficients (2) by including the error component in the utility function (Daly and Hess, 2010)

We first discuss how to implement the random coefficient into the mixed logit model. Consider that the decision makers face a choice $c$ among $C$ alternatives. The utility of person $n$ to choose the alternative $c$ can be written as:

$$U_{nc} = \beta_n' x_{nc} + \varepsilon_{nc} \qquad 4\text{-}7$$

Where $x_{nc}$ are observed attributes that relate to alternative and decision maker characteristics. $\beta_n'$ is a vector of coefficients of these variables for person $n$ representing that person's taste and $\varepsilon_{nc}$ is a random term that follows the IID extreme value. The coefficients $\beta_n'$ vary over the decision makers in the population. This specification is the same as with the standard logit, except that $\beta_n'$ varies over the decision maker rather than fixed.

In this model, the decision makers know the value of their $\beta_n'$ and $\varepsilon_{nc}$ for all $c$, and choose the alternative that gives them the highest utility. On the other hand, the researcher observes the $x_{nc}$ but not the $\beta_n'$ and $\varepsilon_{nc}$. The researcher specifies a distribution for the coefficients and estimates the parameters of that distribution. In the literature, the most common distributions are the normal and lognormal distributions. The lognormal distribution is useful when the coefficient is known to have the same sign for all decision makers (Train, 2009).

Conditional on $\beta_c$ , the probability that individual $n$ selects the alternative $c$ is the standard logit model as follows:

$$\mathcal{L}_{nc}(\beta_c) = \frac{e^{U_{nc}}}{\sum_{c=1}^{C} e^{U_{nc}}} \qquad 4\text{-}8$$

On the other hand, the unconditional choice probability that a decision maker $n$ chooses alternative $c$ is the integral of the standard logit function over the density of $\beta_c$ since $\beta_c$ is random and unknown to the researhcer.

$$P_{nc} = \int \mathcal{L}_{nc}(\beta) f(\beta|\theta) \; d(\beta) \qquad 4\text{-}9$$

Where, $\theta$ is the paramater of the distribution (for instance means and variance)

Besides a random coefficient, the other way to implement the logit model is by simply including error components in the utilities for different alternatives. Error components are the flexible way to allow for heteroskedasticity of the data or to address various correlation pattern in the data.

In the case of introducing the error components, the utilities can be written as:

$$U_{nj} = \alpha_n' x_{nj} + \mu_n' z_{nj} + \varepsilon_{nj} \qquad 4\text{-}10$$

Where, $x_{nj}$ and $z_{nj}$ are vectors of observed variables relating to alternative j, $\alpha_n'$ is a vector of fixed coefficient, $\mu_n'$ is a vector of random terms with zero means, and $\varepsilon_{nj}$ is IID extreme value. The term $\mu_n' z_{nj} + \varepsilon_{nj}$ is the unobserved (random) portion of utility which can be correlated over alternatives depending on the specification of $z_{nj}$. For standard logit model the $z_{nj}$ value is zero, so that there is no correlation among the alternatives.

Error component and random coefficients specifications are formally equivalent. However the way the researcher thinks about the model affects the specification of the mixed logit. When thinking about random parameters, it is natural to allow the coefficients for each variable to vary. However, when it is impractical to estimate the random parameters to the variables, the error component methods can be an alternative. The emphasis is to specifying variables that can induce the correlations over the alternatives.

The mixed logit formulation can be easily generalized to accommodate the repeated choice nature of panel data. The specification treats the coefficients as varying over the respondent but being constant over the choice situation for each person (Revelt and

Train, 1998) . Utility for alternative $c$ in choice situation of $i$ for individual $n$ can be written as:

$$U_{nci} = \beta_n' x_{nci} + \varepsilon_{nci} \qquad \text{4-11}$$

Where, $\varepsilon_{nci}$ is IID extreme value over alternatives, decision makers, and choice situations. Consider a sequence of alternatives, each one for a particular time period, $\boldsymbol{j} = \{j_1, \dots, j_i\}$. Conditional on the $\beta$, the probability of the person makes the sequential decisions is the product of the logit formula:

$$\boldsymbol{\mathcal{L}}_{n\boldsymbol{j}}(\beta) = \prod_i \frac{e^{\beta_n x_{nj_i i}}}{\sum_c e^{\beta_n x_{nci}}} \qquad \text{4-12}$$

Since the $\varepsilon_{nci}$ is independent over the choice situation, the unconditional probability is the integral of this product over all values of $\beta$

$$P_{n\boldsymbol{j}} = \int \boldsymbol{\mathcal{L}}_{n\boldsymbol{j}}(\beta) \, f(\beta) \, d\beta \qquad \text{4-13}$$

The only difference between a model with repeated choice and one with only one decision per decision maker is that the integral in equation above involves a product of logit formulas, one for each time period, rather than just one logit formula. By doing it this way, we make sure that the same draws are applied for a particular individual. A draw of $\beta$ is taken from its distribution. The logit formula is calculated for each period, and the product of these logit is taken. The process is repeated over many draws and the results is averaged.

#### 4.4.2.4 Maximum likelihood estimation

The estimation for the MNL and NL models can be done using maximum likelihood estimation. Maximum likelihood estimation is the most common method to estimate parameters besides the least square method. A maximum likelihood estimator is "*the value of parameters for which the observed sample is most likely to occur*" (Ben-Akiva and Lerman, 1985).

Given a sample of *T* decision makers, the probability of an individual *t* choosing an alternative *c* would be given by:

$$\prod_c P_{ct}^{\phi_{ct}} \qquad \text{4-14}$$

where $\phi_{ct}$ = 1 if the decision maker *t* selected alternative *c* and 0 otherwise. Assuming that the decision maker's choice is independent of the others, the probability of each decision makers on sample *t* that choose the alternative that he was actually observed to choose is:

$$\mathcal{L}\ (\beta) = \prod_{n=1}^{N} \prod\nolimits_{c} P_{ct}{}^{\phi_{ct}} \qquad \text{4-15}$$

Then we can define the Log-likelihood function as follows:

$$\mathcal{LL}\ (\beta) = \sum_{t=1}^{T} \sum_{j} \phi_{ct}\ ln(P_{ct}) \qquad \text{4-16}$$

The estimator of the model is the $\beta$ value that gives the maximum result of the function (Train, 2009; Ben Akiva, 2002).

## 4.5 The bilevel programming framework

Decision-making processes for different stakeholders are often depicted within the framework of bilevel programming. The reason is the decision maker of the upper level (i.e. the local authority transport policies scheme) can influence the decision maker at another level (the road users). In cases where the local authorities can act as a leader above the road users, a bilevel programming approach can be useful to determine the optimal city logistics policy (Taniguchi et al., 2008).

The bilevel programming can generally be formulated as follows (Colson et al., 2007):

$$\begin{aligned} &\min_{x} F\ (x, y) \\ &s.t\ G(x, y)\ \leq 0 \\ &\min_{y} f\ (x, y) \\ &s.t\ g(x, y)\ \leq 0 \end{aligned} \qquad \text{4-17}$$

The upper-level variables are $x\ \in\ \mathbb{R}^n$ and the lower level variables are $y\ \in\ \mathbb{R}^m$. Similarly, the functions $F:\ \mathbb{R}^m\ \times\ \mathbb{R}^n\ \rightarrow\ \mathbb{R}$ and $f:\ \mathbb{R}^m\ \times\ \mathbb{R}^n\ \rightarrow\ \mathbb{R}$ are upper level and lower level problems respectively, whereas the vector functions of $G$: $\mathbb{R}^m\ \times\ \mathbb{R}^n\ \rightarrow\ \mathbb{R}^p$ and $g$: $\mathbb{R}^m\ \times\ \mathbb{R}^n\ \rightarrow\ \mathbb{R}^q$ are upper level and lower level constraints respectively.

By including the UE condition as a constraint for the bilevel problem, the problem becomes one of the most complex optimisation problems, namely a Mathematical program with Equilibrium Constraints (MPEC). As the name suggests, the MPEC problem is an optimisation problem where one of the constraints of the problem is an equilibrium condition. From the perspective of the Stackelberg game, $F$ is the objective function of the local authorities which is the function of their decisions $x$ and the response from the followers $y$. The followers' response to the leader action is in the form of minimisation function $f$. The minimisation in this case represents the equilibrium UE condition. The existence of the UE condition as the constraint of the leader decisions represents the ability of the leader to direct the followers.

In the next subsections, the theoretical backgrounds on which the upper level and lower level formulations are based are elaborated.

## 4.5.1 Upper level problem

As discussed in the previous section, an upper level problem represents the local authority's objective in which the local authorities search for optimal strategies for UGM activities in the study area. One strategy that can be conducted by local authorities is through a pricing strategy. Sumalee (2004) points out that in terms of pricing policy, the objective can be looked at from various perspectives:

- Net economic benefit
- Spatial equity
- Net revenue
- Total travel time
- Total travel distance

This thesis focuses on the net economic benefit as the main objective of the local authorities, as spatial equity is a concept more common in passenger movement. The last three objectives will not be discussed here since the net economic benefit calculation will be able to include the three objectives in the formulation.

To be able to formulate an objective function that counts the net economic benefit, we need to understand the economic cost of congestion. As already discussed in Chapter 2, UGM problems heavily relate to the externality cost associated with delivery activities and the most common externality discussed in the literature is congestion. The objective function should also include the policies the local authority wants to apply to improve the situation.

This thesis focuses on the pricing policies in which the policies then seek to find an optimal traffic pattern in the network. The need for pricing policies arises since the traffic market, if left to its own decisions, will operate in a sub-optimal manner. The pricing intends to alter the behaviour of road users towards a social optimum rather than a user optimum as we will discuss in the next subsections.

### 4.5.1.1 The economic cost of congestion

This section presents analysis of congestion externalities derived from traffic engineering theory (see figure 4-5).

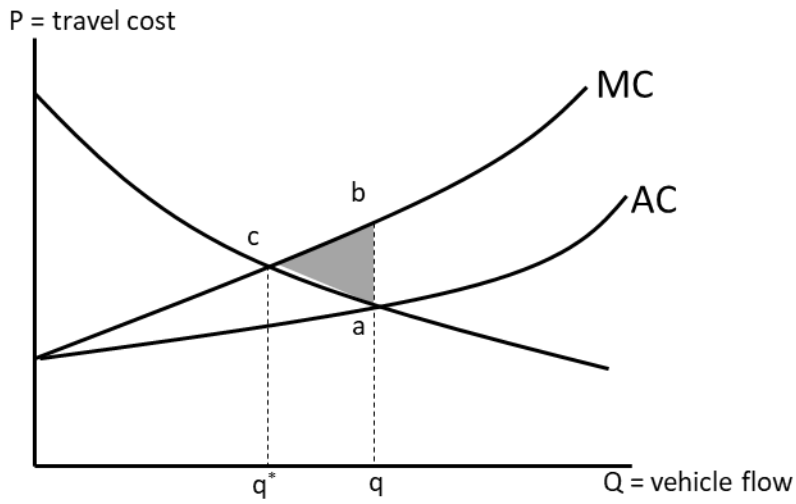



**Figure 4-5. The deadweight loss of traffic congestion (in grey shade)**

The *average cost* (AC) curve represents the average cost of trip making at the different levels of traffic flow. The curves are derived from the inverse of the speed flow curve known in traffic engineering. The speed of the vehicle transverse on the road is the function of the number of flows on the road. At low volumes of traffic, the vehicles can freely transverse the road as fast as possible constrained only by the road capacity or speed limit applied by local authorities. Yet, as the traffic flow increase, they interact with the existing traffic and this slows down the speed on the road. Broadly, faster travel in urban area means cheaper travel, and when the travel is slowing down (i.e. congestion occurs) the cost of travel also increases. Therefore, the AC curve increases as the traffic flow entering the road increases.

The MC curve represents the cost of additional traffic to an existing flow which includes the additional cost of adding extra traffic on to the road. The MC curves may in some limited sense define the costs to the society of the road users (Yang and Huang pg 48). However, any individual entering the traffic flow will only consider the average cost (AC) since he will be either unaware of, or unwilling to consider, the externality of congestion he imposes to the other road users. Or in other words, the actual traffic flows are usually represented when the demand curve equates to the AC curve (point a).

Both the AC and MC curve can also be interpreted as all costs incurred by the road users as a society. The AC curve is equivalent to the road user *individual cost* that is the additional cost incurred by the new-trips maker alone since, as argued before, the AC curve implies the road user does not consider the congestive impact of the new trips on the others. On the other hand, the MC curve relates to the *social cost* for the new trip makers and the existing road users on the traffic. Therefore, the optimal level of traffic flow is represented by the equilibrium condition at point c where the MC curve meets the demand curve. The difference between AC and MC curves at any traffic flow level, therefore, reflects the economic cost of congestion in that flow.

This can be illustrated by Figure 4-5. The optimal flow is where the MC curve is equated with the demand curve (point C). However, it is often not the case since road users are usually selfish and thus the actual flow is where the AC curve equates with the demand curve (point A). The trips flow of $q$ is excessive because the road users are only enjoying a benefit of $\overline{qa}$ while imposing the cost of $\overline{qb}$. The additional traffic flow after the optimal flow at $q^*$ can be seen to be generating cost equal to the area $\overline{qbcq^*}$ yet only enjoying benefit equal to area $\overline{qacq^*}$. A deadweight loss of area $\overline{bca}$ is apparent. A condition where the traffic flow is lower than the $q^*$ is also suboptimal since the potential of consumers' surplus gains from trip making is not fully gained.

#### 4.5.1.2 Welfare economics as outcome indicators

Given the congestion cost can be defined by the trip level differences that appear between the AC and the MC curves, the local authorities can then apply pricing policies to control the behaviour of road users so that rather than conduct selfish behavior, the policy forces road users to modify their behaviour towards optimising social welfare. Welfare economic theory takes this view by looking at the overall welfare of all road users rather than individual welfare. In the context of UGM policies, this is in line with Ogden's (1992) suggestion that the local authority is the only actor that seeks optimal policies for all actors.

The theoretical understanding and the practicality of measuring the effectiveness of transport policies through calculating social welfare are well established in the literature. The welfare measure can calculate the condition within the framework of a free competing market in which transportation activities operate. Within this framework, the benefits of applying a particular transport policy are mainly captured by the idea of the economic benefit derived from Marshallian demand curve. The economic benefit is calculated as a result of time savings. This idea is widely accepted in the transportation literature both for passenger and goods transport (see for example Sumalee, (2004); Verhoef, (1996))

Nevertheless, we aware that measuring the objective of the local authorities as the welfare gain has criticisms in the literature. Two types of criticism arise when calculating welfare as the sole objective of transport policies. The first criticism lies within the limit of welfare calculation to account the for wider impact of transport policies. For example, the welfare calculation in the literature has a tendency to focus on economic efficiency in spite of equity, i.e. the welfare evaluation has a tendency to favour high income groups (Murray and Davis, 2001). Another limitation of using welfare as the sole objective to assess transport policies is that the welfare analysis calculates the economic benefit as an aggregate demand as opposed to disaggregate demand. To be able to consider adverse impact of transport policies, the local authorities need to take into account the impact of these policies on various groups within societies, for which a disaggregated approach is needed (Bureau and Glachant, 2011).

This thesis mainly focuses on how to address optimal city logistics planning through a pricing mechanism. We seek an optimal solution to UGM activities through pricing policies since pricing is seen as an effective instrument for managing UGM. Moreover, since UGM is industry-driven, meaning the activities are most likely to be sensitive to the pricing instrument, pricing can be seen as a comprehensive way to deal with UGM activities (the discussion of the effectiveness of pricing towards regulating UGM activities can be seen on Holguín-Veras, (2010)). However, previous empirical studies reveal pricing can help to alter the behaviour of retailers towards the social objective rather than individual objective (Wang and Zhang, 2017).

Since the commercial vehicle is seen as contributing to congestion, in particular, in dense city centre areas, pricing offers a potential handle to the local authorities to manage their movement. The research regarding road pricing on passenger vehicle movement is enormous (see, for example, de Palma and Lindsey (2011) for a road pricing review). However, studies about road pricing that specifically investigate the UGM activities are scarce in the literature.

The pricing reflects the difference between the marginal cost of making the trips and the average cost. By forcing the individual travellers to make the less selfish choice, the pricing policy generates economic benefits.Mathematically, the economic benefit can be formulated as the difference between *user benefit (UB)* and *total social cost (SC)*.

$$Economic\ Benefit\ (EB) = User\ benefit\ (UB) - Social\ cost\ (SC)$$

This can be illustrated by Figure 4-7 as follows:

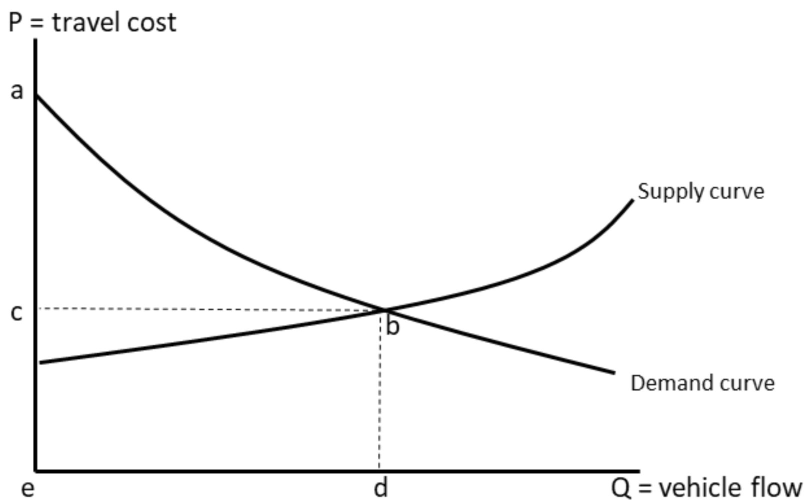



**Figure 4-6. Graphical illustration of the definition of economic benefit**

The user benefit is the area under the demand curve, from zero trips until the equilibrium point at point $b$ (area $\overline{abdea}$). The social cost in other the hand is the area $\overline{cbde}$ . Therefore the economic benefit is the area $\overline{abc}$.

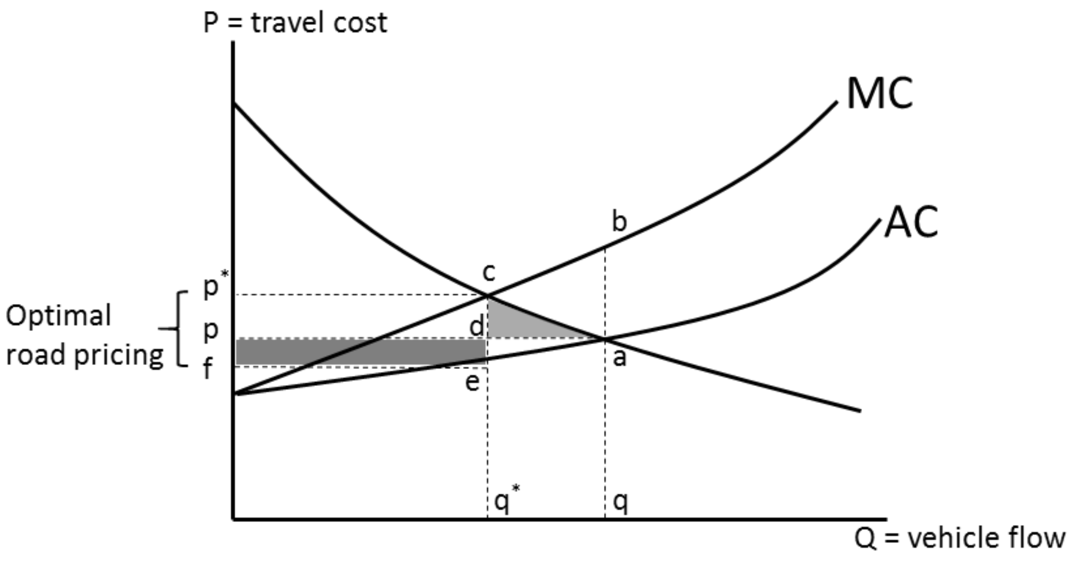



**Figure 4-7. Graphical illustration of the gain in terms of welfare gain**

Now we discuss the concept of the welfare gain achieved through pricing policies which can be illustrated in Figure 4-7. The welfare gain is achieved by charging the road users optimal road pricing that is the toll which equates the vehicle flow demand with the MC curve $(q^*)$. The area of $\overline{caqq^*}$ is the difference between the EB of the no toll and toll cases (negative value), while the change in social cost is represented by $\overline{paqq^*ef}$ (positive value). Thus the welfare gain equates to the difference between $\overline{pdef}$ area and $\overline{dca}$ area. Providing the relevant demand curve has a degree of elasticity, the welfare gain must be positive and thus in general the road pricing should increase the overall social welfare of the travellers, providing that the pricing follows the *marginal cost*.

Welfare gain is maximised when the price is equated to marginal cost. What marginal cost pricing does is to make the transport service provide up to the point where the benefit for the marginal unit equates to the cost of providing that unit. Welfare economics is looked upon as a method of resource allocation, in this case, the road space allocation for private and commercial vehicles. The control variable, i.e. the toll applied to the road users, thus forces their behaviour to maximise the welfare gain rather than selfishly improving their personal welfare.

The theory for optimal road pricing based on marginal pricing has been the subject of many studies over the years (Verhoef, 1996). Previous studies result in a strong base theory, i.e. the theory of first-best tolling (Yang and Huang, 1998) which requires tolling on every link of a network. However, it is understood that it is practically infeasible and politically very difficult to impose road pricing on every link, and thus the problem of solving the optimal toll for a particular link or a set of links arises. The problem deals with questions such as which links to apply the pricing to and how much the local authorities need to charge to optimise the objective function set by them. The problem refers to the second-best tolling problem in the literature.

### 4.5.2 Lower level problem

The key and problematic aspect of designing optimal policies to manage UGM is to include road users' responses to city logistics policies imposed. Naturally, anyone who wishes to capture the real benefit of implementing such policies will need to account for traveller responses (by changing routes, destinations, or deciding not to travel) before calculating the benefit of the scheme. Obviously, the model should be able to accommodate these responses. In the bilevel programming formulation, these responses can be incorporated into the lower level problem.

This thesis adopts one of the most famous modelling philosophies and rules for representing travellers' behaviour on a road transport network, namely the concept of user equilibrium (UE) by Wardrop (1952). The UE concept will be the cornerstone of the lower level of our bilevel formulation.

The next subsections define and formulate the concept of UE equilibrium which needs to be incorporated into the lower level problem. Further, we also extend the UE formulation to be able to account for UGM activities in the model as discussed before.

#### 4.5.2.1 User equilibrium condition

User equilibrium (UE) is a traffic assignment role where "*the travellers cannot decrease their travel cost by unilaterally changing routes"* (Sheffi, 1985, p. 15). The term was coined in transport studies first by Wardrop (1952) hence the UE condition is also known as the Wardrop equilibrium. The UE gives the analyst a system in which all the components of an urban network, namely OD demand, road characteristics, and link performance are analysed simultaneously rather than separately allowing the effect of congestion in the network to be analysed. The key question of the user equilibrium condition here is how the demand is distributed among the possible paths connecting OD pairs in the network. If all of them just take a particular path (presumably the shortest path), congestion will occur and increase the travel time on the path. Some of this traffic then maybe divert to the other path, yet the other path may get congested too and so on.

UE in this thesis refers to deterministic user equilibrium (DUE) as opposed to stochastic user equilibrium (SUE). The difference between the DUE and SUE depends on how the road user *perceived* the travel time for each route. DUE assumes that the travellers have perfect knowledge of the network and each path between their origin and destination. It is also assumed that the travellers always make a correct decision regarding route choice. These two assumptions are widely regarded as a very strong assumption in the literature. One of the alternatives to relax these assumptions is through SUE in which the perceived travel time among routes is assumed to be a random value for the travellers. However, despite the strong assumption, DUE is still widely regarded as playing an important role regarding route choice. The concept has been used to develop modelling software tools such as SATURN (Van Vliet et al., 1986) which has been used to guide real-world problems.

The determination of the UE condition involves a solution that accounts for demand/performance problems. The traffic demand in the network depends on the route choice decisions, while this decision depends on the performance of the links. A performance function is defined individually for each link relating each travel time with traffic flow. This interaction between demand and performance functions is why the system nature of the analysis is needed to address the problem. No links, paths, and traffic demand between an OD pair can be analysed individually; instead they need to be analysed together to find the equilibrium state. The equilibrium state defines what we presume to be the behaviour of the decision maker or, in other words, a set of rules which the road users will follow to determine their route choices. This rule can be seen as the procedure to specify the traffic demand over the possible paths.

**Mathematical formulation for the UE condition**

To be useful in an operational manner, the UE condition needs to be mathematically formulated. First, we will discuss the notation needed to mathematically describe the UE condition.

The traffic network is represented by the Graph function of $G\ (N, A)$ where $N$ is a set of nodes and $A$ is the set of links. A subset of nodes is origin and destination nodes $r, s\ \in N$ where the OD pair is indexed by $w \in W$. Each OD pair is connected by a set of paths $(P_w)$. A path $p$ consists of several links connected to the OD pair. $f_p$ is the path flow representing the total flow using a particular path. The path flow can be seen as the additive of the links flow $(v_a\ )$ in which the particular links are part of the path. Mathematically this can be written as:

$$f_p \ = \sum_a \delta_p^a \, v_a \qquad \text{4-18}$$

where $\delta_p^a$ is a definitional variable that will take a value of 1 if link a is used by path $p$ otherwise 0.

The cost of travelling on the link $a$ is defined as $c_a$ where the travel time on the link $a$ is defined as $t_a(v_a)$. Travel time on link $a$ is a function of the number of vehicles using the link $a$. Like the link flow and path flow, under the assumption of additive path cost, the path cost can also be defined as:

$$C_p \ = \sum_a \delta_p^a \, c_a \qquad \text{4-19}$$

given the definition of path cost, $\mu_w$ represents the minimum path cost connected OD pair w. Note that the link cost may be a combination of travel time and other costs (e.g. toll).

Following the notation and definition described above, the user equilibrium condition for fixed demand can then be mathematically described as a feasible assignment (i.e. an allocation to all path flow) such that:

$$f_p > 0 \quad if \quad C_p = \ \mu_w \ \forall\, p, w \qquad \text{4-20}$$

$$f_p = 0 \quad if \ \ C_p > \ \mu_w \ \forall\, p, w \qquad \text{4-21}$$

Equation 4-20 means that the trips on a path $p$ are higher than zero if the path travel time is equal to the minimum travel time otherwise zero. If the trips using the path $p$ is equal to zero, the cost of using the particular path is greater than the minimum cost. These conditions ensure that at the end of the traffic assignment the travel time across all chosen paths is equal to the minimum travel time.

To accommodate the behaviour rather than route choice into the model, the user equilibrium can also be stated in the case of variable demand. Variable demand means the demand for each OD varies according to the traffic conditions between OD. The user equilibrium condition for variable demand can be described as follows:

$$f_p > 0 \quad if \quad C_p = \mu_w \; \forall \, p, w \tag{4-22}$$

$$f_p = 0 \quad if \quad C_p = \mu_w \; \forall \, p, w \tag{4-23}$$

$$d_w > 0 \; if \; d_w^{-1}(D_w) = \mu_w \tag{4-24}$$

$$d_w > 0 \; if \; d_w^{-1}(D_w) < \mu_w \tag{4-25}$$

Observe that the first two equations are the same as the UE condition with a fixed demand condition. The last two equations are added to account for the demand variability. These equations indicate the demand should be greater than zero if the travel cost between the OD pair is equal to the minimal travel cost. If the demand is equal to zero it means that the OD travel time may be too high to induce any OD flow.

#### 4.5.2.2 Formulating traffic assignment with user equilibrium condition

User equilibrium traffic assignment has been researched extensively in the past 30 years. The research leads to several ways to mathematically define the user equilibrium condition. In this section we review two of them: the minimisation problem and variational inequality. The minimisation problem historically is the first method to mathematically define the UE condition. However, the formulation places some restriction on the assumption; e.g. the Jacobian matrix of the link cost function is symmetrical and positive semidefinite. A particular form of link cost that meets these two conditions is the separable link cost. A link cost function is considered separable if the cost on the link only depends on the flow in that link alone. This is where the variational inequality plays an important role in describing the UE condition where the Jacobian matrix of the cost function is asymmetric (Dafermos, 1972).

In the next subsections, we introduce the concept of traffic UE as a minimisation problem and variational inequality. Note that in the next subsections we use a travel time function as the general travel cost function. One can easily convert the travel time into the cost unit by multiplying the travel time with the value of time (VOT). The difference between travel time and general travel cost will be important when we address the multiuser class case discussed in Chapter 7.

**Traffic User Equilibrium as a minimisation problem**

Mathematically the UE condition can be transformed into a minimisation problem. This method was first introduced by Beckmann (1956), hence it is also known as the Beckmann transformation. The UE problem is to find a solution where the links flow $v_a$ satisfies the UE condition when all the OD demand $D_w$ has been appropriately assign.

Using the notation introduced in Section 8.1, the UE problem for fixed demand can be solved by solving the minimisation problem below:

$$\min Z\,(v_a) = \sum_a \int_0^{v_a} t_a(\omega)\ d\omega \qquad \text{4-26}$$

$$s.t. \qquad \sum_{p\,\in\,P_w} f_p = D_w \ \forall\, w \qquad \text{4-27}$$

$$f_{p_w} \geq 0 \ \forall\, w \qquad \text{4-28}$$

$$v_a = \sum_{p_w} \delta_{p_w}^{a}\ f_{p_w} \qquad \text{4-29}$$

In this formulation, the objective function is the integral of the link performance function. It does not have any behaviour or economic interpretation and should be viewed strictly as a mathematical formulation to describe the UE condition. Equation 4-15-b implies flow conservation constraint in which the total traffic for each OD pair should be equal to the summation of the flow for all paths connecting the OD pair. It is noted that the objective function is formulated in terms of link flow, while the flow conservation constraint is formulated as path flow. It is where the definitional constraint on equation 4-15-d enters the formulation. The definitional constraint allows the network structure to enter the formulation through the path-link incidence relationship ($\delta_p^a$). Equation 4-15-c is the non-negativity constraint to ensure that the results of the mathematical program have a physical meaning.

It is important to note that this UE formulation assumes that the travel time on a given link is a function of the flow in the link only and not of the flow in any other link in the network. Typically, the travel time is assumed to be continuous and strictly increasing.

In this thesis, we follow a standard BPR function in which the travel time on the link is associated with the total flow on the link.

$$t_a = t_0 \ast \left(1 + \pi \ast \frac{v_a}{k_a}\right)^{\alpha} \qquad \text{4-30}$$

A typical BPR link performance can be depicted by Figure 4-8 below:

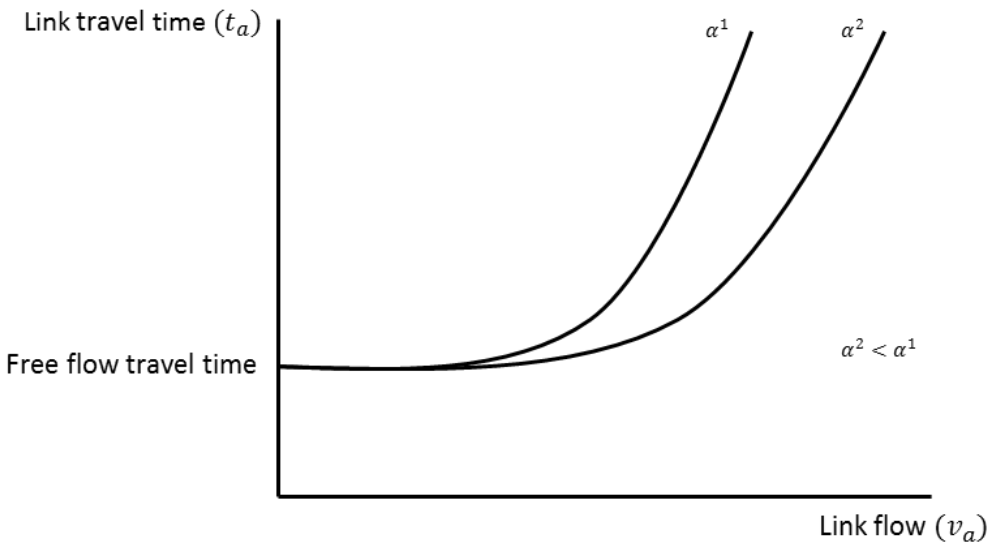



**Figure 4-8. A typical link performance function**

Two constants $\pi, \propto$ in the BPR function (Equation 4-30) define the characteristics of the roads. $\propto$ represents the road geometry with a wider geometry corresponding to a smaller $\propto$ value. It indicates the road with smaller $\propto$ value will be congested more slowly.

Another important point in this thesis is to consider UE condition for a variable demand case. As the case for a standard UE problem, the UE condition for a variable demand problem can be mathematically written as a minimisation problem, as follows:

$$min\, z\left(v_a, D_w\right) = \sum_a \int_0^{v_a} ta\,(\omega)\, d\omega - \sum_w \int_0^{D_w} d_w^{-1}(\omega)\, d\omega \qquad \text{4-31}$$

$s.t.$

$$\sum_{p \in P_w} f_p = D_w \qquad \text{4-32}$$

$$v_a = \delta_p^a\, f_p \qquad \text{4-33}$$

$$D_w \geq 0 \qquad \text{4-34}$$

$$\sum_s D_{rs}^{i=1} = D_r \qquad \text{4-35}$$

The two first constraints (equations 4-32 and 4-33) for the variable demand problem are the same as the original UE formulation. The additional constraint of 4-34 reflects the non-negativity condition of the demand and highlights the fact that $D_w$ is a variable in this formulation. Then, constraint 4-35 reflects the condition in which the total demand originating from the origin zone is assumed to be fixed.

### Traffic UE assignment as a variational inequality problem

Another useful way to define the UE traffic assignment is through variational inequality (VI) (Dafermos, 1980; Smith, 1979). Although the standard formulation for the UE condition through minimisation transformation is satisfactory for many applications, it is incapable of dealing with a situation in which the function of cost travel time does not only depend on the flow of the link, but also depends on the traffic volume in the network. Another example arises when a delay at an unsignalised intersection counts in the travel cost function, and the delay is the function of traffic on all intersecting links. By describing UE traffic as VI, it lessens the strict condition on travel time function by allowing the asymmetric travel cost function.

In general, UE condition for a fixed demand problem such as a VI problem can be stated as: a links load pattern is a traffic user equilibrium satisfying condition 4-20 and 4-21, if and only if it is satisfying the VI condition:

$$\sum_{a \in A} t(v_a)\,(v_a^* - v_a) \le 0, \qquad \forall\, v_a \in \Omega \qquad \text{4-36}$$

Ω is a set of possible link flows and consists of a set of linear constraints following the set of constraints depicted by equation 4-32 until Equation 4-35. Thus, Ω is a bounded polyhedron.

The VI formulation can also be stated in vector form. Let $\boldsymbol{v}^*$ and $\boldsymbol{d}^*$ be vectors with $a$ dimension with component $\begin{bmatrix} v_1 \\ \vdots \\ v_a \end{bmatrix}$ and $w$ dimension with component $\begin{bmatrix} d_1 \\ \vdots \\ d_w \end{bmatrix}$ The link flow $va^*$ gives the UE condition if and only if

$$\boldsymbol{t}(\boldsymbol{v}^*)\,.\,(\boldsymbol{v}^* - \boldsymbol{v}) \le 0 \quad \forall\ \boldsymbol{v} \in \Omega \qquad \text{4-37}$$

The VI condition above can be transformed back into the convex minimisation problem in the case that the travel time functions can be continuously differentiable on Ω and its Jacobian matrix:

$$\nabla \boldsymbol{t}(\boldsymbol{v}) = \begin{pmatrix} \frac{\partial t_{a_1}}{\partial v_{a_1}} & \cdots & \frac{\partial t_{a_1}}{\partial v_{a_n}} \\ \vdots & \ddots & \vdots \\ \frac{\partial t_{a_n}}{\partial v_{a_1}} & \cdots & \frac{\partial t_{a_n}}{\partial v_{a_n}} \end{pmatrix},$$

is symmetric and positive semidefinite. A particular form of travel time function that makes these conditions available is the separable travel time functions whereby travel time on the link is only the function of the link flow and not the link flow vector. However, these conditions are very restrictive and do not hold true in real-world conditions. Therefore, the VI is important in the UE problem literature since it can solve the problem without imposing the strict conditions mentioned above.

### 4.5.3 Solution technique to solve the bilevel programming problem

We choose a cutting constraint algorithm (CCA) as the solution technique to solve the bilevel programming problem. Bazaraa et al. (2006) refer to the algorithm as a cutting plane algorithm, and the others (for example see Migdalas, (1995)) refer to it as the Benders scheme. As the name suggests, the algorithm uses the extreme points to cut away part of the feasible region of the optimisation that is no longer feasible in each iteration.

As discussed in Section 4.5.2.2, the variational inequality problem to describe the UE condition for fixed demand can be written as:

$$\boldsymbol{t}(\boldsymbol{v}^{*},\tau\,)\,.\,(\boldsymbol{v}^{*}-\boldsymbol{v}\,)\;\leq 0 \quad \forall\; \boldsymbol{v}\;\in\Omega \qquad \text{4-38}$$

Based on a theorem by Bazaraa et al. (2006), the $\boldsymbol{v} \in \Omega$ can be defined as a convex combination of a set of extreme points. Therefore, the VI in Equation 4-38 above can be rewritten as the function of extreme points of $\Omega$.

$$\boldsymbol{t}(\boldsymbol{v}^{*},\tau)\,.\,(\boldsymbol{v}^{*}-\boldsymbol{u^{e}}\,)\;\leq 0 \quad \forall\; \boldsymbol{u^{e}}\;\in \mathrm{E} \qquad \text{4-39}$$

where, $\boldsymbol{u^{e}}$ is the vector of extreme link flow and $\mathrm{E}$ is the set of extreme points of $\Omega$. And thus, the bilevel problem can be defined as:

$$\min_{\boldsymbol{v},\tau} Z\,(\boldsymbol{v},\tau) \qquad \text{4-40}$$

$$s.t$$

$$\boldsymbol{v}\in\Omega$$

$$\boldsymbol{t}(\boldsymbol{v}^{*},\tau)\,.\,(\boldsymbol{v}^{*}-\boldsymbol{u^{e}}\,)\;\leq 0 \quad \forall\; \boldsymbol{u^{e}}\;\in \mathrm{E}$$

The problem formulation by Equation 4-41 is proposed by Lawphongpanich and Hearn (2004) and we refer to it as the master problem. The key to solving the master problem is by generating the necessary extreme points from a given $\boldsymbol{v}$ from the master problem. The extreme points are obtained by including the most rapid descent direction to achieve the UE condition, which is by solving the subproblem:

$$\min_{v,\tau} \boldsymbol{t}\,(\boldsymbol{v},\tau)\,.\,\boldsymbol{u} \qquad \text{4-41}$$

$$s.t$$

$$\boldsymbol{u} \in \Omega$$

The subproblem is identical to the simplicial decomposition algorithm found in the Frank-wolve algorithm in which the algorithm decomposes the problem into a number of separated shortest path problem. Or in other words, the sub-problem is to carry an All or Nothing (AON) assignment for each OD movement in a given condition set by the master problem. The CCA for the problem can then be summarised as follows:

Step 0: set *iter* = 0; initialise the problem by defining the extreme aggregate flow $[\boldsymbol{v}\,]^{iter}$ following the shortest path for each user class *i* on each OD pair. Include, the $[\boldsymbol{v}\,]^{l}$ into Ω.

Step 1: *iter* = *iter* + 1*;* solve the upper-level program with all extreme points in Ω and obtain the solution vector of $[\boldsymbol{v}^{*}]$; then set $[\boldsymbol{v}^{*}]$ for upper level.

Step 2: Solve the sub-problem with $[\boldsymbol{v}^{*}]$ and then obtain new extreme point $[\boldsymbol{v}\,]^{iter}$

Step 3: termination check: if $\boldsymbol{t}\,(\boldsymbol{v}^{*},\tau)^{\boldsymbol{T}}(\boldsymbol{v}^{*} - \boldsymbol{u}^{\boldsymbol{e}}) \leq 0$; terminate and $[\boldsymbol{v}^{*}]$ is the solution, otherwise include $[\boldsymbol{v}\,]^{iter}$ into Ω and return to step 1.

## 4.6 Model application

Given the model formulation, the final step of this thesis is to test the model formulation through the model application. This thesis focuses on road pricing policy simulation. In the literature, there are two problems related to toll determinations on the links. The first-best toll pricing problem assumes that every link in the network can be tolled by the marginal cost pricing. These tolls ensure that the tolls give optimal welfare to overall trips on the network. However, for a political or technical reason, it is almost impossible to apply the toll on every link on the network, and therefore the second-best toll pricing problem emerges. The second-best toll problem refers to the problem to find possible tolls that give optimal welfare when applied to the predetermined links. Because the tolls given by this scenario do not generally give the maximum benefit possible, they are referred to as “second-best” tolls.

This thesis focuses on the second-best toll. By comparing the absolute value of welfare for a do-nothing scenario and do-something scenario, we can yield the welfare gain value. The do-nothing scenario is the current condition in which there are no toll scenarios and no city logistics measures implemented on the network, whilst the do-something scenario is the condition where policies are implemented on the network. The detail of the model application in the study area can be seen in Chapter 8.

## 4.7 Chapter summary

This chapter presents the actual process of the research and the methods used to fulfil the research objectives. Generally, the process of the research can be staged into four stages: preliminary studies, data collection process, modelling framework and estimation process, and model application.

In the preliminary stage, the author conducted activities to lay the foundation for this research. These activities included defining the research questions, exploring the literature on UGM modelling attempts and the corresponding methods, and designing the modelling framework. Data collection is the main activity in the second phase. The data collection process involves primary and secondary data. The primary data is collected by interviewing independent retailers using a retrospective questionnaire. The secondary data is collected by visiting the Indonesian statistics office and collecting the necessary data.

Table 4-1. Summary of methods used for each modelling step

| Stage | Model | Methods |
|---|---|---|
| Demand modelling | Generation model | OLS Regression |
| | Distribution model<br>- Supplier location choice<br>- Transport service choice | Discrete choice model |
| Bilevel optimisation problem | Upper level problem | Welfare calculation |
| | Lower level problem | Traffic user equilibrium formulation |
| | Solution technique for bi level problem | Cutting constraint algorithm |

The next step of this study involves the modelling formulation and specification. It is the main work of this thesis. The activities include modelling specification, estimation and formulation. The survey from the second stage is used to estimate the demand model.

Subsequently, the UE traffic assignment for independent retailer activities, and the bilevel programming modelling to include the local authority objective are formulated.

The results provided in the modelling estimation are then used to perform the last activities for this study: testing a few city logistics policies. The aim is to discuss the optimal city logistics measures that can be applied by local authorities. Finally, the thesis is closed by a discussion on policy implications, the limitations of the study, and the possible future works.

This chapter also explains the modelling framework and all models, and the methods included in the framework. A summary of the models and the corresponding methods is given in Table 4-1.

The next chapters will discuss the data collection process, the demand modelling specification and estimation process (Chapter 6), as well as the bilevel programming formulation (Chapter 7) and estimation of the model in a real-world problem (Chapter 8).

# Chapter 5 Data collection and descriptive analysis

This chapter focuses on describing the data collection process and the descriptive analysis of the data. This chapter begins with Section 5.1. describing the study area. Bandung city, in Indonesia, is chosen to be the study area for the thesis. One particular reason Bandung is chosen to be the study area is that independent retailers are prevalent in the city. Therefore, in this chapter, the current condition of UGM activities in Bandung city is highlighted.

Section 5.2. describes the data collection process. The data collection process includes the questionnaire design and carrying out the data collection itself. The response rate and the challenges arising in the data collection are discussed in this section. Lastly, this chapter presents a descriptive analysis of the data collected in Section 5.3.

## 5.1 Bandung city– context of the study area

Metropolitan Bandung is the capital of West Java Province, Indonesia. It is located approximately 180 km south of Jakarta the capital cities in Indonesia (see Figure 5-1). Its elevation is 768m above sea level and it is surrounded by volcanic mountains. Bandung has the fourth highest population within the country and possesses vibrant economic activities. According to the Bandung statistics office, the most important activities in Bandung are trading and services comprising almost 30% of the city's economy. Another important economic activity is clothing manufacturing. These economic activities imply important efficient UGM activities.


(Source: worldguides.com)

**Figure 5-1. Bandung location**

Regarding the city population, according to the last census in 2015, Bandung has over 2.5 million inhabitants and possesses the third largest economy on Java Island. Accounting for the agglomeration that includes satellite cities such as Cimahi, Lembang, and Soreang, the inhabitants of Bandung Greater Area has reached 8 million people and is expected to reach 10 million people in 2025.

Bandung is historically the heart of activities in the agglomeration and the most important area is the city centre located at the heart of the city. The fact that the city is surrounded by volcanic mountains particularly on the north and south border of the city, has constrained urban growth to the eastern and western areas of the city; currently the city is approximately 8 km long and 24 km wide (see Figure 5-2)

The city centre is a compact area bounded by major roads and divided into 11 wards/districts (see Figure 5-3). The city centre area is delimited to the south by BKR street, to the west by Jatmika street, to the north by Kebon Jati street and to the east by Moch Ramdan street. As the city was expanded by the Dutch in the 18th century, the roads in the centre of the city are very narrow. Therefore, to improve the traffic conditions, since 2005, the local authority has applied traffic management policies by making most of the main roads in the city centre into a one-way street system.

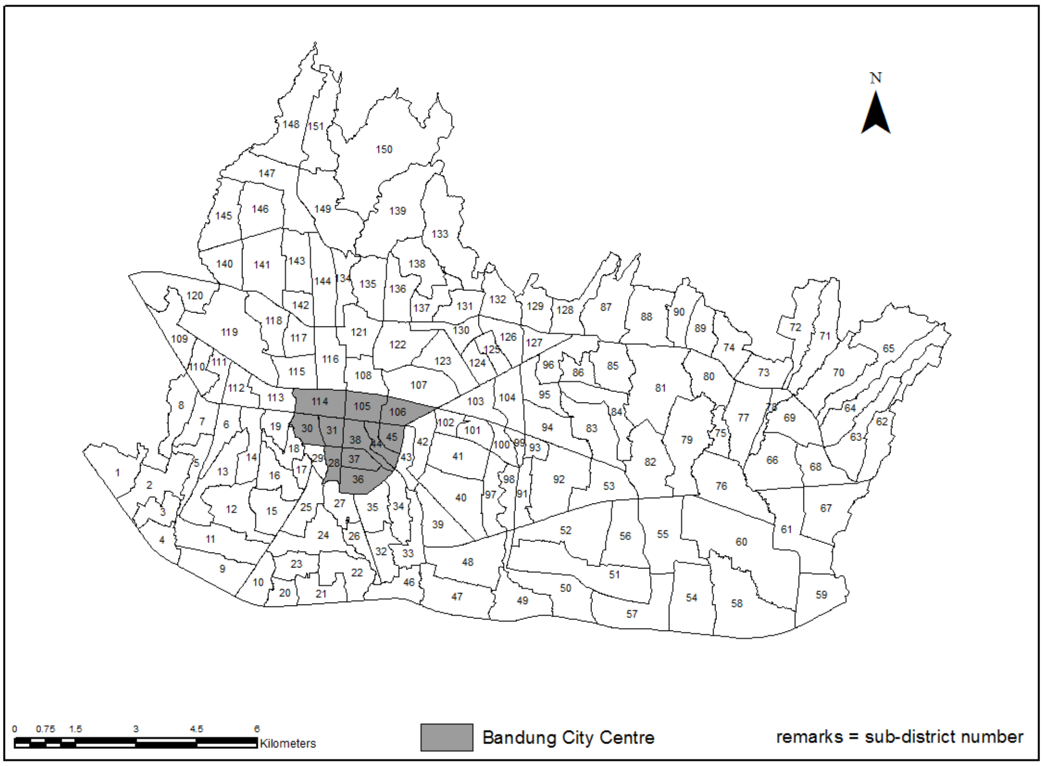



**Figure 5-2. Bandung city wards (the city centre is highlighted in grey)**

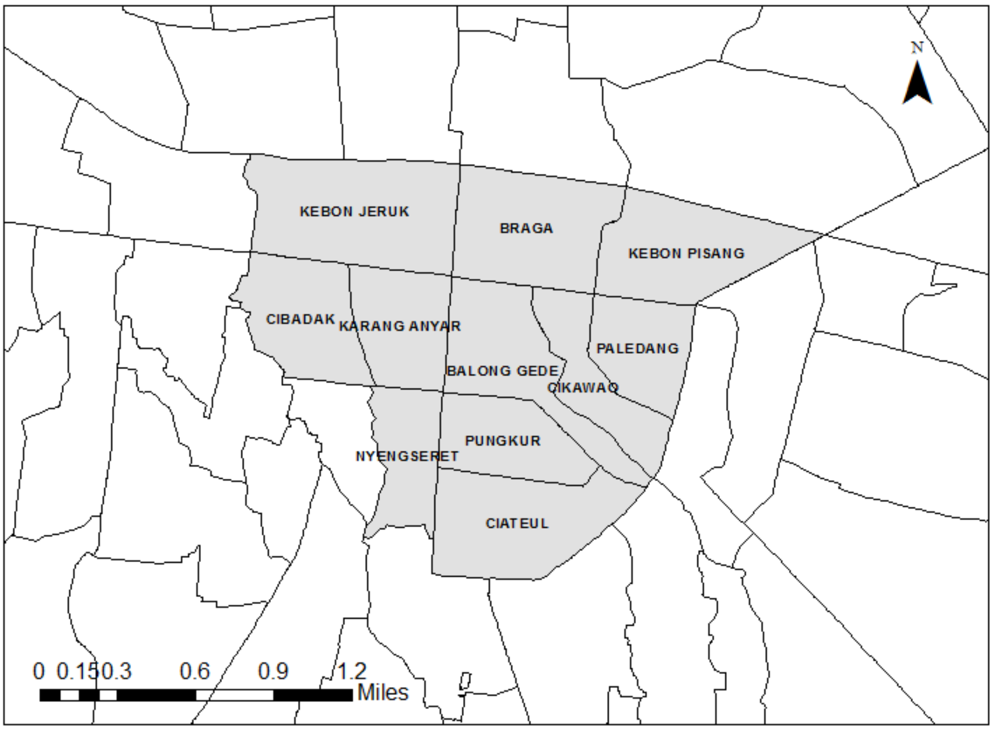



**Figure 5-3. Bandung city centre map**

The city centre is still the most important area in the agglomeration. Besides being the location of the provincial government headquarters and the main train station, the BCC area is the home to a significant number of independent retailers and major traditional markets. BCC has a mixed land use with both commercial and residential areas. Government offices and headquarter offices of major enterprises are located mainly in the central area of BCC, whereas most business establishments are located in the north-west where the biggest traditional market in Bandung, Pasar Baru (meaning “new market”), is also located. In contrast, the south-east area of BCC is mainly residential. The land use pattern thus makes the BCC area very crowded and the trip demands for both passenger and goods vehicles are very high. See Figure 5-4 for Bandung city centre land use.

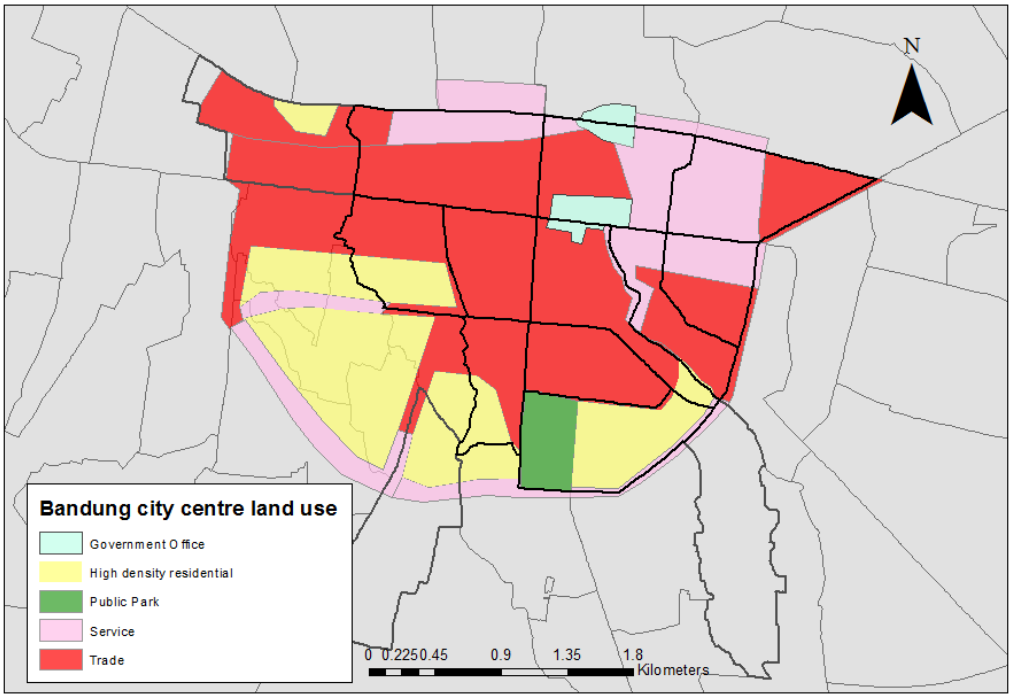



**Figure 5-4. Bandung city centre land use**

### 5.1.1 Goods distribution and the role of independent retailers

Cities in the world are different, and so too are the way goods are transported within cities. In general, urban goods transport is shaped by local economic, cultural and geographic characteristics. In this sense, a concept which has proved useful in cities with developed economies does not necessarily work in cities in developing countries. The reason is that there is a significant difference in the supply chain between cities in a developed and a developing country.

In a typical developed country, the share of private and common carriers tend to be equal (Alho and de Abreu e Silva, 2015). In contrast, in developing countries, private carriers tend to be dominant. This is reflected in the case of Mexico City, in Mexico, and New Delhi, in India. Their urban freight distribution market is not well developed and part of the distribution is done by the informal sector often using non-motorised transport (Dablanc, 2009).

In the cities in developing countries, massive UGM activities exist. These activities can be categorised into four major activities:

- Independent retailing: includes informal sectors, and local convenience store. They usually sell essential daily items (e.g. household items, dairy products, fresh foods, etc.). This sector can represent up to 40% of daily deliveries in cities. The suppliers are diverse, with a predominant number using their own vehicles.

- Chain retailing: is more common in cities in developed countries like northern America, and western Europe. The deliveries are more efficient than for independent retailing with a larger share of consolidated shipments, and better loaded vehicles.
- Food markets: are particularly important for developing countries since the distribution of fresh products represents the daily demand of people living in the cities. Current practices in developing countries have extremely diverse modes including bicycles, hand pushed charts, and two-wheeler powered charts.
- Parcel distributions are one of the fastest growing transport businesses in developing cities, both in developed and developing cities. With the massive introduction to the internet, many people living in the cities now prefer to do many activities such as: shopping for groceries and ordering meals using app-based services (e.g. Uber eats, or in the case of Indonesia, Go-food).

This thesis focuses on independent retailers particularly local convenience stores. Bandung, like Mexico City and New Delhi, is a typical city in developing countries in that independent retailers are prevalent. In fact, though the development of modern retail is progressing, the majority of retailers in the cities are still independent retailers (see Figure 5-5). Bandung city centre (BCC) is the densest in terms of independent retailers with a total of 9909 retailers residing in the BCC area (BPS, 2015).


(Source: BPS Indonesia; PODES survey)

**Figure 5-5. Total number of chain retailer outlets vs independent retailer shops in Bandung**

Restocking activities by independent retailers are often seen as less effective compared to chain retailers. The inefficiency of the restocking activities can be especially important in the case of independent operations. Previous research in

Medan, another city in Indonesia, reflects a very low load factor. For retailers who have less than two employees, the average factor for independent vans is as low as 29% (Kato and Sato, 2006).

The inefficiency also reflects on the number of restocking trips conducted within a week. Alho and de Abreu e Silva (2015) reported that the average number of deliveries for small retailers in Lisbon is 8 deliveries a week. The biggest contributor is the establishment that sells ready to eat food. In Indonesia cotext, a previous study reveals that  the average number of trips conducted by a small independent retailer is up to 2,5 trips per week (Kato and Sato, 2006). The reason why the number is quite high can be related to the limited storage, and thus a preference to restock shops based on “just in time” demand. Another reason is the limited funds that independent retailers possess. The retailers are usually small businesses with limited funds, hence they cannot buy a large amount of goods in one way and thus the number of restocking trips increases.

Regarding the mode for restocking activities, it is not common to use non-motorised transport to transport goods in Bandung. The reason is due to a ban on all non-motorised transport use on roads in Bandung by the local authorities back in 2002. As a replacement, people who cannot afford a delivery van to deliver goods use a two-wheeler vehicle to transport goods. Sometimes they even buy a modified two-wheeler that is specifically designed to carry goods (see Figure 5-6). In Medan, Indonesia, a cordon survey showed that motorbikes had a 20% freight transport modal share during the morning peak hour (Kato & Sato, 2006).

(a) Modified two-wheeler (b) Delivery van

(Sources: google images)

**Figure 5-6. Typical delivery vehicles in Bandung**

### 5.1.2 The significance of traditional markets

As independent retailers are the dominant type of retailer in Bandung, it is important to highlight the typical supply chain for distributing goods to the city. In this case, traditional markets shape the supply chain. In the Bandung context, a total of 37 traditional markets in the area exist and typically serve different parts of the city (see Figure 5-7).

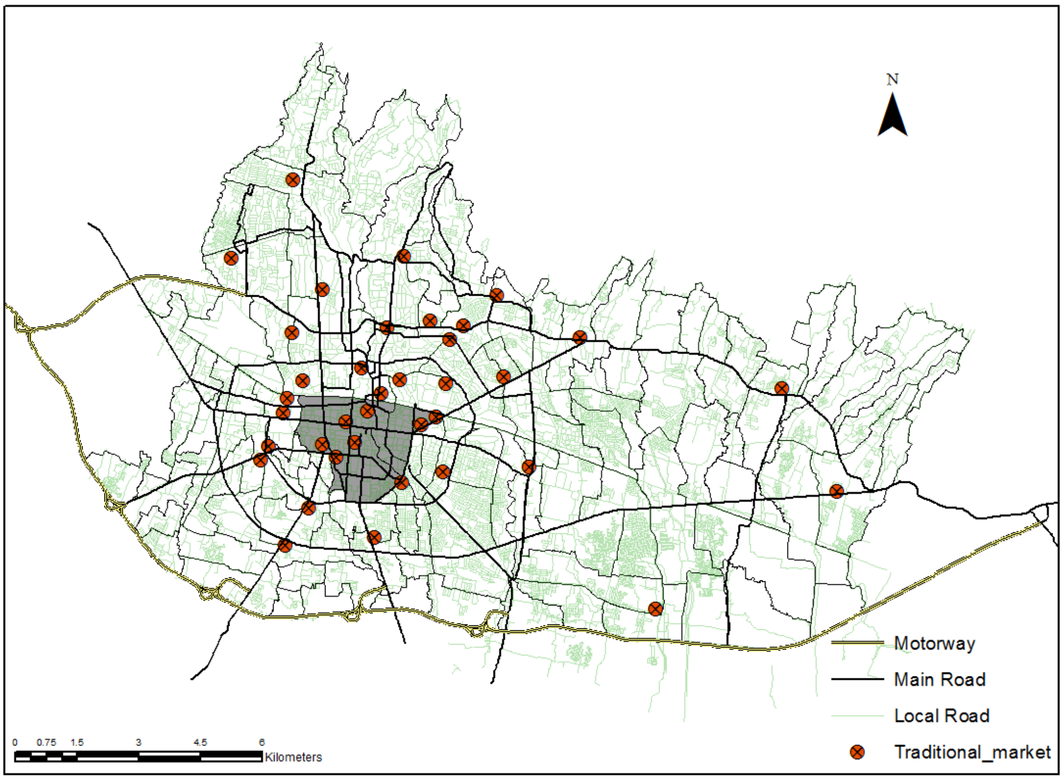



**Figure 5-7. The location of major traditional markets in Bandung**

The role of traditional markets in Bandung is more or less the same as typical traditional markets in other developing countries (see discussion in section 2.5.1). Nonetheless, there is no research which specifically addresses goods distribution in Bandung. Instead we gain insight from a study conducted in Jakarta to address the role of traditional markets in the supply chain as the context may be similar.

A study by Saragih et al. (2015) shows that there are at least 165 traditional markets in Jakarta with two major traditional markets: Kramat Jati and Cipinang. The two markets are located on the outskirts of the cities and act as hubs/wholesalers to the other markets. These two markets play a significant role in food distribution: 61.8% of food consumption in Jakarta or about 1,524 tons per day are served to the population through these two markets.

In the case of Bandung, there are also two major traditional markets acting as wholesalers to other markets: Caringin and Gedebage markets. The two markets are located on the outskirts of the city near the main motorway in the south. The location and the proximity to the highway make these two markets very accessible for receiving goods from outside the city. The other markets in the cities then, as is the case in Jakarta, stand for the next distribution centre serving local independent retailers in their respective locations.

## 5.2 Data Collection

### 5.2.1 Survey questionnaire design

In this study, a specially designed questionnaire is used to determine the retrospective choices made by independent retailers in terms of supplier location decisions as well as the method of transporting goods procured. The objective of the survey is to get data relating to the attributes that are perceived to be significant for restocking decisions.

The questionnaire utilises open questions to ask the supplier's location and name; travel time between shop location and suppliers; direct transport cost; and frequency of restocking activities. Multiple choice options are used to get data such as the type of goods that are sold in the shop; the demand for goods per week, and parking/loading bay availability and activities.

The questionnaire comprises five sections (See Appendix A for the English version of the questionnaire, though the actual form used for the survey was translated into Bahasa). Section A contains compulsory questions to gather basic independent retailer information such as the address of the independent retailer; the number of employees; the total area of the shop; and vehicle ownership. Section B collects data about the goods that are sold by retailers. This section also collects the characteristics of the suppliers including their locations. Section C asks how often and when restocking activities are undertaken by independent retailers. Data on transport costs for each restocking activity are also gathered in this section. Section D collects data about parking and loading and unloading activities, and section E is optional about the identity of the owner or the employee responding to the questionnaire. In Sections A and B we collect the address of the retailers and the location of suppliers and use this information to estimate the crow-fly distance using a GIS map application. These distances were then used to estimate the average distance between retailers and suppliers from/to each traffic zone in the subsequent demand modelling stage.

### 5.2.2 Carrying out the data collection process

The main data collection process was carried out between November and December 2016. We used face-to-face interview and a paper-based questionnaire to conduct the interviews. The population of the survey was all independent retailers residing in Bandung city centre. The sample for the research was chosen using stratified random sampling based on the location of the retailers (see Table 5-1).

To help to conduct the survey, we gathered surveyors from the local university. In total six surveyors were recruited. Before going into the field, the surveyors were trained in the beginning including while doing the pilot survey. The aim of the pilot survey was to familiarise the surveyors with the tasks as well as to test the questionnaire design. After finishing the pilot survey, the main surveys were conducted and divided into two phases. In the middle, between the first and second phases, the data were gathered, and the survey results were evaluated. We divided the surveyors into 3 groups (i.e. each group consisted of 2 persons) and assigned each group to specific zones in Bandung city centre.

**Table 5-1. Survey sample and data collection process**

| Sub District | Population | Planned Sample | Sample taken | | |
|---|---|---|---|---|---|
| | | | 1st phase | 2nd phase | Total (%*) |
| Balong Gede (BG) | 162 | 20 | 8 | - | 8 (40%) |
| Braga (BR) | 812 | 40 | 15 | 14 | 29 (73%) |
| Ciateul (CA) | 19 | 10 | 5 | 4 | 9 (90%) |
| Cibadak (CB) | 4788 | 40 | 15 | 19 | 34 (85%) |
| Cikawao (CK) | 25 | 10 | 5 | 2 | 7 (70%) |
| Karang Anyar (KA) | 260 | 35 | 15 | 17 | 32 (91%) |
| Kebon Jeruk (KJ) | 819 | 40 | 15 | 25 | 40 (100%) |
| Kebon Pisang (KP) | 1432 | 40 | 15 | 18 | 33 (83%) |
| Nyengseret (NY) | 1548 | 25 | 10 | 12 | 22 (88%) |
| Paledang (PA) | 16 | 10 | 5 | 3 | 8 (80%) |
| Pungkur (PU) | 28 | 15 | 10 | 3 | 13 (87%) |
| Total | 9909 | 265 | 118 | 117 | 235 (88%) |

*: percentage from planned sample

The survey was conducted as follows: the retailers were not contacted before and enumerators chose independent retailers randomly based on the location they were assigned to. Then, after receiving the independent retailers' consent to be included in the research, they would ask for the shop keeper who knew about restocking activities. Since independent retailers do not usually have many employees, usually the shop keeper knows the process for restocking activities for the retailers. After finishing with one retailer, the enumerators then went to the next one. The average time for fulfilling the questionnaire was 14 minutes.

In the first phase, we targeted to obtain at least all data from all sub-districts. We targeted to get at least 50% of the number of questionnaires filled in out of what we had planned. We realised some subdistricts had fewer independent retailers due to the high density of residential properties in certain areas. Therefore, in the first phase, we focused on those subdistricts which had fewer retailers so that if we could not meet our target in the first phase, we could then evaluate the process and push to reach the target in the second phase.

During the data collection process, a few challenges were noted:

- Surveyors were not able to find independent retailer easily especially in less-dense retail areas. Subdistricts such as Balong Gede and Pungkur, although located in the city centre, are not retailer dense and thus it takes a longer time to meet retailers.
- Surveyors faced some incomplete questionnaires due to limited time. It was realised that for some retailers the employee is also the owner. The survey was held during a working hour on a weekday thus, on some occasions, the interview time was not enough since the shop keeper needed to work again. Moreover, some retailers refused to answer part of the questionnaire for reasons such as they didn't know, they didn't understand the questions, or they thought the questions were confidential ones.

## 5.3 Descriptive statistics analysis

### 5.3.1 Survey responses

We successfully gathered 235 questionnaires out of 265. The overall response rate was 88%, and the lowest response rate across all sub-districts was 65%. After a preliminary quality check, 224 questionnaires were deemed suitable for detailed analysis. The response rate (88%) was higher than the average response rate mentioned in the literature (85%) (Alho and de Abreu e Silva, 2015). Reasons for the relatively high response rate might include the fact that many independent retailers in

Bandung are very small businesses in which the owner usually also works personally and is knowledgeable about restocking activities. Moreover, the interviewers were specially trained for the survey and conducted the interviews in the local language (i.e. Bahasa) which was key to the high response rate too.

### 5.3.2 Employment and vehicle ownership

The majority of retailers are small businesses and occupy 23.24 $m^2$ on average. Besides the total shop area, the scale of business is represented by the small number of employees. More than 80% of the retailers hire less than or equal to two employees, specifically 16% of the independent retailers operate the store by themselves, 38% of them hire one employee, and 29% hire two employees. Only 17% of them hire more than two employees (see Figure 5-8).

Regarding vehicle ownership, most retailers have at least one vehicle, either a two-wheeler or a delivery van (87%). Among those who have their own vehicle, 19% have only a delivery van, 73% only have a two-wheeler, and 8% have both a two-wheeler and a delivery van. The others operate their shops without owning any vehicles (13%), stating that they operate their shops by requesting the goods to be delivered by their suppliers.

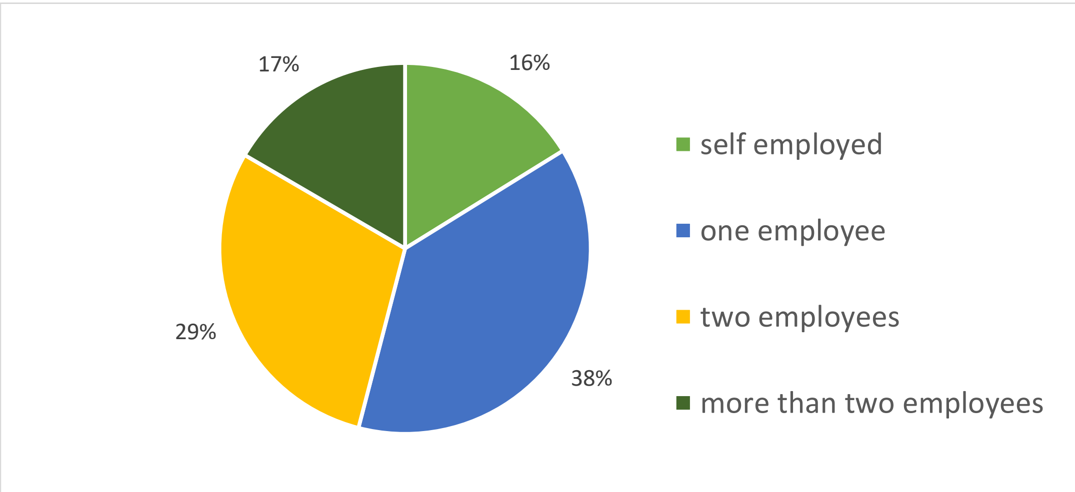



**Figure 5-8. Independent retailers' number of employees**

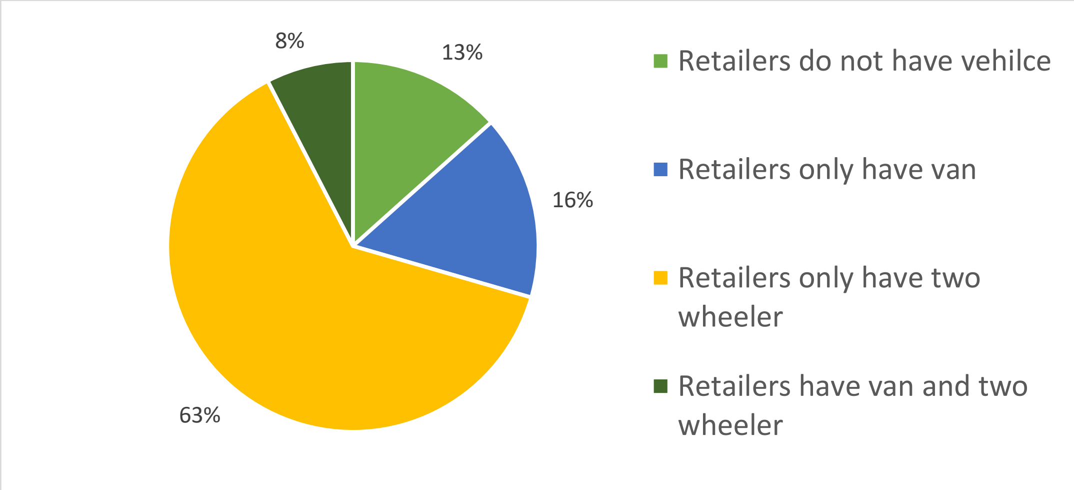



**Figure 5-9. Independent retailers' vehicle ownership**

### 5.3.3 Trades

Independent retailers in Bandung typically sell essential everyday goods to end consumers, ranging from instant food to home appliances (see Figure 5-10). Each independent retailer usually has specific suppliers for each range of goods. Hence it is often necessary to receive multiple deliveries or to make multiple procuring trips to procure the full set of products sold. Because of the large numbers of possible suppliers, the buying price for each product usually varies from one supplier to the other, as can be seen from the coefficient of variation of the buying price (see Figure 5-11). The buying price varies further if the goods have different brands and/or packaging types. If the goods have more generic packaging and measurements, e.g. rice, sugar, flour, and gas cylinders, price variations tend to be lower.

The price of each type of product varies as we can see from the coefficient of variation (Cov) value. Electronics products have the highest CoV while rice has the least. This happens because goods typically do not have a standard measurement on the package. As we pre-define the standard measurement, the retailers then give an average price according to it on the questionnaire. If the goods have a standard measurement such as rice, eggs, or gas tubes, the price tends to have less variation. Secondly, there exist many brands for the same goods. For instance, there are at least ten different brands of vegetable oil, salt, and dairy products. The number is greater in the case of drugs and pharmacy products. Thus, the price variation is inevitable since we asked the average price for each product. Thirdly, an independent retailer buys goods from various suppliers. Thus, even if the goods have exactly the same brand and packaging the price might differ.

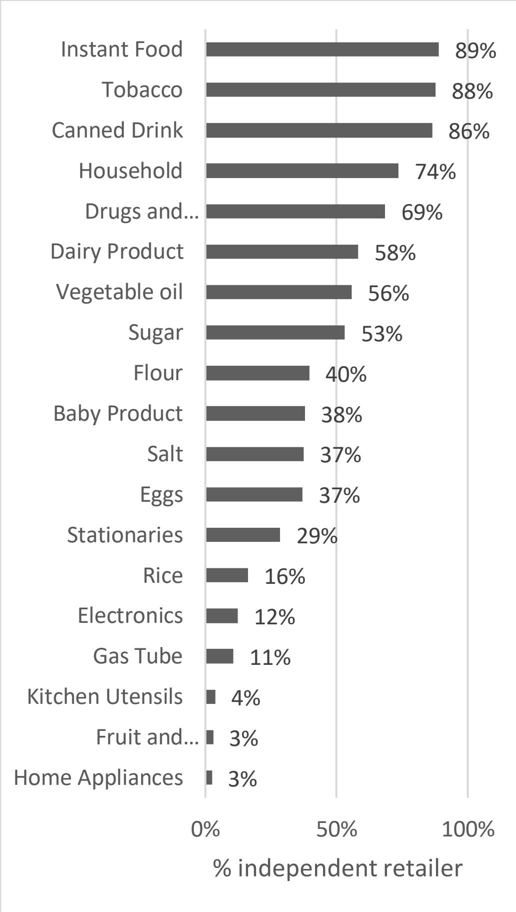



**Figure 5-10. Percentage of independent retailers selling each type of goods**

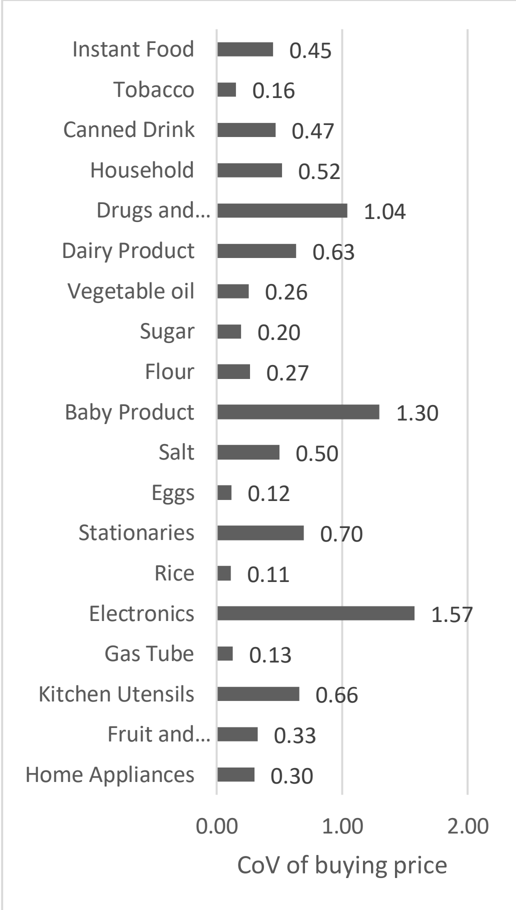



**Figure 5-11. Coefficient of variation of buying price**

### 5.3.4 Restocking activities

Regarding supplier location choice, the survey revealed more than 50% of restocking decisions (224 out of 412) suppliers inside BCC were chosen (Figure 5-12). The proportion increases to 73% (303 decisions out of 412) if we also include supplier location zones adjacent to the BCC, namely Ancol, Ciroyom, and Situsaeur. Interestingly 125 out of 303 decisions (41%) chose the traditional markets, highlighting the importance of such markets for the supply chains concerned. The supplier areas to which independent retailers are less attracted are mostly residential areas, e.g. Paledang, Ciateul and Cikawao where the number of establishments is significantly fewer than in other more commercial areas.

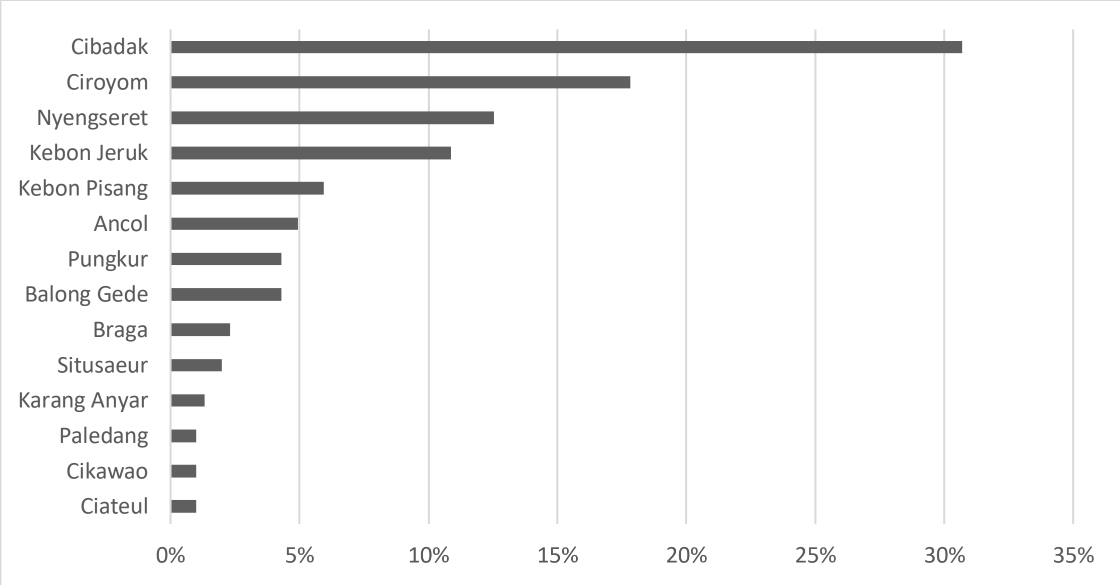



**Figure 5-12. Supplier location choice based on the survey**

The survey reveals that on average more than half the commodities acquired by independent retailers come from traditional markets (54%), hence the traditional markets are successfully attracting retailers from the local area to restock from suppliers based in them. Most types of goods (76%) acquired in this way are not perishables such as dairy products, eggs and fruit/vegetables, which tend to be procured elsewhere. The survey also reveals that the average prices for both unperishable and perishable goods in establishments inside traditional markets tends to be lower than those offered in non-traditional establishments (see Figure 5-13).

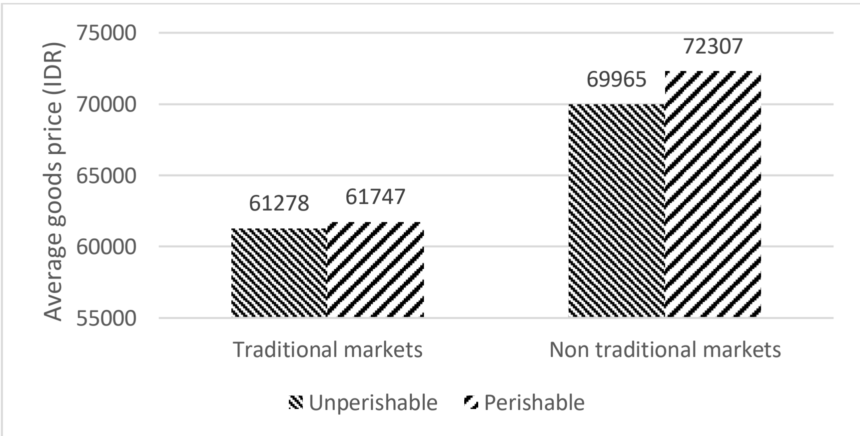
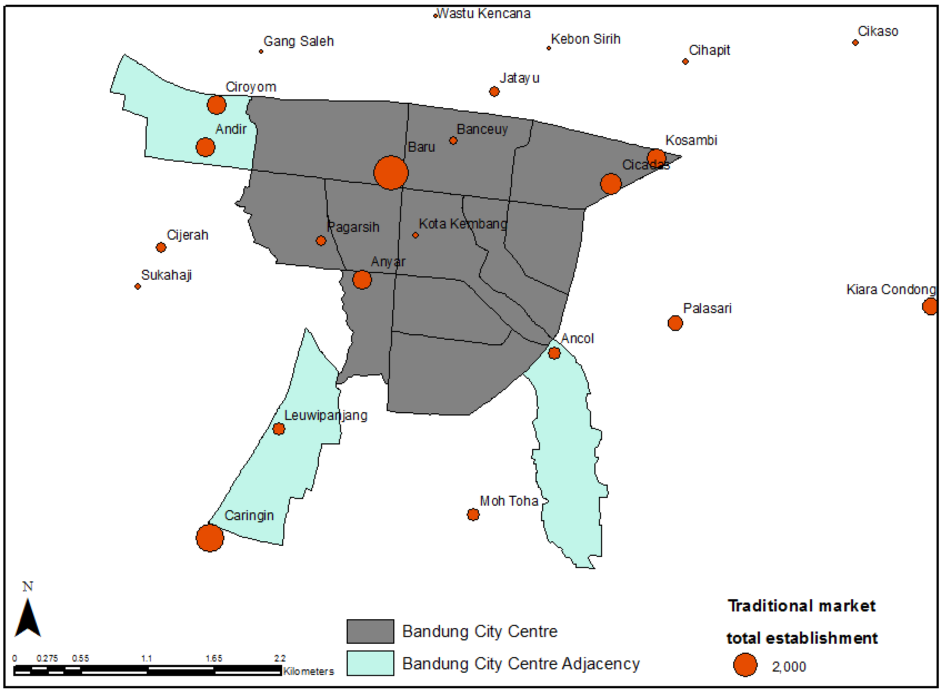


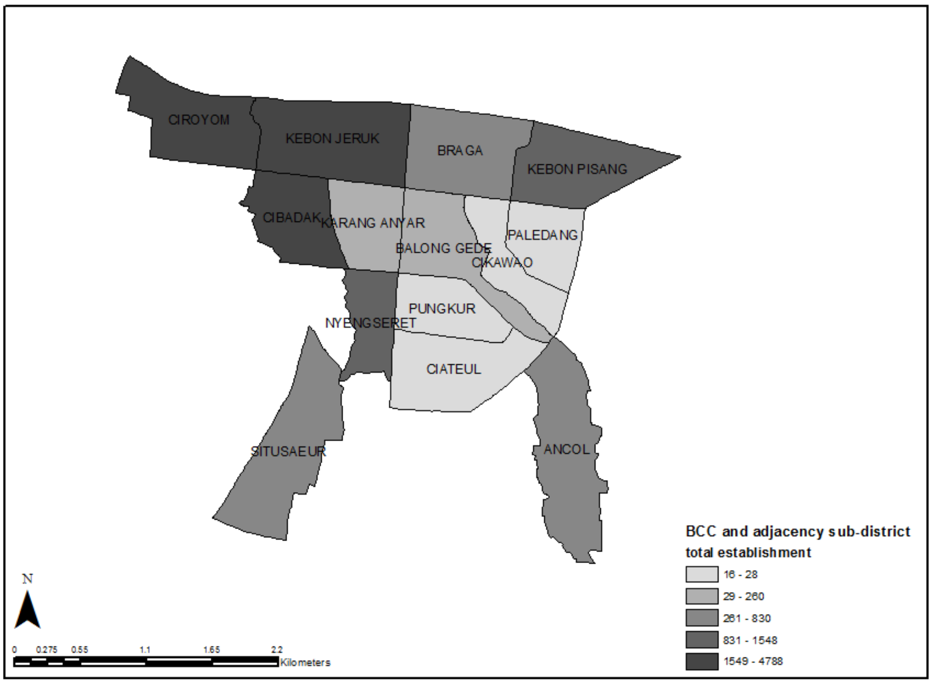

**Figure 5-13. Average goods prices at traditional markets vs non-traditional markets**

The presence of a traditional market boosts the number of establishments in the BCC area as shown by Figure 5-14-a and Figure 5-14-b. The major traditional markets inside BCC viz., Pasar Baru and Kosambi, are home to a large number of establishments and thus increase the total number of establishments in the area.

Meanwhile, adjacent zones to BCC viz., Ancol, Ciroyom, and Situsaer, also have a major traditional market each and thus also have large numbers of establishments. Supplier location attractiveness tends to be affected by the total number of establishments in the area.




**(a)**




**(b)**

**Figure 5-14. (a) Number of establishments in traditional markets in BCC and around; (b) Total number of establishments in BCC and adjacent sub-districts**

Regarding transport service choice, as might be expected from the high vehicle ownership, the majority of restocking trips are made using the retailers' own vehicles (79%). Only 21% of trips are made by delivery services. Interestingly, the survey reveals that relatively few deliveries are charged, implying that independent retailers using the push mode are paying prices inclusive of delivery. However, most independent retailers prefer to procure goods using their own vehicles because this offers greater flexibility in terms of inventory management. Many factors are believed to affect the decisions to choose a particular transport service (Comi and Nuzzolo, 2014; Russo and Comi, 2010).

### 5.3.5 Restocking time

Next, we discuss restocking time for independent retailers. In terms of the days selected for restocking activities, retailers tend to use their own vehicles throughout the week, including at the weekend (see Figure 5-15). In contrast, delivery vehicles make the majority of their deliveries on weekdays, with Mondays being particularly common as weekend deliveries result in extra driver costs due to overtime rates. As for delivery time of day, many retailers start their trips using their own vehicles between 06.00 AM and 09.00 AM in the morning. Restocking trips tend to be routine, with relatively few retailers claiming to go as and when required. Deliveries from suppliers tend to arrive at the shops in the afternoon, although some delivery vehicles also come in the evening and even during the night although the numbers are not significant (see Figure 5-16).

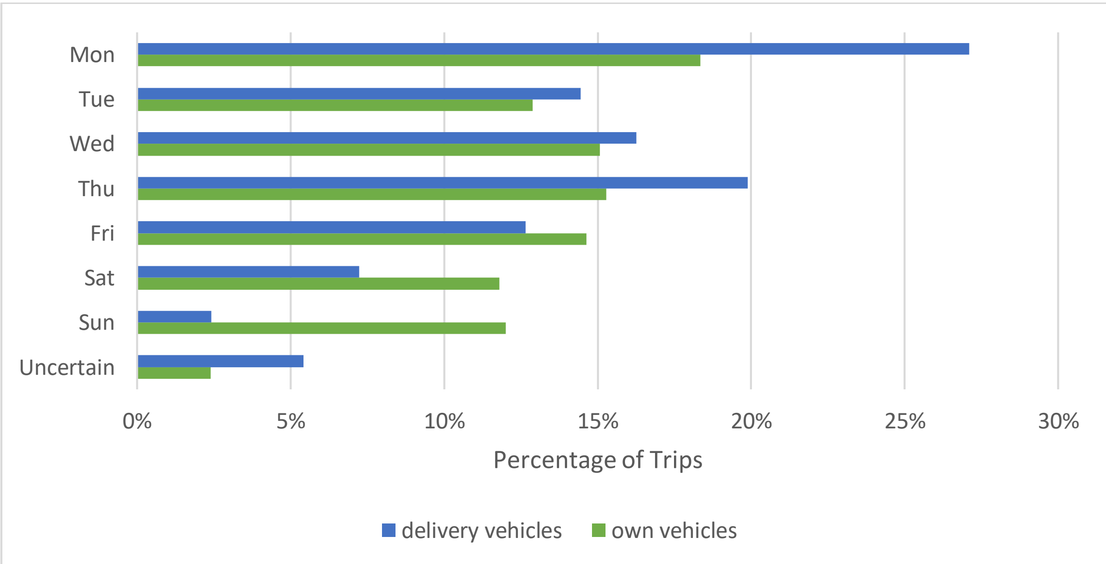



**Figure 5-15. Percentage of trips by day of the week**

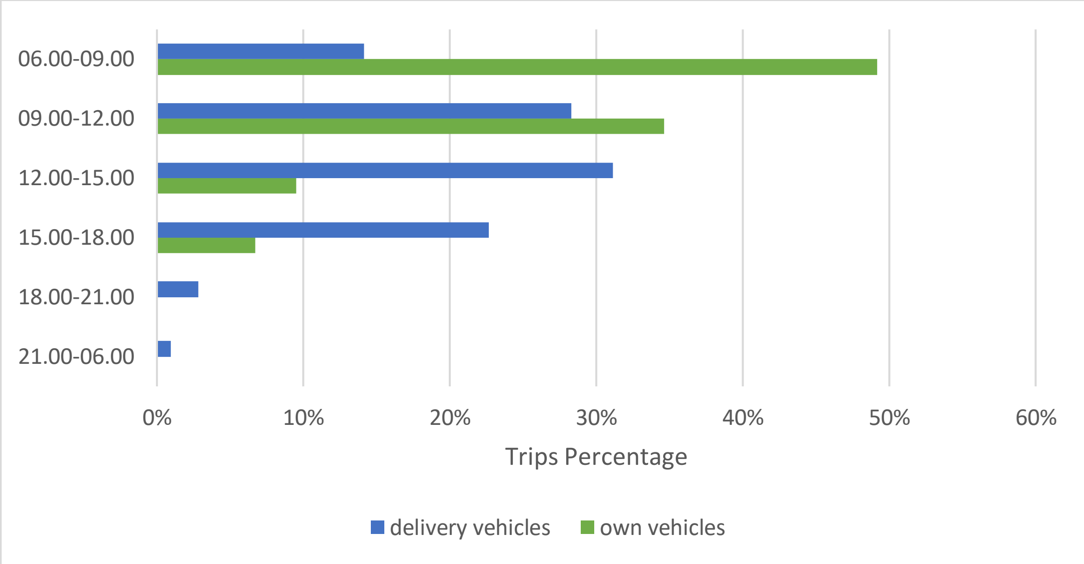



**Figure 5-16. Percentage of trips by time of the day**

### 5.3.6 Parking and loading unloading activities

We now turn our attention to the availability of parking for loading/unloading activities. Currently, the local authority does not apply any parking restrictions on most streets in BCC. Thus, carriageways commonly become parking places for road users as well as becoming unloading bays for retailers. The survey shows that many retailers *perceive* the roadsides to be their parking space and loading/unloading area. More than 50% of the retailers claim that they have a dedicated parking area and a dedicated loading bay at the front of the shop (see Figure 5-17). However, the majority of retailers actually load/unload their goods on public roads (see Figure 5-18). The lack of dedicated loading bays at the back of or to the side of shop premises should be noted. Interestingly, delivery vehicles are found to use unloading bays at shop premises more than their own vehicles. This could be because the delivery vehicles are unloading more goods, so the shop owner provides a dedicated unloading bay for them and this is also in line with another finding that delivery vehicles tend to need more time to unload the goods. The majority of retailers' own vehicles spend less than 30 minutes unloading, whereas delivery vehicles typically spend between 30-45 minutes unloading goods.

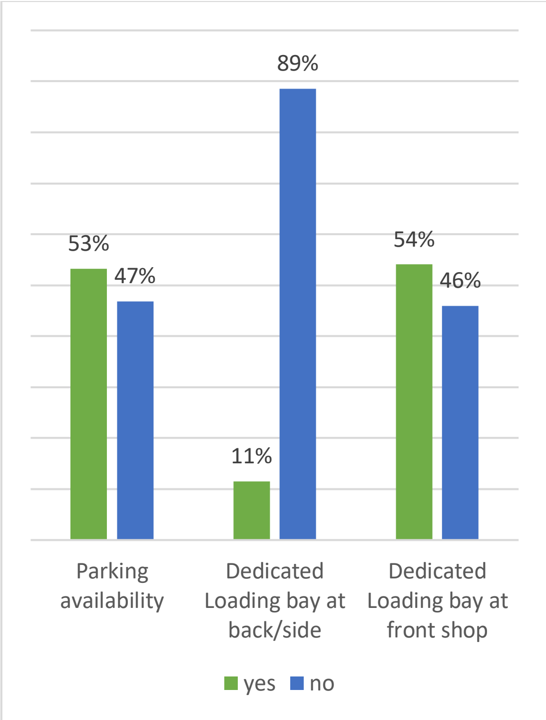



**Figure 5-17. Parking and loading bay availability**

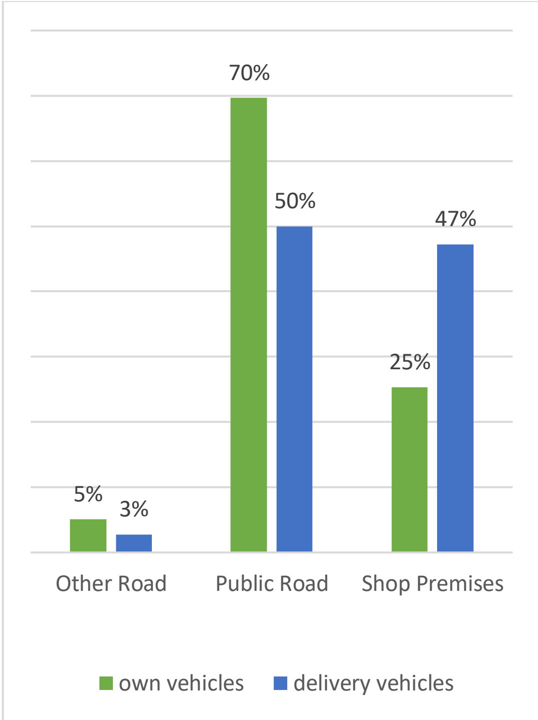



**Figure 5-18. Places for unloading activities**

## 5.4 Chapter summary

This chapter presents the context of Bandung as the study area of this thesis. Further, the questionnaire design and data collection process are discussed.

We can summarise some points for basic output from the independent retailer survey in Bandung city centre area. Although we faced challenges in conducting the survey, the survey's results were quite good with 235 out of 265 or 82% valid responses. The results were parallel with previous research with a high number of valid responses when the survey utilises a face-to-face interview method.

The majority of the retailers are small and occupy just 23.24 $m^2$ on average. The majority of them hire one employee, plus the owner meaning, on average, the shops are operated by two people. The majority of them have their own vehicles and the survey results indicate that the majority of them use their vehicle to restock their shop. Nevertheless, there are some independent retailers that used both their own vehicle and delivery services to restock their shop.

Regarding the parking issue, the majority of independent retailer have their parking area. However, this is the case because Bandung city centre area has not applied parking restrictions. Further, the majority of unloading activities are done in front of the shop using the public road that can lead to the bottleneck problem on the road. The unloading time varies between own vehicle unloading and delivery trip unloading. As delivery trips have more goods to load, the survey indicates that delivery trips need more time to unload than own vehicle trips.

Referring to when the independent retailers do the restocking trips, our survey reveals that own vehicle trips result in higher trip variations. Although the majority of trips are on Monday for both trips, own vehicle trips are done equally between weekends and weekdays. As for delivery trips, most of the trips are made during weekday time. Regarding the actual time the trips are taken, own vehicle trips are done mainly in the morning (06.00-09.00 AM) while delivery trips mainly arrive in the independent retailers' shops between the afternoon and evening (12.00-18.00).

Given our the survey results, we use the data we have gathered for demand model estimation. The list of the data used for demand estimation can be found in the next chapter (Section 6.2.)

In general, we obtain three types of information from the survey: retailer's characteristics, their restocking activities, parking activities. Retailers characteristics data such as: number of employees, vehicle ownership, and the address of the retail shops, are used to estimate the vehicle trips generation model. As for the data regarding restocking activities, data such as: supplier location, revealed travel time between retailers shop and supplier location, shipment weight, transport service, are used to estimate the choice model regarding supplier location choice and transport service choice.

Nevertheless, some of the data gathered in the survey are not used to estimate the demand at all. Data such as parking availability, parking restrictions and loading and unloading activities are not directly related to the restocking activities. Some data is used to indicate the restocking activities characteristics but not directly used to estimate the demand model. The data on time of restocking activities gives us hints as to when the majority of independent retailers travel to restock their shop or when they accept deliveries. These data help us to justify our choice to model a morning peak hour condition since it is revealed that the majority of independent retailers' restocking trips take place in the morning.

In the next chapter, we use the results of the survey to estimate the demand models. The demand models include the generation model, and distribution models and are estimated based on regression analysis and discrete choice modelling.

# Chapter 6 Demand modelling for independent retailer restocking activities

This chapter discusses the demand modelling formulation and estimation. As discussed in Chapter 1, one of the main tasks in this research is to build demand modelling for independent retailers' restocking activities.

The descriptive analysis presented in the previous chapter suggests that the restocking trip performed by independent retailers depends on many factors. In particular, the presence of traditional markets and the ownership of a vehicle appear to have major influences on retailer restocking activities. Therefore, a demand model is proposed to complement the exploratory analysis and to give a quantitative explanation of the factors affecting the retailer decisions. The modelling work aims to address the following questions:

- the effect of two-wheeler ownership and the presence of traditional markets on the generation of trips;
- whether the presence of traditional markets in a supplier location zone improves its attractiveness to retailers; and
- the influence of vehicle ownership on retailer decisions when choosing a supplier location and transport service.

The demand models comprise a *generation model* and a *restocking choice model* within which supplier location choice and transport service choices are embedded.

The rest of this chapter is divided as follows: Section 6.1. describes the data set used to estimate the model; Section 6.2. explains the generation model specification and estimation process. Distribution model specification and estimation are explored in Section 6.3. and finally, Section 6.4. concludes the chapter.

## 6.1 The data set

During the survey, two sets of data are obtained, namely data corresponding to retailer characteristics and data corresponding to retailers' restocking activities. The data corresponding to the retailer characteristics are generally used to estimate the generation model whilst the data corresponding to restocking decisions are used to estimate the distribution model.

The commodity data is gathered to ensure that the surveyor interviewed the correct independent retailers. In this thesis we specifically address neighbourhood shops. In the data gathering process, we planned to get 235 data observations, but of these only

224 proved useful. One reason for the rejection of this data is because the retailers are not neighbourhood shops. This thesis concerns the type of independent retailers that are specialized in the daily and household goods, the type of neighbourhood shops that are operated by a families rather than larger businesses. The commodity data was also gathered to get an insight of common commodities that these shops usually sell. Literature shows that whether goods are perishable and unperishable may have a significant impact on how the independent retailers will plan their restocking activities. However, the survey reveals that the majority of goods sold by independent retailers are unperishable goods, with only a few selling  the perishable goods such as fruit and vegetables. Therefore, the type of commodity is not significant to be considered in estimation of the demand models.

Further, the nature of independent retailers restocking decisions that are similar to the shopping activities does not necessarily give significant importance to the type of commodities. In the literature, the variables relating to type of commodities is either closely associated with the industry classification (Pani et al., 2018) or is closely related to the perishability of the goods (Russo and Comi, 2010). In our case, we specifically studied independent retailers that are specialized in everyday items and household in which the commodities are quite similar in nature. We do not consider other industries such as Hotel, Café, and Restaurants (HoReCa), or service based retailers such as opticians, dentists, or hairdressers which may generate commodities that need special deliveries. For example, HoReCa need perishable fresh milk which may need to be restocked more frequently.

Regarding the generation model, in total we got 224 retailers' characteristic data points from the survey. The possible variables include: number of people employed, weekly goods demand, average shipment weight, and crow fly distance between retailers and the presence of the nearest traditional market.

Regarding the distribution model, the data are obtained at a commodity level (see the survey form in Appendix A). We transform the data into trip-level decisions by grouping the commodity data according to the respective suppliers and modes. In other words, it is possible for an independent retailer to make more than one restocking trip decision based on the supplier location and the mode employed. The data for the restocking choice models are arranged at the trip level because the independent retailers make restocking choice decisions at the trip level. In total, out of 224 retailers producing 412 restocking trip decisions, 303 restocking trips (73%) are included in the data sets. These 303 records are the trips inside the study area and are therefore considered in the model. Table 6-1 summarises the possible attributes and source of data for each model.

**Table 6-1. Data sets and possible attributes for each model**

| Model | Alternative | Data Set (Number of observations) | Possible Attributes | Reference | Source |
|---|---|---|---|---|---|
| Trip Generation Model | NA | Retailer data set (224) | Number of persons employed<br>Weekly goods demand (tonnes)<br>Average shipment weight (tonnes)<br>Crow fly distance between retailers and the nearest traditional market (km)<br>Vehicle ownership<br>Van / two-wheeler ownership<br>Distance to the nearest traditional market | (Pani et al., 2018)<br>(Bastida and Holguín-Veras, 2009) | Survey<br>Survey<br>Survey<br>Survey<br>Survey<br>Survey<br>Survey |
| Restocking choice: Supplier Location | All traffic analysis zones (TAZ) | Trip data set (303) | Travel time between OD pairs (hour)<br>Number of establishments in supplier zone<br>Presence of traditional markets in supplier zone<br>Vehicle ownership | (Wisetjindawat et al., 2006) | SATURN<br>Official data<br>Official data<br>Survey |
| Restocking choice: Transport Service | Delivery service (*ds)* or own vehicle (*ov)* | Trip data set (303) | Revealed travel time (hour)<br>Average shipment weight (tonnes)<br>Presence of traditional markets in supplier zone<br>Vehicle ownership | (Russo and Comi, 2010) | Survey<br>Survey<br>Survey<br>Survey |

The possible attributes for each model are specified by hypothesis and literature review. All possible attribute data for this model are gathered either through the survey or from official data from the Indonesian Statistics Bureau (BPS), except for crow-fly distance and travel times between zones. Crow-fly distance data between each zone pair is calculated using GIS. Travel time data from the survey is the revealed/perceived travel time by independent retailers. The data revealed what they perceived in reality but did not provide information regarding travel time for a different OD alternative. To address this issue, we rely on the results of the Bandung traffic assignment model using the SATURN package from Farda and Balijepalli (2018) to provide travel time information between each OD pair.

## 6.2 Generation model

To represent the independent retailer trip demands, we follow the general architecture of the model described in Chapter 4 in which the sub-districts of BCC act as traffic analysis zones (TAZs). Each TAZ consists of two different nodes: suppliers (s) and retailers (r) (see Figure 6-1. Bandung city centre urban network architecture). Retailer and supplier nodes can be located in the same sub-district, and each node represents different entities. The retailer node represents the demand for the goods in the sub-district, i.e. the quantity of the goods attracted by all the retailers within the sub-district. Meanwhile, the supplier node represents all suppliers located within the sub-district. Goods flow always moves from the supplier nodes to the retailer nodes. However, a vehicle trip can be generated from both nodes. Trips generated from a supplier node represent delivery trips made by suppliers, whereas trips generated from a retailer node represent restocking activities by the retailers' own vehicles.

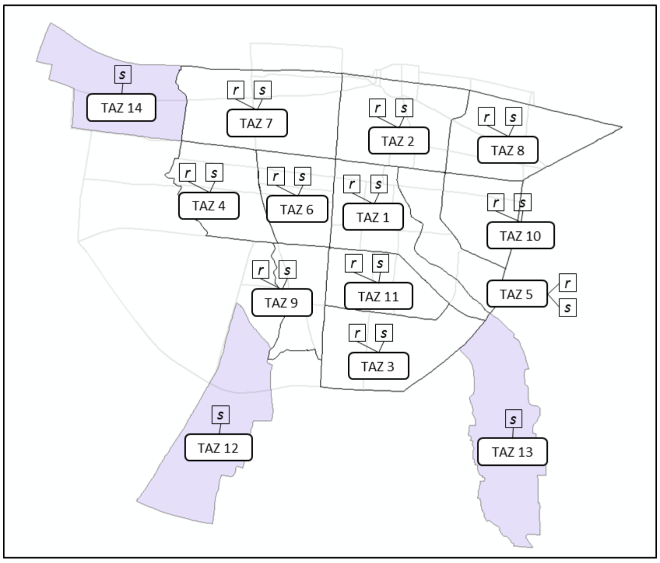



**Figure 6-1. Bandung city centre urban network architecture**

### 6.2.1 Model specification

The trip generation model is an ordinary least squares (OLS) linear regression model based on independent retailer characteristics. The trip generation model is specified as follows:

$$G_r = \alpha_1 x_1 + \cdots + \alpha_n x_n + \omega \qquad \text{6-1}$$

where $G_r$ is the number of trips generated by retailer activities in zone *r*; $x_1 \ldots x_n$ are possible attributes related to independent retailer characteristics in each retailer node (r); $\alpha_1 \ldots \alpha_n$are parameters to be estimated, and $\omega$ is the model intercept. The trip generation model is similar to a household regression model which is usually used to study passenger trip generation (Ortuzar and Willumsen, 2011). The model aims to investigate the factors affecting the total number of restocking trips based on independent retailer characteristics. The generation trips can be taken from a supplier zone to a retailer zone (attraction trips i.e. delivery trips from supplier to retailer) or started from a retailer zone towards a supplier zone (production trips i.e. retailer trips using own vehicles).

### 6.2.2 Multiple linear regression estimation

Referring to the trip generation model, we investigate all possible attributes in the data set for the parameter estimation process. Then we eliminate non-significant attributes stepwise until all the remaining attributes are statistically significant. The intercept covers the value of the dependent variable that is not represented by the chosen attributes.

In the estimation process we consider the inclusion of a dummy variable. A variable is considered as a dummy variable when the variables take the value of 0 or 1 to indicate a categorical effect that may be expected to change the regression result. Dummy variables are usually used to address the problem of a non-linear variable that occurs in different categories. By including dummy variables, the independent variable under consideration for regression is divided into several discrete intervals and treated separately in the model.

#### a. Model estimation without dummy variable

We firstly estimate the regression model without the dummy variables. The result is shown in Table 6-2 below:

**Table 6-2. Independent retailer trip generation model estimation without dummy variable**

| Attribute | Model 1 Coefficient | *p*-value | Model 2 Coefficient | *p*-value | Model 3 Coefficient | *p*-value |
|---|---|---|---|---|---|---|
| Intercept | 0.744 | 0.09 | 2.30 | 0.00 | 2.36 | 0.00* |
| $x_1$ | 0.257 | 0.09 | 0.05 | 0.52 | - | - |
| $x_2$ | 0.001 | 0.92 | - | - | - | - |
| $x_3$ | 0.196 | 0.24 | 0.14 | 0.05 | 0.14 | 0.05** |
| $x_4$ | 22.40 | 0.00 | 16.40 | 0.00 | 16.58 | 0.00* |
| $x_5$ | - | - | -32.32 | 0.00 | -32.28 | 0.00* |
| $x_6$ | -0.03 | 0.22 | -0.03 | 0.22 | -0.03 | 0.18 |
| $R^2$ | 0.18 | | 0.68 | | 0.68 | |
| Adjusted $R^2$ | 0.16 | | 0.67 | | 0.67 | |
| F-test | 9.53 | | 92.46 | | 115.77 | |
| Observations | 224 | | 224 | | 224 | |

$y$: Number of weekly trips
$x_1$: Number of suppliers associated with retailers
$x_2$: Store area
$x_3$: Number of persons employed
$x_4$: Weekly goods demand (tonnes)
$x_5$: Average shipment weight (tonnes)
$x_6$: Crow-fly distance between retailers and the nearest traditional market (km)

*significance at 99% confidence level **significance at 95% confidence level

We initially estimate the regression by including all variables collected from the survey. All variables in the initial model have a correct sign, yet the initial model (Model 1) results in a poor R-square value (R-square = 0.18). Further, the store area variable has a p-value of 0.92 indicating the variable is not statistically significant, hence we remove the variable for the next estimation. To improve the model, we then include *average shipment weight* ($x_5$) as an additional variable. The average shipment weight variable is not known directly from the survey, rather average shipment weight is calculated by dividing the weekly goods demand with the total number of weekly trips.

By adding the average shipment weight variable, the model results improve significantly. The model (Model 2) produce a good R-squared value ($R^2$ = 0.68), and the signs are as expected. The average shipment weight has a negative sign and it makes sense since by increasing the average shipment weight we then expect the number of trips to reduce. However, the number of suppliers associated with the retailers variable is not significant, and thus the variable is removed from the next estimation process.

The final model without a dummy variable (Model 3) results in a good R-squared value ($R^2$ = 0.68), and the signs are as expected. However, the crow-fly distance between retailers and the nearest traditional markets ($x_6$) is not significant. To improve the model, we replace $x_6$ attribute with a dummy variable indicating the presence of traditional markets ($x_9$) and also introduce another dummy variable for two-wheeler ownership ($x_7$) and van ownership ($x_8$).

**b. Model estimation with dummy variables**

The previous estimation without dummy variables already removes the store area variable ($x_1$) and the number of suppliers associated with the retailer variable ($x_2$). Therefore, we continue the estimation with the dummy variable by not including those two variables. Initially, three dummy variables are considered in the estimation: the dummy variable for two-wheeler ownership ($x_7$).; the dummy variable for van ownership ($x_8$). and the dummy variable for the presence of a traditional market in the retailers' proximity ($x_9$).

The estimation result for the trip generation model including dummy variables can be seen in Table 6-3.

**Table 6-3. Independent retailer trip generation model estimation with the dummy variables**

| Attribute | Model 4 | | Model 5 | | Model 6 | |
|---|---|---|---|---|---|---|
| | Coefficient | *p*-value | Coefficient | *p*-value | Coefficient | *p*-value |
| Intercept | 1.74 | 0.00 | 1.80 | 0.00* | 1.59 | 0.00* |
| $x_3$ | 0.21 | 0.00 | 0.19 | 0.00* | 0.19 | 0.00* |
| $x_4$ | 16.61 | 0.00 | 16.84 | 0.00* | 16.84 | 0.00* |
| $x_5$ | -30.55 | 0.00 | -31.14 | 0.00* | -31.18 | 0.00* |
| $x_6$ | -0.04 | 0.15 | - | - | - | - |
| $x_7$ | 0.55 | 0.00 | 0.56 | 0.00* | 0.58 | 0.00* |
| $x_8$ | -0.09 | 0.68 | - | - | - | - |
| $x_9$ | - | - | 0.11 | 0.05** | 0.16 | 0.05** |
| $x_{10}$ | - | - | - | - | 0.06 | 0.01* |
| $R^2$ | 0.69 | | 0.69 | | 0.69 | |
| Adjusted $R^2$ | 0.69 | | 0.68 | | 0.68 | |
| F-test | 81.9 | | 97.9 | | 80.9 | |
| Observations | 224 | | 224 | | 224 | |

$y$: Number of weekly trips
$x_3$: Number of persons employed
$x_4$: Weekly goods demand (tonnes)
$x_5$: Average shipment weight (tonnes)
$x_6$: Crow-fly distance between retailers and the nearest traditional market (km)
$x_7$: Dummy for two-wheeler ownership,1 if the retailer has a two-wheeler, otherwise 0
$x_8$: Dummy for van ownership, 1 if the retailer has a two-wheeler, otherwise 0
$x_9$: Dummy for the presence of a traditional market, 1 if the retailer is located <= 3 km from the traditional market, otherwise 0
$x_{10}$: Product of $x_7$ and $x_9$

*significance at 99% confidence level **significance at 95% confidence level

We firstly estimate the model by introducing the dummy variable for vehicle ownership (Model 4). The survey reveals there are two types of vehicles that are usually owned by independent retailers: two-wheelers and delivery vans, hence we introduce two dummy variables: *dummy for two-wheeler ownership* and *dummy for van ownership*. The result shows the estimation produces a good R-square, yet two variables are found to be not statistically significant: crow-fly distance between retailers and the nearest traditional market, and dummy for van ownership. The dummy for van ownership has a coefficient value of -0.99. This suggests that owning a van is expected to decrease the number of trips per week. However, the dummy variable for van ownership is omitted from the final model runs since it was not statistically significant ($p$-value = 0.68).

To improve the model, we remove the insignificant variables, and we replace the $x_4$ attribute with a dummy variable indicating the presence of traditional markets $(x_9)$. The result (Model 5) shows all variables are significant, and the signs are as expected. Two-wheeler dummy variable has a positive sign, meaning the retailer who owns a two-wheeler is expected to make more trips than the one who does not. This makes sense, since if the retailer uses a two-wheeler to restock the shop, it would require more trips to move the goods compared to a van. The dummy variable for traditional market presence has a positive sign indicating the presence of traditional market increases the number of trips by retailers. However, the value of the two-wheeler dummy variable is higher than the dummy for the traditional market variable, implying that two-wheeler ownership has a greater influence on the number of weekly trips than the proximity of a traditional market.

Model 6 included an interaction variable between the two dummy variables $x_5$ and $x_6$. The aim is to explain the influence of the presence of a traditional market on retailer trip generation for those owning a two-wheeler. As expected, the sign is positive meaning the joint effect of owning a two-wheeler and the presence of a traditional market tends to encourage the retailers to make even more trips. This highlights the nature of many independent retailers as small businesses heavily reliant on two-wheeler vehicles for their on-demand restocking trips.

## 6.3 Restocking choice model: supplier location and transport service choice models

### 6.3.1 Model specification

The restocking choice models are discrete choices based on random utility theory. Each retailer is assumed to be a rational decision maker who maximises utility relative to their choice (Ben-Akiva and Lerman, 1985). In this case, the decision makers consider a choice set $C$. Then, the decision maker assesses each alternative $c$ from the choice set $C$ and selects the alternative that maximises his/her utility ($U_c$). Generally, the utility function for alternative $c$ ($U_c$) can be formulated as

$$U_C = \beta_n \, a_{c_n} + \gamma_{c_n} \, b_n + ASC_c + \epsilon_c \qquad 6\text{-}2$$

The utility function comprises measurable characteristics (attributes). $a_{c_n}$ are the attributes related to the alternative $c$ and $b_n$ are attributes related to the decision maker. The utility assigned by the decision makers is not known with certainty by the analyst due to a number of factors and therefore represented by the random error variable $\epsilon_c$.

### 6.3.2 Model estimation

From the perspective of transport demand, the main independent retailer decision regarding supply chain is to choose the *supplier location*. The model aims to distribute trips generated by each retailer zone and link them to respective supplier zones. The alternative locations are all possible supplier zones within the study area. Location impedance and location attractiveness parameters are the major attributes influencing the decisions of such independent retailers (Wisetjindawat *et al.* 2006; Russo and Comi, 2010; Nuzzolo and Comi, 2014). Crow-fly distance, travel time and travel cost between retailers and suppliers are related to impedance parameters influencing independent retailer decisions (Mei, 2013). Meanwhile, the attractiveness parameters give a particular supplier location benefit compared to other locations. The number of suppliers in the destination location, the floor area of the suppliers, the number of employees working at the supplier location, and the total parking area are a few attributes related to zonal attractiveness found in the literature. Nevertheless, since the traditional markets are the focus of the current study, a dummy variable for the presence of a traditional market in the supplier zone is also included in the model as one of the attraction factors (see Table 6-4).

The *transport service* model determines how the goods are transported. From the modelling point of view, the transport service model gives the vehicle movement direction. The model includes two options: delivery service or own vehicle. Delivery service *(ds)* means the trips will be arising from supplier nodes to retailer nodes, whereas own vehicle *(ov)* transport service means the trips will be originating from retailer nodes to supplier nodes. The literature suggests the number of deliveries per week; the quantity acquired per trip; the type of goods (whether the goods are food/beverage or not); and the vehicle ownership to be important factors influencing whether an independent retailer decides to use his own vehicle or not (Nuzzolo and

Comi, 2014b; Russo and Comi, 2010). We also include these attributes in our models setting as can be seen in Table 6-4.

#### 6.3.2.1 Multinomial logit model (MNL) estimation

As for the restocking choice model, the modelling system is initially estimated using the attribute data from Table 6-1. We also included the interaction variables with the aim of obtaining the best specification based on combinations of the possible attributes and interactions between the attributes. Maximum likelihood estimation method by BIOGEME software is used to estimate the parameter values (see Appendix B for an example of BIOGEME syntax).

**Table 6-4. Independent retailer restocking choice model estimation**

| Attribute | Model 1 | | | Model 2 | | |
|---|---|---|---|---|---|---|
| | Coefficient | *p*-value | Exp(B) | Coefficient | *p*-value | Exp(B) |
| *Supplier Location Choice* | | | | | | |
| $x_8$ | -0.295 | 0.00* | 0.74 | -0.291 | 0.00* | 0.75 |
| $x_9$ | 0.042 | 0.00* | 1.04 | 0.042 | 0.00* | 1.04 |
| $x_{10}$ | 0.547 | 0.09** | 1.72 | 0.328 | 0.03* | 1.38 |
| $x_{12}$ | - | - | - | 0.287 | 0.04** | 1.33 |
| Initial *LL* | -799.634 | | | -799.634 | | |
| Final *LL* | -558.89 | | | -555.724 | | |
| $\rho^2$ adjusted | 0.22 | | | 0.23 | | |
| Number of alternatives | 14 | | | 14 | | |
| Number of observations | 303 | | | 303 | | |

$x_8$: Travel time between OD pairs (in hours)
$x_9$: Number of establishments in supplier zones (in hundreds unit)
$x_{10}$: Dummy for traditional market presence in supplier zones, 1 if there is a traditional market on the zone, otherwise 0
$x_{11}$: Dummy for vehicle ownership, 1 if the retailer has a vehicle, otherwise 0
$x_{12}$: Product of $x_{10}$ and $x_{11}$

| Attribute | Model 1 | | | Model 2 | | |
|---|---|---|---|---|---|---|
| | Coefficient | *p*-value | Exp(B) | Coefficient | *p*-value | Exp(B) |
| *Transport Choice* | | | | | | |
| alternative *ov* | Fixed (0) | (n/a) | | Fixed (0) | (n/a) | |
| ASC (alternative *ds*) | -1.26 | 0.00* | 0.28 | -1.26 | 0.00* | 0.28 |
| $x_6$ | -0.69 | 0.09*** | 0.50 | -0.38 | 0.04** | 0.68 |
| $x_{11}$ | -1.26 | 0.00* | 0.28 | -1.26 | 0.01* | 0.28 |
| $x_{13}$ | 0.69 | 0.05** | 1.07 | 0.78 | 0.02** | 2.18 |
| $x_{14}$ | 4.74 | 0.05** | 114.43 | 4.72 | 0.05** | 112.17 |
| $x_{15}$ | - | - | - | -0.39 | 0.05** | 0.68 |
| Initial *LL* | -210.024 | | | -210.024 | | |
| Final *LL* | -127.519 | | | -126.591 | | |
| $\rho^2$ adjusted | 0.36 | | | 0.36 | | |
| Number of alternatives | 2 | | | 2 | | |
| Number of observations | 303 | | | 303 | | |

$x_6$: Dummy for the presence of traditional market, 1 if the retailer located <= 3 km from a traditional market, otherwise 0
$x_{11}$: Dummy for vehicle ownership, 1 if the retailer has a vehicle, otherwise 0
$x_{13}$: Revealed travel times (hours)
$x_{14}$: Average shipment weight (tonnes)
$x_{15}$: Product of $x_6$ and $x_{11}$

*significance at 99% confidence level **significance at 95% confidence level

The results for the retailer restocking choice models (see Table 6-4) show a good fit of the models and are in line with previous research found in the literature with rho-square values ($\rho^2$) between 0.22 and 0.49. Further, overall results show the signs for each attribute for all models are as expected and in line with previous research (Wisetjindawat, Sano and Matsumoto, 2006; Nuzzolo and Comi, 2014).

The supplier location zone model predicts the probability that the retailers will choose a particular TAZ. Model 1 for supplier location choice is the model with no interaction variable. The model fits well with good $\rho^2 = 0.22$, and all the variable signs are as expected. Travel time has a negative sign, implying that increasing travel time to a particular supplier location means that the suppliers in that location are less likely to be chosen by the retailer. In this case, travel time acts as an impedance factor in the retailer decision. On the other hand, the number of establishments and the presence of traditional markets in the supplier zone act as zone attractiveness factors. Both variables have positive signs meaning zones with more establishments and zones with traditional markets are more attractive for independent retailers since the zones provide more supplier options.

Model 2 includes an interaction variable between vehicle ownership and the presence of traditional market in the destination zone. The model also fits well with good $\rho^2$ value (0.23), and all the variable signs are as expected, and all variables are statistically significant. The result shows a positive sign for the interaction variable with a 1.33 odds-ratio value which implies that the retailers are 33% more likely to go to the TAZ which has a traditional market, given that the retailers have their own vehicle.

As for transport choice models, Model 1 fits well with a good $\rho^2$ value (0.49). In this model *delivery service* (*ds*) is the base alternative to the alternative own vehicle (*ov*). The variables are significant and have the expected signs. The revealed travel time variable and the average shipment weight have positive signs, meaning that higher values for both variables increase the utility of the *delivery service* alternative. Hence if there is an increase in perceived travel time (i.e. the supplier location is harder to reach), retailers will opt to use a delivery service. The positive sign for the shipment size variable reflects the context in Bandung, where the delivery services to independent retailers are mostly free, as long as the independent retailers agree with the suppliers to meet a minimum scale of deliveries. Hence a delivery service is a better option for independent retailers receiving larger shipments. The dummy variables for vehicle ownership and the dummy variable for the presence of a traditional market have negative values, meaning that the variables have a negative impact on *delivery service* utility. This implies that retailers who possess a vehicle and are located within the proximity of a traditional market tend to use their own vehicle to restock their shop.

Model 2 depicts the interaction variable between vehicle ownership and the proximity of a traditional market to retailer location. This interaction variable has a negative sign, which implies that if the retailers have their own vehicle and the location of the shop is relatively close to a traditional market, they would tend to use their own vehicle to restock their shop. The odds- ratio of 0.68 shows that the retailers who own a vehicle and are located near a traditional market are 32% less likely to use a *delivery service* to restock their shop.

#### 6.3.2.2 Joint choice model with multinomial logit model (J-MNL) estimation

The similarity of the attributes between supplier location choice and transport service choice points towards further analysis involving joint choice between them. Note also, in real life, the decisions of supplier location and transport service may not be sequential. Hence a joint model is estimated using MNL (J-MNL).

The results of the approach using a joint MNL model are presented in Table 6-5. The initial model (Model 1) for joint supplier location and transport choice model gives a good rho-square value ($\rho^2 = 0.30$) meaning the data is quite robust and fits well with the model. All parameters are significant at the 95% confidence level, and the signs are as expected. The travel time attribute has a negative sign while the number of establishments and the dummy variable for traditional market presence have positive signs as in the previous model. The dummy for vehicle ownership has a negative sign relative to the *delivery service* option, meaning that retailers would prefer to choose their own vehicle to restock their shop.

Lastly, the dummy for average shipment size has a positive sign meaning that an increase in shipment size would increase the probability of using the delivery service transport option. Model 2 includes interaction variables between the dummy for the presence of traditional markets and vehicle ownership attributes. However, the result indicates that this interaction variable is not significant ($p$-value = 0.17), suggesting that in the presence of the vehicle ownership attribute the interaction variable is unnecessary as the effect has already been absorbed by the vehicle ownership variable.

**Table 6-5. Independent retailer choice model joint choice with multinomial logit model (MNL) normalised to retailers' characteristics**

| Attribute | Model 1 Coefficient | Model 1 *p*-value | Model 1 Exp(B) | Model 2 Coefficient | Model 2 *p*-value | Model 2 Exp(B) |
|---|---|---|---|---|---|---|
| *Joint supplier location and transport service choice MNL* | | | | | | |
| $x_8$ | -0.296 | 0.00* | 0.74 | -0.293 | 0.00* | 0.74 |
| $x_9$ | 0.043 | 0.00* | 1.04 | 0.043 | 0.00* | 1.24 |
| $x_{10}$ | 1.00 | 0.00* | 2.71 | 1.03 | 0.02** | 2.80 |
| $x_{12}$ | - | - | | 0.01 | 0.17 | 1.01 |
| $x_{11}$ | | | | | | |
| Alternative *ov* | Fixed (0) | (n/a) | | Fixed (0) | (n/a) | |
| Alternative *ds* | -2.36 | 0.00* | 0.09 | -2.36 | 0.00* | 0.09 |
| $x_{14}$ | | | | | | |
| Alternative *ov* | Fixed (0) | (n/a) | | Fixed (0) | (n/a) | |
| Alternative *ds* | 4.18 | 0.03** | 65.36 | 4.18 | 0.03** | 65.36 |
| Initial *LL* | -985.39 | | | -985.39 | | |
| Final *LL* | -676.12 | | | -674.72 | | |
| $\rho^2$ adjusted | 0.30 | | | 0.31 | | |
| Number of alternatives | 28 | | | 28 | | |
| Number of observations | 303 | | | 303 | | |

$x_8$: Travel time between OD pairs (in hours)
$x_9$: Number of establishments in supplier zones
$x_{10}$: Dummy for traditional market presence in supplier zones, 1 if there is a traditional market on the zone, otherwise 0
$x_{11}$: Dummy for vehicle ownership, 1 if the retailer has a vehicle, otherwise 0
$x_{12}$: Product of $x_{10}$ and $x_{11}$
$x_{14}$: Average shipment weight (tonnes)

*significance at 99% confidence level **significance at 95% confidence level

#### 6.3.2.3 Joint choice model with nested logit model (J-NL) estimation

In addition, we have also tested a nested logit model (NL) to investigate whether indeed a hierarchical approach provides a better explanation of retailer behaviour. The hypothesis is that some supplier zones are more attractive to those retailers that choose their own vehicle to restock. Therefore, we nested the alternative based on the transport service choice (Figure 6-2 Nesting structure for NL choice model).

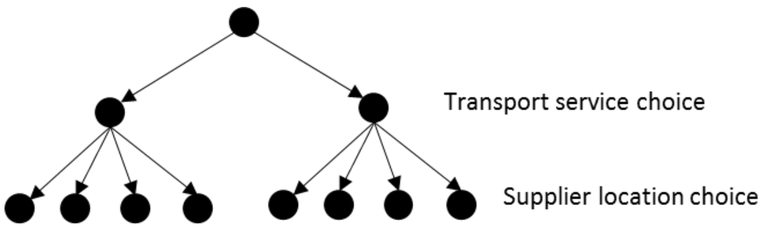



**Figure 6-2 Nesting structure for NL choice model**

Table 6-6 shows the estimation result. The results show expected signs with a fair rho-square value ($\rho^2$ = 0.20). However, the model resulted in a negative nesting coefficient value ($\alpha$ = -0.283). The result is same for the model with the interaction variable ($x_{12}$). This suggests that the model is not consistent with the theoretical derivation of random utility models and thus we reject this approach.

**Table 6-6. Independent retailer choice model joint choice with nested logit (NL) normalise to retailer characteristics**

| Attribute | Model 1 Coef | Model 1 P-value | Model 2 Coef | Model 2 P-value |
|---|---|---|---|---|
| *Joint supplier location and transport service choice (NL)* | | | | |
| $x_8$ | -0.293 | 0.00 | -0.295 | 0.00 |
| $x_9$ | 0.039 | 0.00 | 0.038 | 0.00 |
| $x_{10}$ | 0.824 | 0.00 | 0.824 | 0.00 |
| $x_{12}$ | - | - | 0.01 | 0.90 |
| $x_{11}$ | | | | |
| Alternative *ov* | Fixed (0) | (n/a) | Fixed (0) | (n/a) |
| Alternative *ds* | -1.9 | 0.05 | -1.9 | 0.05 |
| $x_{14}$ | | | | |
| Alternative *ov* | Fixed (0) | (n/a) | Fixed (0) | (n/a) |
| Alternative *ds* | 6.77 | 0.08 | 5.67 | 0.00 |
| $x_{15}$ | -0.283 | 0.00 | -0.289 | 0.00 |
| Initial *LL* | -914.81 | | -914.81 | |
| Final *LL* | -737.56 | | -710.56 | |
| $\rho^2$ adjusted | 0.20 | | 0.22 | |
| Number of alternatives | 28 | | 28 | |
| Number of observation | 303 | | 303 | |

$x_8$: Travel time between OD pairs (in hours)
$x_9$: Number of establishments in supplier zones
$x_{10}$: Dummy for traditional market presence in supplier zones, 1 if there is a traditional market on the zone, otherwise 0
$x_{11}$: Dummy for vehicle ownership, 1 if the retailer has a vehicle, otherwise 0
$x_{12}$: Product of $x_{10}$ and $x_{11}$
$x_{14}$: Average shipment weight (tonnes)
$x_{15}$: nesting (scale) parameter for *delivery service* alternative; *own vehicle* alternative is base nesting alternative

*significance at 99% confidence level **significance at 95% confidence level

### 6.3.2.4 Considering the panel nature of the data.

In many settings, the analysis of discrete choice models can face the situation where numerous choices are made by a single decision maker. For example, in our survey the retailers may have various numbers of supplier and hence the numbers of responses given by each retailer may differ. In this case, we are presented with the case in which the responses from one individual are not 'independent', in a way that responses from the different individual would be. In the literature the case in which one individual has given multiple responses is usually called panel data.

When addressing panel data, the standard MNL model may create an error in its assumption in which the MNL model assumes each observation / response to be independent. The standard MNL model explicitly assumes the independency of each observation in the data, in which applying the model to the data in which the observation is not independent is simply not accurate. However, this approach is not necessarily wrong. It is shown that the standard MNL model that does not consider the correlation across the observation yields consistent estimates of true parameters (Liang and Zeger, 1986). In this section, we address the panel nature of our data (303 observations from 224 respondents) in two ways: (1) by applying a correction procedure so that the MNL model takes into account the nature of the repeated choice, (2) by specifying and estimating the model that explicitly address the repeated nature of the panel data.

***Correction procedure***

To address the dependency across observation in panel data, a correction procedure is applied in the model estimation.The basic concept of the correction procedure is to retain the results given by the standard MNL model but correct the results after the estimation process. Therefore, the main emphasis of the correction procedure is not to improve the parameter estimation, instead the procedure improves the current error measures which are biased.

Without considering panel nature of the data, the log likelihood function could be formulated as

$$L = \sum_{n} \log \prod_{t} P_{cnt} = \sum_{nt} \log P_{cnt} \qquad 6\text{-}3$$

Where, $P_{cnt}$ is the probability given by the model for the observed choice $c$ made by individual $n$ at choice occasion $t$.

With correction approach, the log likelihood of the models is not the equation 6-3, rather the true log likelihood follows

$$L = \sum_{n} \log P_{\{c\}n} \qquad 6\text{-}4$$

Where, $P_{\{c\}n}$ is the probability given by the model for the observed sequence of choice $\{c\}$ made by individual $n$. Equation 1 and equation 2 will only be the same when the successive choice $t$ are independent for individuals. Mathematically this condition can be written as:

$$P_{\{c\}n} = \prod_{t} P_{cnt} \qquad 6\text{-}5$$

In the case in which there are dependencies between the choice made by an individual, theoretically the analyst would need to use equation 6-5 rather than equation 6-4. However, the estimation results are still acceptable since we know that the maximum likelihood coefficient estimators for that model are consistent with the true estimators (cite paper). The correction procedure, then, is used to get the better estimation for error estimators.

This thesis uses correction methods known as sandwich estimators or robust standard error estimators (Daly and Hess, 2010). In the context of the analysis of the panel data, the aim of calculating the robust standard error is to calculate the potential bias in the current standard errors caused by not considering the nature of repeated choices in the panel data. Generally, the robust standard error would differ from the current standard error as the robust standard error is calculated taking into account the nature of panel data.

**Table 6-7 Independent retailer restocking choice MNL model with robust standard error.**

| Attribute | Model 1 | | | Model 2 | | |
|---|---|---|---|---|---|---|
| | *Coefficient* | *Std-error* | *Robust std-error* | *Coefficient* | *Std-error* | *Robust std-error* |
| *Supplier Location Choice* | | | | | | |
| $x_8$ | -0.295 | 0.027* | 0.027* | -0.291 | 0.027* | 0.027* |
| $x_9$ | 0.042 | 0.005* | 0.005* | 0.042 | 0.005* | 0.005* |
| $x_{10}$ | 0.547 | 0.190** | 0.194** | 0.328 | 0.040* | 0.043* |
| $x_{12}$ | - | - | - | 0.287 | 0.041** | 0.044** |
| Initial *LL* | -799.634 | | | -799.634 | | |
| Final *LL* | -558.89 | | | -555.724 | | |
| $\rho^2$ adjusted | 0.22 | | | 0.23 | | |
| Number of alternatives | 14 | | | 14 | | |
| Number of observations | 303 | | | 303 | | |

$x_8$: Travel time between OD pairs (in hours)
$x_9$: Number of establishments in supplier zones (in hundreds unit)
$x_{10}$: Dummy for traditional market presence in supplier zones, 1 if there is a traditional market on the zone, otherwise 0
$x_{11}$: Dummy for vehicle ownership, 1 if the retailer has a vehicle, otherwise 0
$x_{12}$: Product of $x_{10}$ and $x_{11}$

| Attribute | Model 1 | | | Model 2 | | |
|---|---|---|---|---|---|---|
| | *Coefficient* | *Std-error* | *Robust std-error* | *Coefficient* | *Std-error* | *Robust std-error* |
| *Transport Choice* | | | | | | |
| alternative *ov* | Fixed (0) | (n/a) | | Fixed (0) | (n/a) | |
| ASC (alternative *ds)* | -1.26 | 0.386* | 0.392* | -1.26 | 0.438* | 0.437* |
| $x_6$ | -0.69 | 0.357** | 0.368** | -0.38 | 0.226** | 0.233** |
| $x_{11}$ | -1.26 | 0.327* | 0.326* | -1.26 | 0.490* | 0.487* |
| $x_{13}$ | 0.69 | 0.008* | 0.007* | 0.78 | 0.008* | 0.007* |
| $x_{14}$ | 4.74 | 2.524** | 2.861** | 4.72 | 2.434** | 2.556** |
| $x_{15}$ | - | | | -0.39 | 0.248** | 0.257** |
| Initial *LL* | -210.024 | | | -210.024 | | |
| Final *LL* | -127.519 | | | -126.591 | | |
| $\rho^2$ adjusted | 0.36 | | | 0.36 | | |
| Number of alternatives | 2 | | | 2 | | |
| Number of observations | 303 | | | 303 | | |

$x_6$: Dummy for the presence of traditional market, 1 if the retailer located <= 3 km from a traditional market, otherwise 0
$x_{11}$: Dummy for vehicle ownership, 1 if the retailer has a vehicle, otherwise 0
$x_{13}$: Revealed travel times (hours)
$x_{14}$: Average shipment weight (tonnes)
$x_{15}$: Product of $x_6$ and $x_{11}$

*significance at 99% confidence level **significance at 95% confidence level ***significance at 90% confidence level

The results in Table 6-7 of post estimation correction show the difference between the standard error and the robust standard error is small. This result implies that the bias caused by the  panel data in which a respondent can give multiple reponse is not significant.

#### 6.3.2.5 Mixed Logit (MXL) Estimation

Another way to address the nature of repeated choice of panel data is to address this issue in the model specification and estimation. In the literature this model is known as the mixed logit model. The mixed logit is the most generalized choice model that obviates the limitations of the standard MNL model. In the case of addressing the repeated choice of panel data, the emphasis has been on extending the model to include a random parameter that addresses the correlation between the observations.

The mixed logit implementation can be done in two ways: (1) by including the random coefficients (2) by including the error component in the utility function(Daly and Hess, 2010). The estimation is based on the Mixed logit model using python BIOGEME program *panel.py* and *panelNormalized.py.* The first program is to estimate the panel problem using the random coefficient, and the latter is to estimate the panel problem using the error component.

In our case, the random coefficient method is used to estimate the SL choice model. We estimate random coefficient parameters for *travel time* and *number of establishment* variables using a normal distribution probability function for each variable.

The CL model is binomial choice and thus all the attributes are normalized to the own vehicle alternative (*alternative ov)*. The mixed logit model is estimated using error component method. In this approach the emphasis is not to investigate the different taste of particular variables for different retailers, instead the emphasis is to create variables that can induce correlations among alternatives. In this estimation we estimate the error components in the J-1 of the utility functions (J is the set of the alternatives) as suggested byYáñez et al. (2011), and advocated in manual of Biogeme software (Bierlaire, 2003) Therefore, the error component is calculated only for the delivery service alternative.  As with the random coefficient in SL choice, the error component in the CL model follows a normal distribution.

The estimation results can be seen in Table 6-8 below:

**Table 6-8. Independent retailer choice model with MXL analysis**

| Attribute | | Model 1 | | | Model 2 | | |
|---|---|---|---|---|---|---|---|
| | | Coefficient | *Robust Std error* | t-test | Coefficient | *Robust Std error* | t-test |
| *Supplier Location Choice (SL choice)* | | | | | | | |
| $x_8$ | Mean | -0.309 | 0.032* | -9.66 | -0.309 | 0.031* | -9.66 |
| | St-dev | 0.134 | 0.049* | 2.73 | 0.134 | 0.057* | 2.33 |
| $x_9$ | Mean | 0.051 | 0.005* | 10.22 | 0.052 | 0.004* | 11.5 |
| | St-dev | $4.9 \times 10^{-3}$ | 0.007 | 0.64 | - | - | - |
| $x_{10}$ | | 0.516 | 0.298** | 1.73 | 0.518 | 0.298** | 1.73 |
| $x_{12}$ | | 0.305 | 0.120* | 2.54 | 0.305 | 0.120* | 2.54 |
| Initial *LL* | | -799.634 | | | -799.634 | | |
| Final *LL* | | -535.664 | | | -536.660 | | |
| $\rho^2$ adjusted | | 0.25 | | | 0.25 | | |
| Alternative | | 14 | | | 14 | | |
| Observation | | 303 | | | 303 | | |
| Draws | | 1000 | | | 1000 | | |

$x_8$: Travel time between OD pairs (in hours)
$x_9$: Number of establishments in supplier zones (in hundreds unit)
$x_{10}$: Dummy for traditional market presence in supplier zones, 1 if there is a traditional market on the zone, otherwise 0
$x_{11}$: Dummy for vehicle ownership, 1 if the retailer has a vehicle, otherwise 0
$x_{12}$: Product of $x_{10}$ and $x_{11}$

| Attribute | Model 1 | | | Model 2 | | |
|---|---|---|---|---|---|---|
| | Coefficient | *Robust Std-error* | t-test | Coefficient | *Robust Std-error* | t-test |
| *Transport Choice* | | | | | | |
| alternative *ov* | Fixed (0) | (n/a) | (n/a) | Fixed (0) | (n/a) | (n/a) |
| ASC (alternative *ds)* | -1.33 | 0.472* | -2.83 | -1.63 | 0.542* | -3.01 |
| $x_{16}$ (EC) | 0.767 | 0.426** | 1.80 | 0.768 | 0.428** | 1.79 |
| $x_6$ | -0.48 | 0.285*** | -1.70 | -1.01 | 0.565*** | -1.78 |
| $x_{11}$ | -2.03 | 0.485* | -4.15 | -1.44 | 0.592* | -2.28 |
| $x_{13}$ | 0.54 | 0.245* | 2.18 | 0.34 | 0.180** | 1.88 |
| $x_{14}$ | 6.19 | 3.480*** | 1.78 | 6.08 | 3.56*** | 1.69 |
| $x_{15}$ | - | - | - | -0.98 | 0.564*** | -1.75 |
| Initial *LL* | -210.024 | | | -210.024 | | |
| Final *LL* | -126.877 | | | -125.972 | | |
| $\rho^2$ adjusted | 0.38 | | | 0.38 | | |
| Alternatives | 2 | | | 2 | | |
| Observation | 303 | | | 303 | | |
| Draws | 1000 | | | 1000 | | |

$x_6$: Dummy for the presence of traditional market, 1 if the retailer located <= 3 km from a traditional market, otherwise 0
$x_{11}$: Dummy for vehicle ownership, 1 if the retailer has a vehicle, otherwise 0
$x_{13}$: Revealed travel times (hours)
$x_{14}$: Average shipment weight (tonnes)
$x_{15}$: Product of $x_6$ and $x_{11}$
$x_{16}$: Error component for alternative *ds*

*significance at 99% confidence level; **significance at 95% confidence level; ***significance at 90% confidence level

By incorporating random coefficient in the SL model, we can investigate the pattern of the taste for each attribute. In model 1 for panel data analysis, we first estimate the random coefficient for both *travel time between OD* $(x_8)$ and *number of establishments in supplier zone attributes* $(x_9)$. The estimation result indicates that the $x_8$ has a considerable degree of heterogeneity across the decision makers as shown by statistically significant estimation, while $x_9$ does not has a significant heterogeneity and has a very small standard deviation, and hence we cancel $x_9$ as a random coefficient in the next model (Model 2). The subsequent result for Model 2 shows that following the normal distribution there is a significant heterogeneity towards travel time attributes by the decision makers. We can ignore the sign of the standard deviation, and if the result gives a negative sign, we can treat it as a positive value (Hole, 2007)

In the CL model, we incorporate the error components to investigate the correlations among the utilities in different alternatives. Like random coefficient in SL model, the error component for alternative delivery service (*ds)* in CL model follows the normal distribution. The result shows that the error component in the model is statistically significant. This large heterogeneity in taste for transport choice for restocking activities suggests that the large portion of observed heterogeneity is due to demographic factors such as the relationship between retailers and suppliers, and total sales per month, which are not included in the model.

As expected, the statistics for panel analysis with mixed logit model are improved compared to the standard MNL analysis. The rho-square of the MXL models for SL and CL models are higher than the MNL models.

## 6.4 Demand model application

The result of demand models estimation in this chapter will be used as inputs to the optimization model in the next chapter. There are two inputs provided from the demand model:

Firstly, the generation model (model 6 in Table 6-3) is used to calculate the number of weekly restocking trips for each zone in the study area. Or in other words, the generation model gives the number of weekly commercial vehicle trips demand originated from and attracted by the zones on BCC. Nevertheless, our model is a peak hour model and to convert the weekly trips to the modelled trips certain assumptions are applied:

- We model commercial vehicle trips demand in peak hour between 08.00-09.00 in a typical working day.

- We explicitly only consider commercial vehicles trips that originated from the BCC area or in other words we only consider commercial vehicle trips that choose the *own vehicles* transport service. The reasons are two fold: firstly, the origin of vehicle trips by the delivery services is unknown. In a delivery service, the suppliers are the decision maker in terms of transport delivery service choice and can opt to use their own vehicles or order third party carriers to deliver the goods, and thus the origin of the vehicle trips is unknown to us. Secondly, the survey suggests most of the restocking activities by independent retailers in peak hour time are undertaken using their own vehicles.
- We only consider the trips that are originated from Bandung city center and have destinations within the study area (BCC area plus three adjacent suppliers zones). The survey revealed that the majority of retailers inside BCC are restocking their shops from suppliers inside the BCC and three adjacent areas (see Figure 6-3).

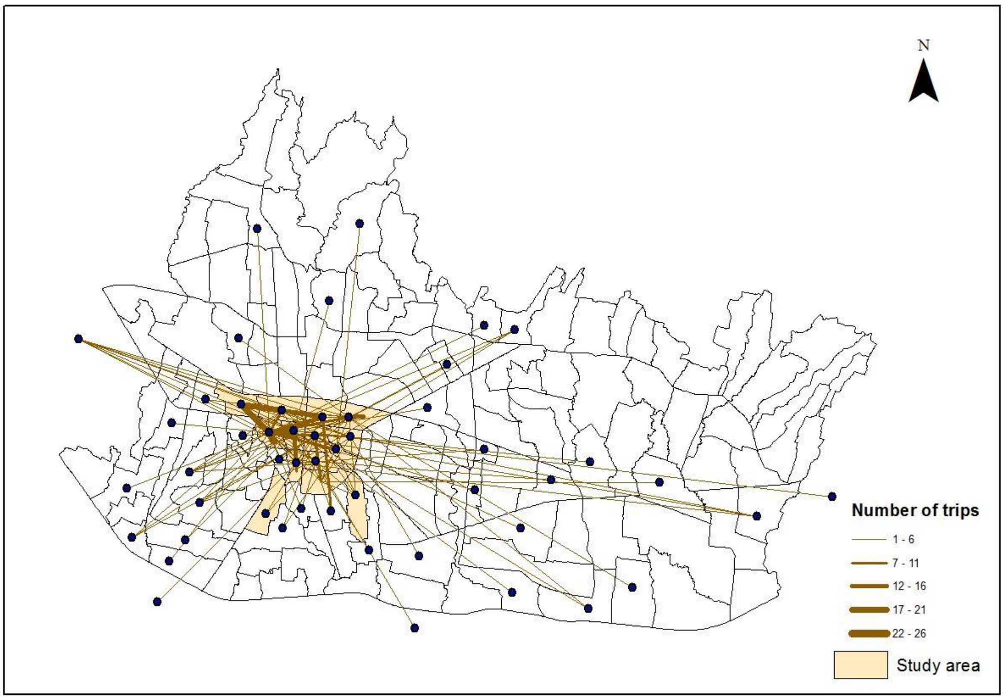



**Figure 6-3. The restocking OD trips (desire lines) from the survey**

By restricting the study area, we realise that we might miss actual trips that are happening in the real world. In that case, the findings and results of this study can only be applied to the trips inside the BCC area rather than the actual city of Bandung. However, by restricting the model into smaller area, there are advantages that can be gained: The model estimation result becomes more consistent particularly estimation that includes the revealed travel time data (i.e. transport service choice model). Further, in term of solving the optimisation problem, we can have more options since we are not dealing with a very large network.

Secondly, in our model we consider the commercial vehicle trips that generated from the retailers' shops and thus we only use a *supplier location choice model* as the decision for commercial vehicle demand. In particular we will use the result of MNL model estimation (model 1) as an input into the lower level problem of the bi-level programming. Although the MXL estimations show an improvement in terms of the fitness of the model ($\rho^2$ adjusted in MXL model is higher than MNL model), the results show that the estimated coefficients are not significantly different from the MNL model. The MNL model is preferable in this thesis since in the process of including the supplier location decision in the traffic assignment formulation, the MNL model is more manageable. The details of how the supplier location choice will be included in the lower level problem of the bilevel programming will be provided in chapter 8.

## 6.5 Chapter summary

This chapter presents the demand model specification and estimation for UGM activities in which the predominant retailer activities are independent retailers. The demand model reveals the explanatory factors that significantly affect the logistics decisions of independent retailers.

The trip generation model identifies the significant attributes to be the attributes related to the activities of the independent retailers (e.g. weekly goods demand, vehicle ownership) and not the physical attributes of the independent retail store (i.e. the store area and the number of employees). The physical attributes do not have a significant influence on restocking trips since the physical attributes of one independent retailer are not very different to those of the others. The generation of restocking trips is more related to the operational characteristics of the retailers. In particular, the importance to include the average shipment weight is crucial to the model estimation. The result corresponds to previous research indicating the shipment size is one significant factor (Holguín-Veras et al., 2014b), particularly to estimate the goods vehicle trips movement rather than goods movement. The shipment weight variable represents the mode limitation for transporting the goods. In our case, the two-wheeler and the van have a distinctive ability to move the goods per trip. Two-wheelers may need several trips to transport particular goods while a delivery van can transport the same goods with just a single trip.

Regarding supplier location choice, besides travel time between the retailer zone and supplier zone, the large numbers of establishments located in traditional markets and their proximity to the independent retailers play a significant role in making such markets attractive to independent retailers. Meanwhile, attributes such as the number of weekly trips, shipment size, travel times, van / two-wheeler ownership play a significant role in transport choice for restocking activities. In particular, the high rate of vehicle ownership (particularly of two-wheelers) results in the majority of restocking trips being made by own vehicle. The model results and the estimation value for each attribute are largely consistent with previous research in the cities of the developed world (see for example the estimation results in Russo and Comi, 2010; Wisetjindawat et al., 2007).

The next chapter discusses the bilevel optimisation formulation. The optimisation model aims to bring a condition in which the city logistics policies result in an optimal traffic condition for all actors on urban road networks. Nevertheless, the demand model presented in this chapter will be used in Chapter 8 when we are trying to assess the optimal city logistics policies in Bandung city centre. The demand model, in particular the supplier location choice model, acts as the tool to assess the behaviour of independent retailers in various traffic conditions.

# Chapter 7 Bilevel programming formulation considering the independent retailer restocking activity problem

This chapter formulates the previous problem involving three actors in UGM activities as an optimisation problem. The mathematical program needs to incorporate retailers' restocking behaviour while simultaneously incorporating the objective of local authorities. The key problem we address here involves the fact that local authorities are the only stakeholders in UGM activities that are interested in achieving benefit for all road users. The road users, including commercial vehicles, are assumed to be selfish in their decisions. However, to be able to apply optimal policies, the local authority needs to consider the decisions of all the road users. In our case, the two road users are considered viz. commercial vehicle and private vehicles.

We formulate the three-sided interaction between the independent retailer restocking activity decisions, other road users, and the local authority's transport policies as a bilevel optimisation problem. A bilevel optimisation problem is often used to solve a continuous network design problem (CNDP) such as determining links expansion or links toll for the existing links in the network (Koh et al., 2009; Wang et al., 2014). However, in our case, the bilevel programming is used to represent a local authority's objective and retailers' behaviour. The upper levels represent the local authority's objective while the lower level represents the retailers' behaviour and its interaction with other road users. The lower level problem depicts the retailer behaviour in the user equilibrium condition.

This chapter is arranged as follows: Section 7.1 will describe the notation used in the chapter. Then in Section 7.2 we describe the problems followed by an explanation of how the bilevel programming framework will address the problem. Section 7.3 deals with upper level problem formulation depicting the objective of the local authority. The user equilibrium condition formulation and its extension to depict our problem are explained in Section 7.4. Section 7.5 discusses the actual formulation of bilevel programming and the proposed algorithm to solve the problem. Section 7.6 discusses the specific demand function that governs the behaviour of the retailers as well as other road users. Finally, the numerical example is provided in Section 7.7, and this chapter is closed with a Chapter summary in Section 7.8.

## 7.1 Notations

The notation for all equation describing the bilevel optimisation formulation is listed as follows unless otherwise specified.

| | |
|---|---|
| $A$ | Set of links in the network |
| $a$ | Index of links in the network, $a \in A$ |
| $W$ | Set of all OD pairs |
| $w$ | Index of OD pairs. Each OD pair formed by a combination of *r* and *s*, where *r* denotes retailer location (origin) and *s* denotes supplier location (destination). $r \in R, s \in S, rs \in W$ |
| $i$ | User class index; *i* = 1 for commercial vehicle user class; *i* = 2 for private vehicle user class |
| $l_a$ | Length of the link *a* in km |
| $D_w^i$ | Trip demand for OD pair *w* by user class *i* |
| $D_r$ | Total trip demand for all retailers within the retailer zone *r* |
| $P_w$ | Set of all paths connecting OD pair $w \in W$ |
| $t_a(v_a)$ | Link travel time function on link *a* |
| $k_a$ | Capacity of link $a \in A$ |
| $v_a^i$ | Link flow on link *a* by user class *i* |
| $f_p^i$ | Path flow by user class *i* using path *p*, $p \in P_w, w \in W$ |
| $c_a^i$ | Generalised travel cost for user class *i* on link *a* |
| $C_p^i$ | Path generalised travel cost for user class *i* using path *p*, $p \in P_w, w \in W$ |
| $\lambda_i$ | Value of time for user class *i* |
| $\theta_i$ | Vehicle operational cost for user class *i* |
| $\tau_a$ | Toll on link *a* |
| $\delta_p^a$ | $\delta_p^a$ = 1 if path *p* uses link *a* otherwise zero, $p \in P_w, w \in W$ |
| $d^i(\omega)$ | Demand function for user class $i, i \in I$ |
| $d^{i^{-1}}(\omega)$ | Inverse demand function for user class $i, i \in I$ |
| $\mu_w^i$ | Minimal travel cost for OD pair *w* for user class *i*, $w \in W$ |
| $\beta$ | Logit parameter related to travel time attributes from supplier location choice model |
| $S$ | Supplier zones, $s \in S$ |
| $R$ | Retailer zones, $r \in R$ |
| $u_s$ | Utility for supplier zones *s* |

Given the notations as above, the following relations hold throughout the paper:

$$v_a = \sum_{i \in I} v_a^i \quad (7\text{-}1)$$

$$v_a^i = \sum_{w} \sum_{p \in P_w} \delta_p^a \, f_p^i \quad (7\text{-}2)$$

$$D_w^i = \sum_{p \in P_w} f_p^i \quad (7\text{-}3)$$

$$D_r^i = \sum_{s} D_{rs}^i \quad (7\text{-}4)$$

Equation 7-1 shows that the total flow on each link is obtained by summing the flow of each user class on that link. The relationship between link flow and path flow is defined by Equation 7-2 implying the flow of a user class on a link is equal to the path flow of the user class summed over all paths that use the link. Equation 7-3 conserves the travel demand for user class *i* for OD pair *w* by setting it as equal to the sum of all the path flows of the particular user class connecting the OD pair *w*. Equation 7-4 defines the total number of trips going from a particular zone *r* to all possible destination zones which is equal to the trip demand for a given user class (say, *i=1* for commercial vehicles) generated from the zone.

## 7.2 Bilevel programming problem framework

Decision-making processes of different actors can often be modelled within the framework of bilevel programming. The interaction between the local authorities who aim to find optimal policies and the road users can be depicted as Figure 7-1 below:

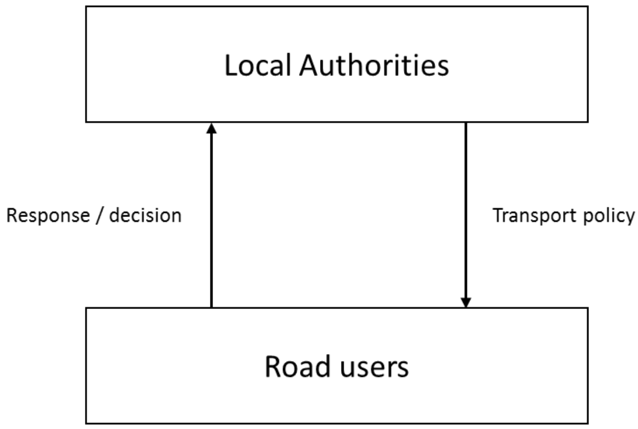



**Figure 7-1. Local authorities – road user interaction**

Figure 7-1 implies that the objective of the local authorities is a function of the response from the road users. Two different approaches found in the literature relate to this problem. First, the local authorities could iteratively design and implement the transport policies scheme based on the current conditions, then observe the response of the road users to the scheme following the UE condition, evaluate the benefit for a particular scheme, and redesign the scheme to optimise the local authority's objective with the updated travel pattern, then go through the process iteratively until the solution converges. Alternatively, the local authority could take into account the potential response of road users during the design process. In this setting, the local authority is assumed to be able to anticipate the response of the road users to the transport policies applied using the UE condition. Note that the first and second approach may lead to different solutions. The former iteration leads to Nash equilibrium while the latter leads to a Stackelberg equilibrium condition (Fisk 1984).

Mathematically, we can define bilevel programming as a mathematical program with equilibrium constraint (MPEC). MPEC is an optimisation problem in which the constraint of the problem is the equilibrium condition. Let $x \in R^n$ and $y \in R^m$ be two sets of variables in MPEC. $f$ is the objective function of the MPEC and $F$ is the parameterised equilibrium function in variational inequality form. Let $X$ be the feasible region of $x$ and $\Omega(x)$ be the feasible region of $y$ given a vector $x$. In general, the MPEC can then be written as:

$$\min_{(x,y)} f(x,y) \qquad \text{7-5}$$

$$s.t.$$

$$x \in X$$

$$y \in S(x)$$

where, $S(x) = \{y^* \in \Omega(x) \mid F(x,y^*)^T.(y^* - y) \le 0,\ \forall\, y \in \Omega(x)\}$

The last line in Equation 7-5 implies that for each vector $x$ , $S(x)$ is the set of the solution to the variational inequality $(F, \Omega(x))$.

The MPEC formulation can be used to describe various optimisation problems. E.g. MPEC can be used to determine discrete decisions such as the locations of the toll points, the number of toll points, or, in more general terms, decisions to select or not to select a particular policy. Sumalee (2004) considers this problem to be a mixed 1-0 optimal toll problem (MOTP). The inclusion of the binary (1-0) variable representing the state if a particular policy is taken or not turns the problem into a mixed 1-0 optimisation problem. Yamada et al. (2007) use this approach to determine the optimal design for a freight transport network in a regional area context.

Another problem that can be formulated as MPEC is the continuous design problem. The design problems include finding the optimal toll (Yang, 1999), finding the optimal link capacity enhancement (Wang et al., 2014), or both (Koh et al., 2009). This thesis focuses on the continuous problem in particular *selecting an optimal toll level for each predefined links* in the network. The MPEC for this problem can be written as:

$$\min_{(\boldsymbol{v},\boldsymbol{d},\boldsymbol{\tau})} f(\boldsymbol{v},\boldsymbol{d},\boldsymbol{\tau}) \qquad \text{7-6}$$

$$s.t.$$

$$0 \leq \tau_a \leq \varepsilon_a \overline{\tau_a}$$

$$(\boldsymbol{v},\boldsymbol{d}) \in \Omega$$

$$\boldsymbol{c}\,(\boldsymbol{v}^*,\tau)^{\boldsymbol{T}}(\boldsymbol{v}^* - \boldsymbol{v}) - \boldsymbol{d}^{-\boldsymbol{1}}(\boldsymbol{d}^*,\tau)^{\boldsymbol{T}}(\boldsymbol{d}^* - \boldsymbol{d}) \leq \boldsymbol{0}, \quad \forall \boldsymbol{v},\boldsymbol{d} \in \Omega$$

where $\varepsilon_a$ is binary variables indicating whether a link in the network can be tolled or not. Next, we discuss the formulation for a local authority's objective.

## 7.3 Formulation of the local authority's objective considering UGM activities

In Chapter 4 we discussed that the objective of the local authority can be looked at from various perspectives. However, this thesis focuses on the welfare economic objective in which the objective of the local authority is to maximise economic benefit which is obtained as the net benefit equal to the difference between user benefits and social costs.

$$economic\ benefit\ (\mathrm{Z}) = User\ benefit\ (UB) - social\ cost\ (SC)$$

The demand function is a crucial determinant of social welfare as it represents the aggregate willingness to pay by the road users for accessing the destinations (implying a benefit to road users when accessing a destination). In general, for each OD pair, the lower the cost of travel, the higher the demand to travel. Some transportation economics (e.g. Verhoef, 2002) view the area under the inverse demand curves the benefit gained from making the trips, and thus for any given demand function the user benefit can be expressed as:

$$User\ benefit\ (UB) = \sum_{w \in W} \sum_{i \in I} \int_0^{D_w^i} {d_w^i}^{-1}(\omega) \qquad \text{7-7}$$

On the other hand, the total social cost is the total travel time that all road users spend on the network. We assume that delays in the network occur solely on the links and that the travel cost on a particular link is a function of the total flow on the link only. The link cost function can be written as:

$$c_a^i = \lambda_i \, t_a(v_a) + \theta_i l_a \tag{7-8}$$

Note that the toll is not included in the total social cost as the toll revenue is transferred to the authorities. Further, given the cost function, the total social cost in the system is given by:

$$social\ cost\ (SC) = \sum_{i \in I} \sum_{a \in A} c_a^i \, v_a^i \tag{7-9}$$

The economic benefit $(\mathrm{Z})$ then can be defined as the net difference between UB and SC, as follows:

$$\mathrm{Z} = \sum_{w \in W} \sum_{i \in I} \int_0^{D_w^i} {d_w^i}^{-1}(\omega) - \sum_{i \in I} \sum_{a \in A} c_a^i \, v_a^i \tag{7-10}$$

There is a long-established consensus on the form of social welfare. Several studies on the design of optimal road pricing have adopted the objective function as depicted by Equation 7-10 (see for example Koh et al., 2009; Yang and Huang, 2004, although with a single user class demand in their case). This thesis extended the objective function to consider multiple user classes with different demand functions as described so far. Note that the Equation 7-10 has the superscript $i$ indicating that the user benefit is calculated for each user class.

## 7.4 Formulation of the user equilibrium condition

The lower level problem depicted the *follower* decisions in the Stackelberg game set up. In this set up, the players are following the *leader* policies to the system and make decisions until reaching an equilibrium condition. There are two players in our case: commercial vehicles for retailers and private vehicles for passengers who tried to move from their origin to their destination.

Note that the optimisation lower level problem, i.e. the retailer behaviours, would be a constraint to the local authority’s optimisation problem regarding optimal city logistics transport policies. To be able to consider the combined distribution and traffic assignment problem as well as a multi-user class problem, the user equilibrium is formulated as variational inequality (VI).

In the lower level problem, two problems should be addressed in the model: firstly, we address the problem of involving independent retailers' decisions in the model formulation. We incorporate the retailer decisions in the model by making the particular demand model the input for the combined traffic assignment problems. In the combined traffic assignment problem, the retailer decision for supplier location is then simulated simultaneously with the route choice decisions embedded in the traffic assignment model. In terms of private vehicle demand, the demand is also not static. Rather, the private vehicle demand follows the variable demand function in which the other option is not to travel at all. Secondly, we address the problem of multi-user class traffic assignment since our traffic assignment problem includes private vehicle demand.

The basic formulation of the traffic user assignment has been discussed in Chapter 4, including the mathematical formulation of UE traffic assignment using variational inequality. In the next subsections, we extend the formulation of the user equilibrium (UE) traffic assignment using VI accommodating the two conditions discussed above.

### 7.4.1 Representation of road user behaviour: combined UE traffic assignment formulation

The issue for a UGM model is not only an issue of formulating a standard user equilibrium condition as formulated in the previous section. The standard UE network assignment problem can be viewed as a model of travellers choosing a route from origin to destination. However, in the UGM context, the model needs to include another decision by the retailers as a way to capture their behaviour corresponding to the traffic conditions.

This thesis involves allowing destination choice (supplier location choice) for commercial vehicles (CVs) whilst also being elastic for private vehicles (PVs) in response to the traffic conditions. Both the destination choice for CVs and the demand level for PVs involves the function of travel cost between origin and destination. Both problems imply the necessity to include demand variability in the UE formulation albeit in slightly different ways.

The literature describes the destination choice for CVs as a combined trips distribution and assignment model (Lam and Huang, 1992). Here, the problem involves a situation where the total number of trips originating from each origin is fixed. The question then becomes how to distribute the trips to the available destinations based on the attractiveness of the destination zone. In this case, the trips demand $D_r$ is a variable which has to be determined and is a subject to the constraint:

$$D_r = \sum_s D_{rs} \quad 7\text{-}11$$

In this problem, the attractiveness of the supplier location is determined by the choice model involving a multinomial logit model. In this choice, the attractiveness of supplier location attribute (e.g. the number of establishments in the destination zone) interplay with travel impendence, i.e. the total travel cost to travel between origin and destination.

Meanwhile, the PV demand is described as a UE traffic assignment problem with variable demand. It involves an additional choice dimension that can be looked upon as either the choice to travel or not to travel. In order to take this decision into account, the rate of the trip between the OD pair $w$ is assumed to be a function of travel time between OD as follows:

$$D_w = d \ \ (\mu_w) \quad 7\text{-}12$$

In this setup, typically the form of the demand function will be the same for all OD pairs.

The key to formulating the UE condition that includes the combined decisions of each user class is by considering demand variability in the UE formulation. As we discussed in Chapter 4, the UE condition for variable demand can be written as variational inequality:

$$\sum_{a \in A} c_a(t_a(v_a^*))\,(v_a^* - v_a) - \sum_{w \in W} d_w^{-1}(d_w^*)(d_w^* - d_w) \leq 0; \quad 7\text{-}13$$
$$\forall\,(v_a, d_w) \in \Omega$$

$\Omega$ in Equation 7-13 is described as a set of linear equation constraints including flow conservation constraint, definitional constraint, and flow positivity constraint and thus it is a polyhedron.

$$\Omega = \left\{ \begin{matrix} \mathbf{v},\ \mathbf{d} \mid \sum_{p_w} d_{p_w}^i = d_w^i, v_a^i = \sum_w \sum_{p \in P_w} \delta_p^a f_p^i, v_a = \sum_{i \in I} v_a^i, d_{p_w} \geq 0 \\ \forall\, w \in W,\ a \in A, i \in I \end{matrix} \right\} \quad 7\text{-}14$$

We include trip distribution for commercial vehicles into the VI formulation by specifying it as a demand function. By including the choice dimension into the demand function in the VI formulation, the problem becomes a combined destination choice and route choice model.

Suppose the travel choice for commercial vehicles can be written as:

$$D_w^{i=1} = d_w^{i=1}\,(\mu_w^{i=1}) \quad 7\text{-}15$$

and $d_w\ (c_p)$ represents the demand function. Then, as long as the demand function in Equation 3.8 is invertible (i.e. the demand function can be inverted), the inverse demand function can then be presented as:

$$\mu_w^{i=1} = \left[d_w^{i=1}\right]^{-1}(D_w^{i=1}) \qquad 7\text{-}16$$

By defining the inverse demand function in terms of demand flow, the inverse demand function can then be included in VI formulations for variable demand.

The specific functions for each user class (multinomial logit function for commercial vehicle demand, and power function for private vehicle demand) and the inverse transformation for each function is discussed in Section 7.6.

### 7.4.2 Representation of mix traffic conditions: Multiuser class UE traffic assignment formulation

In this subsection, we address the problem to introduce multi-user class cases into our user equilibrium traffic assignment formulation. Previous studies on network design problems mostly assumes the traffic condition to be a homogenous user class (see for example Koh et al, 2009). However, since in our case we include two vehicle types: commercial vehicle (CV) and private vehicle (PV), it is inevitable that we must consider multi-user class in our user equilibrium formulation.

Further, previous studies suggest that CV and PV demands have different value of time (VOT) and value of direct transport cost (VOC) parameters. This is reasonable, given the practical studies noting that the VOT for working trips is usually different from any other trip purposes including goods trips (Prasetyo et al., 2003). In general, VOT and VOC for CV are higher than PV. The reason is that VOT for CV transport counts the inherent value of the goods (Holguín-Veras and Cetin, 2009) whilst VOC for CV is generally higher because, in general, CV has a bigger dimension and consumes more fuel compared to PV.

This thesis, in particular, is interested in multi-criteria traffic equilibrium in which the model explicitly identified travel cost and travel time for each user class as criteria in route selection. Specifically, each class of traveller will perceive his travel disutility as a subjective weighting of two criteria given i.e. travel time and direct travel cost. In the presence of distinct VOTs $(\lambda_i)$ and VOC $(\theta_i)$ for each user class, the travel disutility can be measured in money terms by Equation 7-17.

$$c_a^i = \lambda_i\, t_a\,(v_a) + \theta_i l_a \qquad 7\text{-}17$$

where, $l_a$ is the length of link $a$. Observe that the travel time is a function of the number of vehicles of all user classes using a particular link, $t_a(v_a)$.

The VOT and VOC can be seen as a weighting scheme for the different user classes. The weight represents the priority of the user class over the two criteria. The weighting scheme can be in the form of $\lambda_i + \theta_i = 1$, and the absolute value of $\lambda_i/\theta_i$ can be from 0 to 1. $\lambda_i = 0$ indicates a user class that is only concerned with the shortest path. Dafermos (1972) uses this weighting scheme to distinguish the user class in her paper. However, in this paper, we do not limit the VOT and VOC values to the weights. As such we can be more general and represent the situation where two user classes can have distinguished VOT and VOC.

Given the cost of the links given by Equation 7-17, we now can denote the travel cost for class $i$ associated with travelling using path $p$ to be:

$$C_p^i = \sum_{a \in A} c_a^i \, f_p^i \, \delta_p^a \qquad \text{7-18}$$

Now, we define equilibrium for traffic equilibrium cases with multi-user class as variational inequality. As with the case with combined UE traffic in the previous subsection, the UE condition needs to be written as VI so that it can be subsumed as a constraint of our bilevel programming problem.

It is known that the VI for multi-user class problems can be formulated as the sum of VI for each user class, given different VOTs for each user class (see e.g. Nagurney, 2000; de Cea *et al.*, 2005).

$$\sum_{i \in I} \sum_{a \in A} c_a^i(t_a(v_a^*))\left(v_a^{i^*} - v_a^i\right) \leq 0, \qquad \forall\, v_a \in \Omega \qquad \text{7-19}$$

Ω is the set of possible link flows and consists of a set of linear constraints following the set of constraints. Observe that the VI is consistent with the VI in a combined UE traffic assignment in which the VI is written in the link flows variable and not in the path flows variable.

### 7.4.3 Formulation of UE condition considering retailers' restocking activities

In this section, we formulate the lower level problem that represents the user equilibrium condition considering retailers' retailing activities, i.e. we formulate the traffic equilibrium problem that considers commercial vehicle and private vehicle decisions, with respect to both route choice and the mixed traffic condition.

Firstly, in the case where road pricing is considered a way to improve retailers' restocking activities, we need to consider toll as an additional cost in the link. The extended cost function can be formulated as:

$$\check{c}_a^i = \lambda_i \, t_a \,(v_a) + \theta_i l_a + \tau_a^i \qquad \text{7-20}$$

where $\tau_a^i$ is specific toll value for a given user class on a particular link.

Finally, using Equations 7-13, 7-19, and 7-20, the problem of user equilibrium traffic assignment, formulated as a VI for variable demand with multiple user classes, can be formulated as:

$$\sum_{i \in I} \left[ \sum_{a \in A} \check{c}_a^i (\, t_a(v_a^*), \tau_a^i)(v_a^{i^*} - v_a^i) - \sum_{w \in W} {d_w^i}^{-1} \left(d_w^{i^*}, \tau_a^i\right)\left(d_w^{i^*} - \, d_w^i\right) \right] \leq 0 \qquad \text{7-21}$$

$$\forall (v_a^i, d_w^i) \, \in \, \Omega$$

Equation 7-21 represents the lower level problem in our bilevel programming. The lower level problem involves allowing destination choice (supplier location) for commercial vehicles whilst also being elastic for private vehicles in response to the congestion. Thus, we need to extend the lower level VI to depict two features: (i) the combined destination cum route choice model for commercial vehicles; and (ii) traffic assignment with multiple user classes with variable demand. The proposed extension to include destination choice and multiple user classes requires further consideration as described below.

Trip distribution of commercial vehicles ($i$ = 1) can be achieved by defining a demand function in the form of a multinomial logit choice model which shares the demand amongst destinations (Fisk and Boyce 1983). This result is important since it allows the other travel choice (supplier location) to be assessed simultaneously with route choice. For private vehicles ($i$ = 2), we assume that the demand is variable and responds to the cost of travel: the higher the cost of travel, the lower the demand for travel and vice versa. This can be modelled by specifying a more general demand function such as power function, exponential function or even logit function.

## 7.5 Bilevel optimisation problem formulation

In this section, we formulate the actual bilevel programming formulation considering independent restocking activities.

The upper level problem is following equation 7-23, as follows:

$$Z = \sum_{w \in W} \sum_{i \in I} \int_{0}^{D_w^i} {d_w^i}^{-1}(\omega) - \sum_{i \in I} \sum_{a \in A} c_a^i \, v_a^i \qquad \text{7-22}$$

Where Z is social welfare that local authority tries to maximize. The first term of equation 7-23 depicts the user benefit for each user class, and the second term formulates the social cost user class implied to the road network. As for the lower level problem, this is formulated as follows:

Let $\boldsymbol{v}^*$ and $\boldsymbol{d}^*$ respectively be vectors with $a \times i$ dimension with:

components $\begin{bmatrix} v_1^1 & \cdots & v_1^i \\ \vdots & \ddots & \vdots \\ v_a^1 & \cdots & v_a^i \end{bmatrix}$ and $w \times i$ dimension with components $\begin{bmatrix} d_1^1 & \cdots & d_1^i \\ \vdots & \ddots & \vdots \\ d_w^1 & \cdots & d_w^i \end{bmatrix}$.

Then the lower level problem formulated in Equation 7-23 can be rewritten in vector form as follows:

$$\boldsymbol{c}\,(\boldsymbol{v}^*, \tau)^{\boldsymbol{T}}(\boldsymbol{v}^* - \boldsymbol{v}) - \boldsymbol{d}^{-\boldsymbol{1}}(\boldsymbol{d}^*, \tau)^{\boldsymbol{T}}(\boldsymbol{d}^* - \boldsymbol{d}) \le \boldsymbol{0}, \quad \forall \boldsymbol{v}, \boldsymbol{d} \in \Omega \qquad \text{7-23}$$

Combining the upper level probem and the lower level problem, the bi level optimisation for our problem can be formulated as:

$$\max_{\boldsymbol{v}, \boldsymbol{d}, \tau} Z\,(\boldsymbol{v}, \boldsymbol{d}, \tau)$$

$$s.t$$

$$0 \le \tau_a^i \le \varepsilon_a \overline{\tau_a^i} \qquad \text{7-24}$$

$$\boldsymbol{c}\,(\boldsymbol{v}^*, \tau)^{\boldsymbol{T}}(\boldsymbol{v}^* - \boldsymbol{v}) - \boldsymbol{d}^{-\boldsymbol{1}}(\boldsymbol{d}^*, \tau)^{\boldsymbol{T}}(\boldsymbol{d}^* - \boldsymbol{d}) \le 0 \;\; \forall\, \boldsymbol{v}, \boldsymbol{d} \in \Omega$$

Where $Z$ is the objective function, $\varepsilon_a$ are binary variables indicating whether the link in the network can be tolled or not, and $\overline{\tau_a^i}$ is the upper boundary of the toll which can be applied. The second constraint formulates the lower level problem in which the traffic equilibrium condition is formulated as a variational inequality. The last constraint defines the possible solution for traffic flow, and demand follows the set of flow conservation and demand constraints defined by Ω.

### 7.5.1 Model formulation for specific demand functions

Note that in the above formulation, the demand function is generally noted as $d^i(\omega)$. The demand function expresses the demand between the OD pair as a function of the cost of travel. This thesis adopts different forms of demand function to reflect the decisions faced by each user class.

The demand function expresses the demand between an OD pair as a function of the cost of travel. Many functional forms such as power function, exponential function, logit function etc. are typically used, but their characteristics may imply certain outcomes. In our research, the total demand generated by retailers from each retailer zone *r,* ($d_r^1$) is fixed, and yet the trip distribution for each OD pair is based on the utility associated with each supplier location *s*. Meanwhile for private vehicle demand ($d_w^2$), the demand responds to travel cost for each OD pair *w*. They will have a choice of route as well as having a choice not to travel at all (elastic demand).

In this thesis, demand function for commercial vehicles (*i* = 1) is depicted as a multinomial logit function (7-25). The logit function in 3-20 calculates the fraction of aggregate originating demand for each destination based on relative attractiveness. Equation 7-26 specifies the utility function for destination (supplier) zones, which is dependent on the shortest travel time between the OD pair, $\mu_w^1$, and *n^th^* character of the supplier zone *s* such as the number of establishments in the destination zone, the presence of wholesalers/traditional markets in the supplier zone etc and $\delta$ is a Gumbel distributed i.i.d random term.

$$d_w^1(\mu_w^1) = D_r \frac{e^{-\alpha(u_s)}}{\sum_{s\in S} e^{-\alpha(u_s)}}; \quad w \in W \tag{7-25}$$

$$u_s = \beta * \mu_w^1 + \alpha_{s_n} * z_{s_n} + \delta \tag{7-26}$$

$\alpha$ is a scale factor, in which in the MNL model the value is equal to 1.

From Fisk and Boyce (1983) the inverse of the demand function can be written as Equation 7-27 (proof of this can be seen in Appendix E)

$$d_w^{1\ -1}(d_w) = -\frac{1}{\alpha} \ln\left(\frac{d_w}{D_r - \sum_{s\neq w_s} d_w}\right), \forall w; \; w \in W \tag{7-27}$$

Integrating the inverse demand function in 7-27 gives the user benefits for CVs as below (proof of this can be seen in Appendix F):

$$UB^1 = -\frac{1}{\alpha\lambda_i} \sum_{w\in W} D_w^1 \ln D_w^1 \tag{7-28}$$

Since user benefit needs to be counted in money units, we multiply Equation 7-28 with VOT ($\lambda_i$).

The demand function for private vehicles (*i* =2) is based on power law as in Koh et al. (2009):

$$D_w^2 = \breve{D}_w^2 \left(\frac{\mu_w^2}{\breve{\mu}_w^2}\right)^{-0.57} \qquad \text{7-29}$$

where $\breve{D}_w^2$ and $\breve{\mu}_w^2$are the initial demand and cost respectively. $\mu_w^2$ is minimal travel cost between OD pair *w* for private vehicle user. The user benefit can then be calculated by integrating the inverse demand function:

$$\mu_w^2 = \breve{\mu}_w^2 \left(\frac{D_w^2}{\breve{D}_w^2}\right)^{-1.75} \qquad \text{7-30}$$

and can be expressed by Equation 7-31.

$$UB^2 = -1.33\, {\breve{D}_w^2}^{1.75} {D_w^2}^{-0.75} \breve{\mu}_w^2 \qquad \text{7-31}$$

Thus, for the particular case of logit function for commercial vehicles and power function for private vehicles, the first term of Equation 7-10 can be equivalently replaced with the summation of $UB^1$ and $UB^2$ as shown by Equations 7-28 and 7-28.

Thus, the upper level objective function can be specified as below:

$$\mathrm{Z} = -\frac{1}{\beta\lambda_i} \sum_{w\in W} D_w^1 \ln D_w^1 - 1.33\, {\breve{D}_w^2}^{1.75} {D_w^2}^{-0.75} \breve{\mu}_w^2 - \sum_{i\in I} \sum_{a\in A} c_a^i\, v_a^i \qquad \text{7-32}$$

Finally, the VI for the traffic assignment problem with two types of demand, i.e. logit-based function for commercial vehicles and power-law based function for private vehicles, can be stated as below:

$$\left\{\sum_{a\in A} c_a^1 \left(\lambda_1, t_a(v_a^*), \tau_a^1\right)\left(v_a^{1^*} - v_a^1\right) - \sum_{w\in W} \frac{1}{\beta} \ln\left(\frac{d_w^1}{D_r - \sum_{s\neq w_S} d_w}\right)\left(d_w^{1^*} - d_w^1\right)\right\} + \left\{\sum_{a\in A} c_a^2 \left(\lambda_2, t_a(v_a^*), \tau_a^2\right)\left(v_a^{2^*} - v_a^2\right) - \sum_{w\in W} {\mu_w^2}^0 \left(\frac{d_w^2}{{d_w^2}^0}\right)^{-1.75} \left(d_w^{2^*} - d_w^2\right)\right\} \leq 0; \qquad \text{7-33}$$

$$\forall (v_a^i, d_w^i) \in \Omega$$

The first and second terms specify the cost and demand function for commercial vehicles while the third and fourth terms give us the cost and demand function for private vehicles. Thus, equation 7-33 and the subsequent constraint $\Omega$ formulated as Equation 7-34 form the lower level problem in our bilevel modelling set up.

$$\Omega = \left\{ \begin{array}{c} \mathbf{v},\ \mathbf{d} \mid \sum_{p_w} d^i_{p_w} = d^i_w\,, v^i_a = \sum_w \sum_{p \in P_w} \delta^a_p f^i_p\,, v_a = \sum_{i \in I} v^i_a\,, d_{p_w}\ \geq 0 \\ D_r = \sum_w d^1_w(\mu^1_w);\ \forall\, w \in W,\ a \in A, i \in I \end{array} \right\} \qquad \text{7-34}$$

## 7.6 Solution Procedure

Since the optimisation problem stated above has the lower level equilibrium condition included as a constraint, the problem can be stated as a mathematical program with equilibrium constraints (MPEC). To solve the MPEC problem, we use the cutting constraints algorithm (CCA) that is commonly used to solve continuous network design problems.

The key to the algorithm is to solve the master problem by generating necessary extreme points while solving the sub-problem. The number of elements in Ω is limited but huge. Therefore, to solve the problem, it is necessary to generate one extreme point at a time that results in a constraint that cuts away part of the region that is not feasible for the solution of the master problem.

As mentioned above, $\Omega$ is a set of the linear equations of flow conservation, and demand constraints formulated by equation 7-34. It is known that any point in $\Omega$ can be defined by a linear combination of extreme points (Koh et al., 2009). This condition implies that $\boldsymbol{v}^*, \boldsymbol{d}^* \in \Omega$ can be defined as a convex combination of a set of extreme points . Thus, the VI for the lower level problem can then be redefined as a function of extreme functions, assuming the monotonic condition of $\boldsymbol{c}$ and $\boldsymbol{d^{-1}}$:

$$\boldsymbol{c}\,(\boldsymbol{v}^*, \tau)^{\boldsymbol{T}}(\boldsymbol{v}^* - \boldsymbol{u^e}) - \boldsymbol{d^{-1}}(\boldsymbol{d}^*, \tau)^{\boldsymbol{T}}(\boldsymbol{d}^* - \boldsymbol{q^e})\ \leq \boldsymbol{0},\quad \forall\, \boldsymbol{u^e}, \boldsymbol{q^e} \in E \qquad \text{7-35}$$

where $(\boldsymbol{u^e}, \boldsymbol{q^e})$ is the vector of extreme points for link flow and demand flow respectively, and $E$ is the set of extreme points of $\Omega$. Given the constraint in equation 7-35, the bilevel optimisation problem then can be rewritten as:

$$\max_{\boldsymbol{v},\boldsymbol{d},\tau} Z\ (\boldsymbol{v},\boldsymbol{d},\tau)$$

$$s.t$$

$$0\ \leq \tau_a^i \leq \varepsilon_a\, \overline{\tau_a^l} \qquad \text{7-36}$$

$$\boldsymbol{c}\ (\boldsymbol{v}^*,\tau)^{\boldsymbol{T}}(\boldsymbol{v}^* - \boldsymbol{u}^{\boldsymbol{e}}) - \boldsymbol{d}^{-\boldsymbol{1}}(\boldsymbol{d}^*,\tau)^{\boldsymbol{T}}(\boldsymbol{d}^* - \boldsymbol{q}^{\boldsymbol{e}})\ \leq 0$$

$$e\ \in\ E$$

Equation 7-36 above refers to the master problem. The key strategy of CCA algorithm to solve the master problem is to use a sub problem to give necessary extreme points from a given $(\boldsymbol{v},\boldsymbol{d},\tau)$, that is to solve the sub problem:

$$\min_{\boldsymbol{v},\boldsymbol{d}} \boldsymbol{c}\ (\boldsymbol{v},\tau)^{\boldsymbol{T}}.\boldsymbol{u} - (\boldsymbol{d}^{-\boldsymbol{1}}(\boldsymbol{d},\tau)^{\boldsymbol{T}})\ .\boldsymbol{q}$$

$$s.t \qquad \text{7-37}$$

$$(\boldsymbol{u},\boldsymbol{q})\ \in\ \Omega$$

The sub problem is intended to separately solve the shortest path problem for each OD pair to obtain the auxilliary flow of link flow. This problem is similar to Simplical Decomposition Algorithm in the Frank-Wolfe algorithm to solve the traffic assignment problem.Wang et al. (2014) develop a CCA algorithm for multi-user classes given each user class has a different VOT. However, since the demand in their paper is fixed demand, the necessary extreme point is generated based on the total demand by all user classes. Nevertheless, in our paper, since we have multiple user classes with different variable demand functions, the necessary extreme point condition is generated for each class separately.

The CCA algorithm to solve our bilevel problem can be summarised as follows:

Step 0: set *iter* = 0; initialise the problem by defining the extreme aggregate flow $[\boldsymbol{v},\boldsymbol{d}\ ]^{iter}$ following the shortest path for each user class *i* on each OD pair. Include, the $[\boldsymbol{v},\boldsymbol{d}\ ]^{l}$ into Ω. Notice that the shortest path for different user class might differ.

Step 1: *iter* = *iter* + 1*;* solve the upper level program with all extreme points in Ω and obtain the solution vector of $[\boldsymbol{v}^*,\boldsymbol{d}^*]$; then set $[\boldsymbol{v}^*,\boldsymbol{d}^*]$ for the upper level.

Step 2: Solve the sub-problem with $[\boldsymbol{v}^*,\boldsymbol{d}^*]$ and then obtain new extreme point $[\boldsymbol{v},\boldsymbol{d}\ ]^{iter}$

Step 3: termination check: if $\boldsymbol{c}\ (\boldsymbol{v}^*,\tau)^{\boldsymbol{T}}(\boldsymbol{v}^* - \boldsymbol{u}^{\boldsymbol{e}}) - \boldsymbol{d}^{-\boldsymbol{1}}(\boldsymbol{d}^*,\tau)^{\boldsymbol{T}}(\boldsymbol{d}^* - \boldsymbol{q}^{\boldsymbol{e}})\ \leq \boldsymbol{0}$; terminate and $[\boldsymbol{v}^*,\boldsymbol{d}^*]$ is the solution, otherwise include $[\boldsymbol{v},\boldsymbol{d}\ ]^{iter}$ into Ω and return to step 1.

## 7.7 Small network numerical example

The modelling set up discussed in previous sections builds a framework that explicitly accounts for UGM activities in the model.

Local authorities around the world emphasise the importance of a UGM model that can capture the real-world conditions realistically. Urban road networks are typically very crowded, and the local authorities need to plan to utilise the road networks properly to manage issues such as congestion, and emissions from transport activities. Planning for the urban road network is traditionally addressed by a network design problem (NDP). NDP research has been continuously studied during the past 50 years due to the problem being highly complicated, theoretically interesting, and practically important (Farahani et al., 2013).

In this section, we present a numerical example to demonstrate the feasibility of the proposed model and the solution approach, as well as to give an insight into how the model can aid local authorities to manage UGM activities.

### 7.7.1 Modelling set up

We use a numerical example to illustrate the working of the model formulation and CCA algorithm. The numerical example also gives an example of how model formulation can be applied to test real-world city logistics measure.

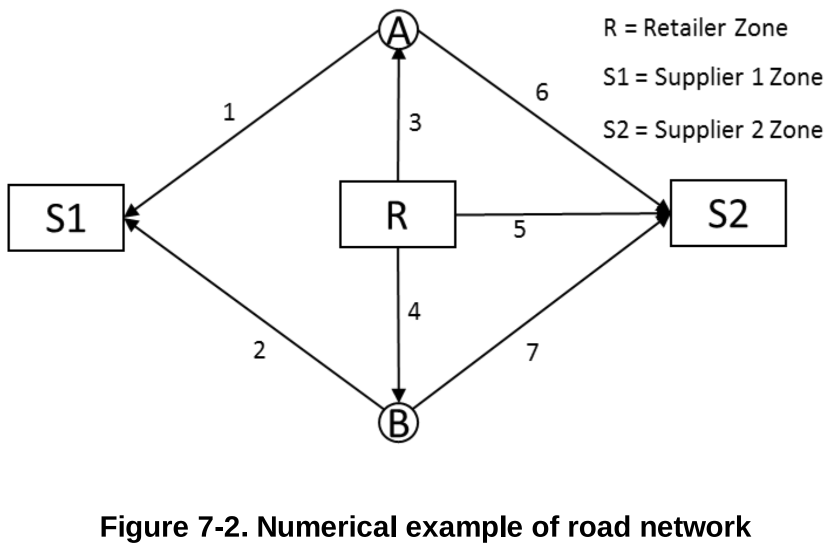



**Figure 7-2. Numerical example of road network**

The numerical example involves the case where the retailers try to procure goods from the suppliers in two supplier zones. The decision follows the utility value for each supplier in which we assume $u_s = \beta_{TT} . TT$ ; where $\beta_{TT}$ is a parameter associated with attribute $TT$ (travel time). In this case, we assume the value of $\beta_{TT}$ to be -0.031. The negative value represents the disutility of travel time attribute. The utility function only depends on the travel time attribute to see the sensitivity of the retailer decision towards various traffic conditions. The numerical example involves a seven links network serving one retailer zone (R) and two supplier zones (S1, S2) (see Figure 7-2).

The travel time for each link follows the standard BRP function:

$t(a) = t_0( 1 + 0.15 \left(\frac{v_a}{k_a}\right)^4)$. The $t_0$ and $k_a$ value for each link can be seen in Appendix F. Networks link cost.

Finally, in the case of multi-user class cases, we need to introduce the value for VOT and VOC for the different user classes. For CV demand, the VOT and VOC values are 1 and 0.5 cost units respectively, and for PV demand, the VOT and VOC values are 1.25 and 1 cost units respectively.

### 7.7.2 The demand functions for each user class

The specific demand function is assigned for different demands in this numerical example. The demand function for each user class follows the specific formulation in Section 7.6. The CV demand ($i = 1$) follows the *supplier location choice model* incorporating a logit model. Since, in this numerical example the option is only between S1 and S2, the model becomes a binomial logit model as follows:

$$d_w^{i=1}\left(\mu_w^{i=1}\right) = D_r \frac{e^{(u_1)}}{e^{(u_1)} + e^{(u_2)}}; \qquad 7\text{-}38$$

$$u_w = \beta_t * \mu_w^1 \qquad 7\text{-}39$$

In this numerical example, the utility is purely based on the travel time between OD.

The PV demand ($i = 2$) follows the variable demand function in which the other choice is not to travel. The demand function for PV demand follows the typical power function as formulated by Equation 7-29.

### 7.7.3 The experiments

In this numerical example, we set up three experiments. We set up the experiment incrementally and begin with solving the lower level problem, increasing the complexity of the lower level problem by including the case of multiuser class, and finally include the upper level problem into the formulation.

In the first experiment (T1) and second experiment (T2), we are not solving the bi-level programming yet. In these experiments, we solve the lower level problem and highlight the advantage of depicting retailers' behaviour by formulating the problem as a variational inequality. By doing that, we subsume the retailer supplier location choice as a lower level constraint and solve the route choice and supplier location choice simultaneously (combined method). Below is the minimization program for combined method:

$$\min_{\boldsymbol{v},\boldsymbol{d}} \boldsymbol{c}^{i=1}(\boldsymbol{v},\boldsymbol{d}) \qquad \text{7-40}$$

$$s.t.$$

$$\boldsymbol{c}\,(\boldsymbol{v}^*,\tau)^{\boldsymbol{T}}(\boldsymbol{v}^* - \boldsymbol{v}) - \boldsymbol{d}^{-\boldsymbol{1}}(\boldsymbol{d}^*,\tau)^{\boldsymbol{T}}(\boldsymbol{d}^* - \boldsymbol{d}) \le \boldsymbol{0}, \quad \forall \boldsymbol{v},\boldsymbol{d} \in \Omega$$

We solve the combined problem using the CCA, in which we begin by finding the shortest path solution for a given $(\boldsymbol{v},\boldsymbol{d})$. Then we solve the minimization problem 7-40 to get the solution of the master problem. We iterate the process following the CCA algorithm described in section 7.6. until the model is converged. To express the convergence value we use VI gap as the convergence criteria (see equation 7-44). VI gap express the condition in which the solution reach the equilibrium condition both in term of travel cost and demand. Notice that in this experiment we only consider commercial vehicle demand (*i=1*).

We compare the results of the combined model with a traditional step-by-step iterative approach which can be described as follows (see Figure 7-3):

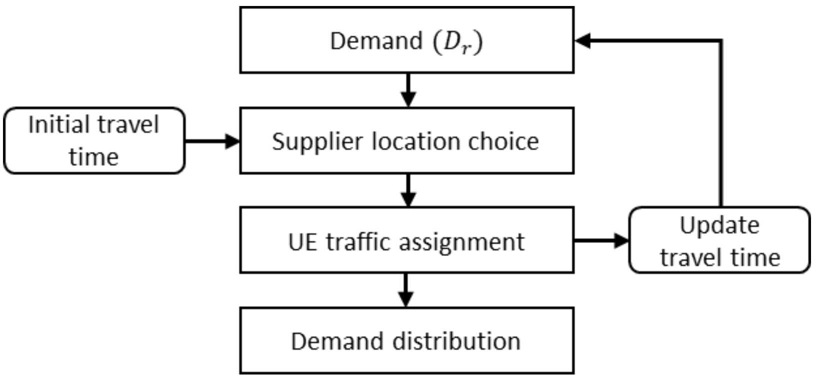



**Figure 7-3. A step-by-step iterative approach to retailers' decisions**

Step 1: The retailers have a fixed demand rate originating from zone *r* $(D_r)$.

Step 2: Supplier location choice is then applied to determine trip distribution. This is done by applying the MNL choice model. Note that in the beginning of the simulation, the trip distribution is determined by the initial travel time.

Step 3: Then, a standard user equilibrium traffic assignment is applied to get the travel pattern in the network. To solve the UE for SBS methods we solve the following minimization problem:

$$\min_{\boldsymbol{v},\boldsymbol{d}} \; c\,(\boldsymbol{v},\boldsymbol{d}) \qquad \text{7-41}$$
$$s.t.$$
$$\boldsymbol{c}\,(\boldsymbol{v}^{*},\tau)^{\boldsymbol{T}}(\boldsymbol{v}^{*}-\boldsymbol{v}) \leq \boldsymbol{0}, \quad \forall\, \boldsymbol{v} \in \Omega$$

Note that we have taken out the demand function that depicts the supplier location choice from the VI constraint since we only solve the UE traffic assignment. Indeed, equation 7-41 is the standard UE traffic assignment for fixed demand that can be solved using a well-known algorithm such as Frank-Wolfe Algorithm. The UE solution results in a new travel pattern updating he previous travel time.

Step 4: The updated travel time is then used to determine a new trip distribution. The iterative process continues until the difference between the current trip distribution and the previous one is small.

The second experiment (T2) involves a model with multiuser class in which the model takes into account the destination choice of commercial vehicles and the private vehicle variable demand (M2). The aim is to demonstrate how the model can be applied to a multiuser class condition. The experiment also investigates how the model influences retailers' supplier location choice based on the congestion level so that a different set of PV demand levels is set up. By setting up the different PV demand, the convergence of the model in a distinct traffic condition (congested or uncongested) is also investigated.

The minimization problem for experiment 2 can be written as follow:

$$\min_{\boldsymbol{v},\boldsymbol{d}} c\,(\boldsymbol{v},\boldsymbol{d}) \qquad \text{7-42}$$
$$s.t.$$
$$\boldsymbol{c}\,(\boldsymbol{v}^{*},\tau)^{\boldsymbol{T}}(\boldsymbol{v}^{*}-\boldsymbol{v}) - \boldsymbol{d}^{-\boldsymbol{1}}(\boldsymbol{d}^{*},\tau)^{\boldsymbol{T}}(\boldsymbol{d}^{*}-\boldsymbol{d}) \;\leq \boldsymbol{0}, \quad \forall\, \boldsymbol{v},\boldsymbol{d} \in \Omega$$

Lastly, in experiment 3, we apply the bilevel problem we defined in section 7.5 to provide insights into the advantage of the modelling framework to meet the local authorities' objective to improve overall welfare. The optimization for experiment 3 follows equation 7-36. However, to be consistent with the previous experiment, we change the maximisation problem formulated in equation 7-36 into a minimisation problem. Hence, the bilevel programming problem for experiment 3 is as follows:

$$\min_{\boldsymbol{v},\boldsymbol{d},\tau} -Z\ (\boldsymbol{v},\boldsymbol{d},\tau) \qquad \text{7-43}$$

$$s.t$$

$$0\ \leq \tau_a^i \leq \varepsilon_a \overline{\tau_a^i}$$

$$\boldsymbol{c}\ (\boldsymbol{v}^*,\tau)^{\boldsymbol{T}}(\boldsymbol{v}^* - \boldsymbol{v}) - \boldsymbol{d}^{-\boldsymbol{1}}(\boldsymbol{d}^*,\tau)^{\boldsymbol{T}}(\boldsymbol{d}^* - \boldsymbol{d})\ \leq 0\ \ \forall\, \boldsymbol{v},\boldsymbol{d}\ \in\ \Omega$$

We consider three scenarios involving the multiuser class model with demand variability. The three scenarios involve: (i) scenario without imposing a toll on any link; (2) scenario with fixed toll (toll = 5 cost units); (3) scenario with the optimal toll. The toll is only imposed on the commercial vehicle user class since in this research we are focusing on city logistics measures. The location of the toll is predetermined and in this numerical example, the toll is imposed on link 6. In this experiment, the MPEC formulation and solution algorithm for the optimal toll scenario follows the MPEC formulation in Section 7.5. In this formulation, the toll is included as one of the variables in the optimisation process. In the fixed toll scenario, we use the same MPEC formulation, but the toll is predetermined and is not included as a variable in the optimisation process. As for the no toll scenario, the MPEC formulation does not include a toll variable at all in the link cost calculation.

The numerical example includes the optimisation process involving iteration since we plan to use a cutting constraint algorithm as the solution technique. Therefore, it is important to define the convergence criteria as the indicator to stop the iteration. In this model, we use VI gap for each user class as a convergence criterion. The VI gap expresses the traffic user equilibrium condition of the solution found for each user class.

The VI gap is formulated as:

$$\sum_{w}\sum_{p} x_{p_w}^i * c_{p_w}^i - \sum_{w} D_w^i\ \mu_w^i \leq\ \varepsilon^i \qquad \text{7-44}$$

In this numerical example, we used $\varepsilon^i$ = 10. To sum up, each experiment's aim and model as well as various demands associated with it can be seen in Table 7-1.

**Table 7-1. Summary of experiments**

| Experiment | Scenario | MUC | VD | | Initial Traffic Demand | | | Toll |
|---|---|---|---|---|---|---|---|---|
| | | | CV | PV | CV | PV | | |
| | | | | | | (R-S1) | (R-S2) | |
| T1 | S1 | × | ✓ | N/A | 1250 | N/A | N/A | N/A |
| T2 | S2.1 | ✓ | ✓ | ✓ | 500 | 250 | 250 | N/A |
| | S2.2 | ✓ | ✓ | ✓ | 500 | 250 | 500 | N/A |
| | S2.3 | ✓ | ✓ | ✓ | 500 | 1250 | 500 | N/A |
| T3 | S3.2 | ✓ | ✓ | ✓ | 500 | 250 | 500 | Fixed toll |
| | S3.4 | ✓ | ✓ | ✓ | 500 | 250 | 500 | Optimal toll |

VD: variable demand; MUC: multi-user class; CV: commercial vehicle; PV: private vehicle

### 7.7.4 Results of the numerical example

**Experiment 1**

The first experiment compares the combined model methods and step-by-step (SBS) methods to incorporate retailers' behaviour into the UE traffic assignment formulation. Note that in the first experiment we only solve the lower level problem of the bi-level programming problem we proposed. The combines model subsumed the demand function as a constraint whilst the step-by-step model uses the results of the UE traffic assignment as the input for the demand function.

The experiment reveals that both methods produce the same results as can be shown by the same travel time and demand between the OD pair (see Table 7-2 and Table 7-3). Both methods meet the convergence criteria (VI GAP $\leq$ 2). However, it is clear that combined methods perform better compared to the step-by-step (SBS) methods. This is the case since the route choice and the supplier location problems are solved simultaneously when we solve the minimization problem (equation 7-40).

It is clear that the SBS method needs a separate process to solve the route choice problem, and update the supplier location choice accordingly. Iteration 0 until iteration 2 in table 7-2 shows the process to solve the traffic user equilibrium problem. Then after solving the UE condition for the given demand, the travel time for each OD pair is updated. The new travel time for each OD then is used to update the demand configuration for the next iteration. Iteration 3 depicts the initial condition again after the demand is updated. Then the processes of solving the UE traffic assignment and updated the demand continue until the convergence criteria is met. Iteration 0, 3 and 6 have a huge VI-GAP value since it depicts the initial condition in which the network is empty.

**Table 7-2. Travel time and distributed demand using step-by-step method**

| Iteration | Minimum Travel Time | | Demand | | VI_GAP |
|---|---|---|---|---|---|
| | R-S1 | R-S2 | R-S1 | R-S2 | |
| 0 | 8.40 | 11.64 | 604.5 | 395.5 | -9680.6 |
| 1 | 8.56 | 11.76 | 604.5 | 395.5 | 22.9 |
| 2 | 8.56 | 11.76 | 604.5 | 395.5 | 19.2 |
| 3 | 8.40 | 11.64 | 603.4 | 396.6 | -9685.0 |
| 4 | 8.56 | 11.76 | 603.4 | 396.6 | 23.9 |
| 5 | 8.56 | 11.76 | 603.4 | 396.6 | 3.6 |
| 6 | 8.40 | 11.64 | 602.9 | 397.1 | -9686.5 |
| 7 | 8.55 | 11.76 | 602.9 | 397.1 | 24.1 |
| 8 | 8.55 | 11.76 | 602.9 | 397.1 | 1.7 |

In contrast with the SBS method, the combined method solves the route choice and supplier location choice simultaneously. The combine methods utilize the demand function in the VI form to subsume the supplier location choice in the user equilibrium condition. Table 7-2 depicts the result for combined method.

**Table 7-3. Travel time and distributed demand using combined method**

| Iteration | Minimum Travel Time | | Demand | | VI_GAP |
|---|---|---|---|---|---|
| | R-S1 | R-S2 | R-S1 | R-S2 | |
| 0 | 8.40 | 11.64 | 604.5 | 395.5 | -9680.6 |
| 1 | 8.56 | 11.76 | 604.5 | 395.5 | 22.9 |
| 2 | 8.56 | 11.75 | 603.4 | 396.6 | 3.7 |
| 3 | 8.55 | 11.76 | 602.9 | 397.1 | 1.5 |

**Experiment 2**

Given the superiority of combined methods, we use the combine method to formulate the problem on experiment 2. In experiment 2 we extend the formulation of combined method to includes a multiuser class model in which the model includes two different user classes associated with two distinct values of VOT, VOC and more importantly, two different demand functions. The experiment involves different scenarios with various levels of PV demand. In this experiment, we test the ability of the model to:

- Produce a traffic pattern that gives the UE condition for both user classes (the model successfully adapts the multiuser class problem).
- Capture different demand distribution based on traffic conditions for each OD pair

- Converge in different traffic conditions

The results of both CV and PV traffic patterns for the different scenarios in Experiment 2 are shown in Table 7-4 below.

The results show that the multiuser class is adaptable in our model formulation. Regarding the traffic pattern, firstly notice that the path flow for both CV and PV demand follows the UE condition for all three scenarios. The UE condition is satisfied since all used paths for each OD pair by each class have equal and minimal travel time. However, as congestion increases, the UE condition becomes more difficult to achieve.

**Table 7-4. Traffic pattern for Experiment 2**

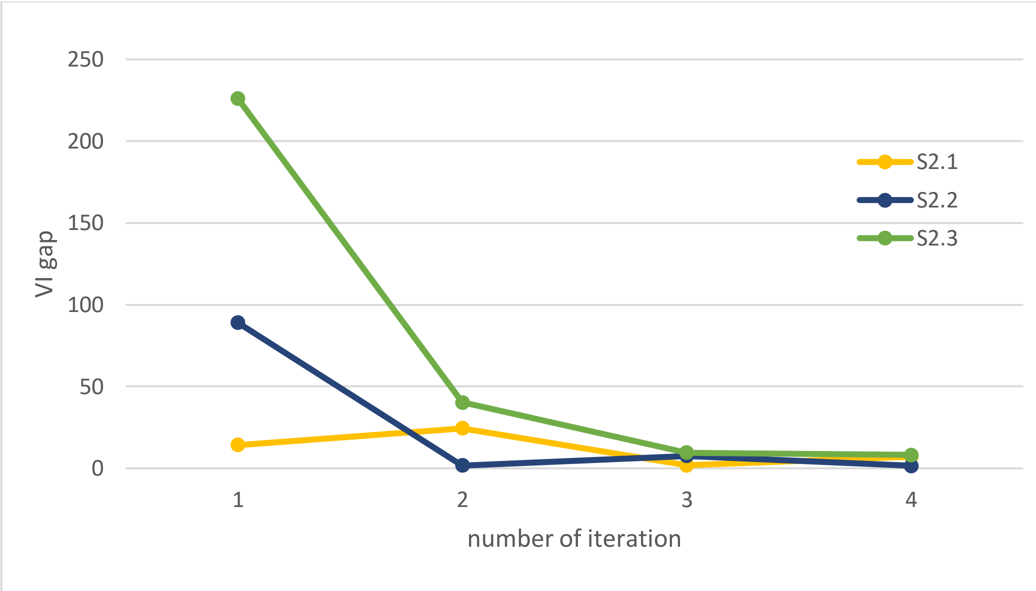
| Scenario | | S2.1 | | S2.2 | | S2.3 | |
|---|---|---|---|---|---|---|---|
| OD (path) | | Path cost | Path flow | Path cost | Path flow | Path cost | Path flow |
| R-S1 (1) | | 12.4 | 106.9 | 12.5 | 85.9 | 15.3 | 349.1 |
| R-S1 (2) | | 12.4 | 259.4 | 12.5 | 285.6 | 15.3 | 0.0 |
| R-S2 (1) | CV | 16.7 | 5.5 | 16.9 | 0.0 | 18.8 | 0.0 |
| R-S2 (2) | | 16.7 | 128.2 | 16.9 | 128.5 | 18.8 | 144.3 |
| R-S2 (3) | | 17.4 | 0.0 | 17.4 | 0.0 | 19.4 | 6.6 |
| Total Trips | | | 500 | | 500 | | 500 |
| R-S1 (1) | | 18.3 | 0.0 | 18.4 | 0.0 | 21.8 | 308.6 |
| R-S1 (2) | | 18.1 | 246.0 | 18.3 | 246.1 | 21.8 | 809.3 |
| R-S2 (1) | PV | 24.5 | 248.8 | 24.8 | 306.8 | 27.1 | 467.6 |
| R-S2 (2) | | 24.5 | 0.0 | 24.8 | 187.1 | 27.2 | 4.3 |
| R-S2 (3) | | 25.4 | 0.0 | 25.5 | 0.0 | 28.0 | 0.0 |
| Total trips | | | 495 | | 740 | | 1589 |

Note also the results show that different demand function is successfully adapted in the model. The PV demand follows the power function, and thus after assignment, the total PV demand that is actually assigned is less than the initial demand. The reason is, after the assignment, the travel cost is higher than the initial condition in which the network is empty. The CV demand follows the multinomial logit function that determines the distribution of commercial vehicle trips. Note that the total demand after the assignment is still the same as the initial demand.

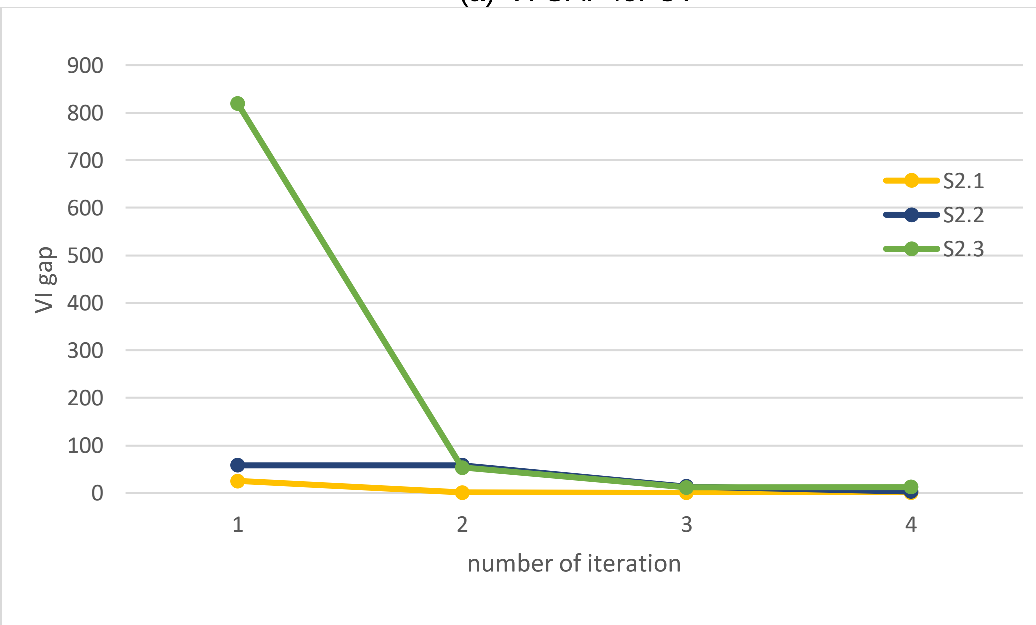
**Table 7-5. Demand distribution for Experiment 2**

| Scenario | Demand Distribution | | | |
|---|---|---|---|---|
| | R-S1 | R-S2 | % R-S1 | % R-S2 |
| S2.1 | 366.3 | 133.7 | 73.3% | 26.7% |
| S2.2 | 371.5 | 128.5 | 74.3% | 25.7% |
| S2.3 | 349.1 | 150.9 | 69.8% | 30.2% |

As for retailer demand distribution, the result for all scenarios in Experiment 2 can be seen in Table 7-5. The results show that the model is able to capture the distribution of restocking trips. The results make sense since the more congested a particular supplier location, the less preferred the supplier location is by the retailers. Observe that as the congestion in the R-S2 OD pair increases in Scenario S2.2, the demand for restocking activities between R-S2 decreases. The results show the same pattern in Scenario S2.3 in which the increase of congestion in the R-S1 OD pair results in the decreasing demand for the particular OD pair.




(a) VI GAP for CV




(b) VI GAP for PV

**Figure 7-4. VI gap for CV user class CV (a) and PV user class (b)**

The VI gap is calculated for each user class for all scenarios. The results for VI gap value in each iteration are depicted in Figure 7-4. In general, the results show that the models converge. However, notice that in some scenarios the VI gap values are wiggly (e.g. VI gap value for CV user class in Scenario S2.2.) indicating the difficulty of the model satisfying the UE condition.

**Experiment 3**

In the third experiment, we now consider the possibility of applying a road pricing measure. In this experiment, we solve the proposed bilevel programming using the CCA as the solution technique.

Three scenarios are considered: scenario without toll, scenario with fixed toll, and scenario with optimal toll. The toll is applied to link 6 (see Figure 7-5).

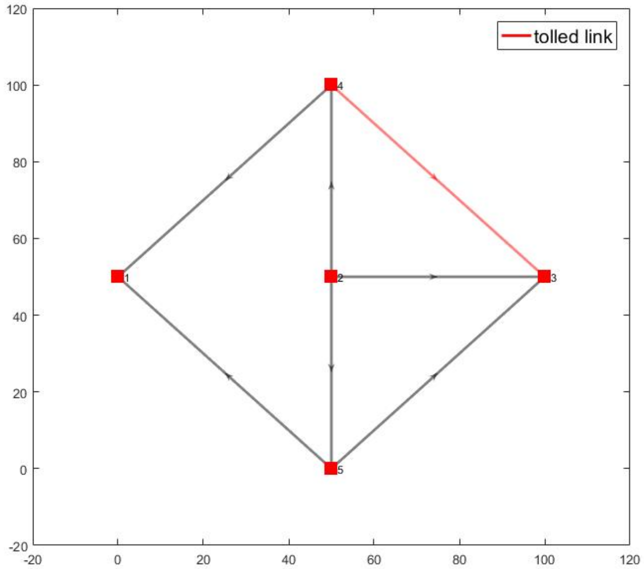
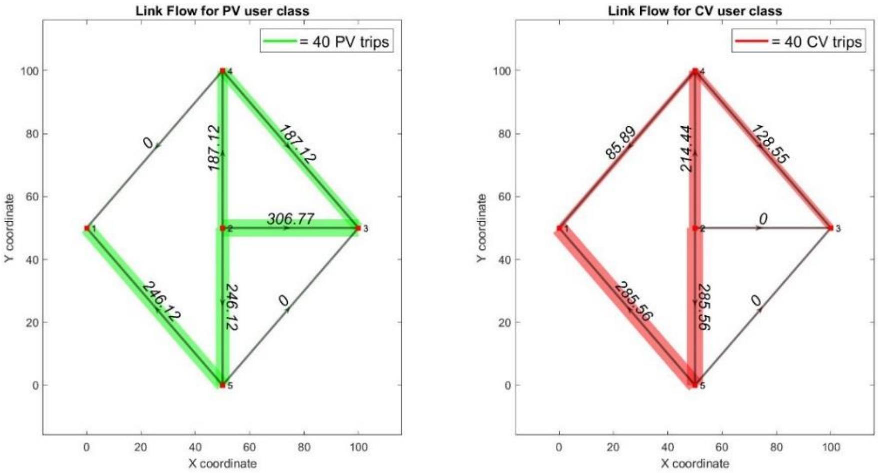
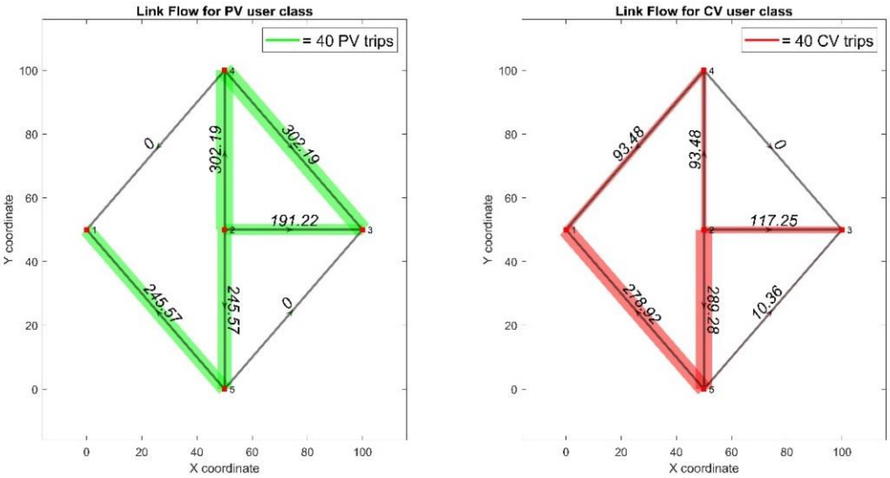



**Figure 7-5.Tolled link in the numerical example**

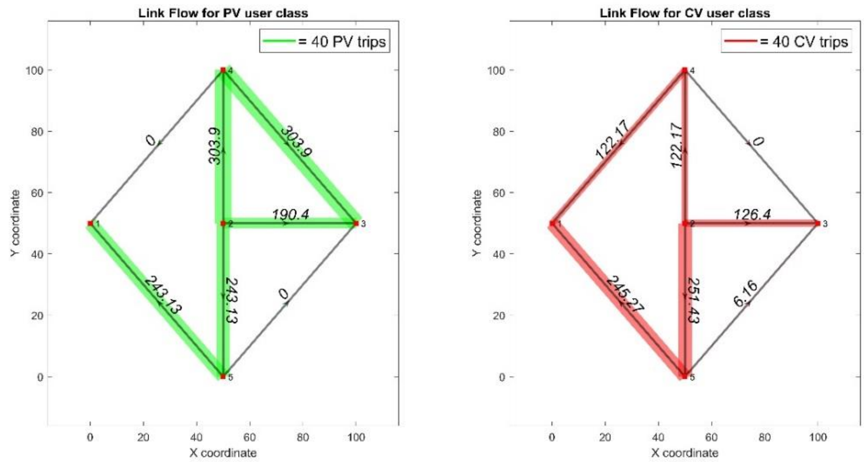
The experiment shows that the proposed model can evaluate the impact of the toll introduction on a specific user class. Two behavioural changes are spotted. The first is the *redistribution* of supplier location choice by independent retailers. In the fixed toll scenario, the commercial vehicle demand for the R-S2 OD decreases. This means the toll increases the impendence between the R-S2 OD pair and thus consequently there are some retailers who then decide to restock their goods from suppliers in S1 rather than S2. The toll also alters the route choice decisions of both user classes. As we can see in Figure 7-6, the traffic of the commercial vehicle on the tolled link decreases, and the traffic for the private vehicle increases. This indicates that the toll is able to move the unwanted commercial vehicles from the tolled link. As a result, the alternative route is filled with commercial vehicles.




(a) No toll scenario




(b) Fixed toll scenario




(c) Optimal toll scenario

**Figure 7-6. Traffic pattern for no toll (a), fixed toll (b), and optimal toll (c) scenarios**

Next, we turn our attention to the issue of optimal toll. Visually, the traffic patterns between the fixed toll scenario and optimal toll are more or less the same. However, a closer look at the results shows the difference between optimal and fixed toll is quite significant in terms of welfare gain. Table 7-6 shows the results of three different toll scenarios: no toll scenario (S2.2.), fixed toll scenario (S3.1), and optimal toll scenario (S3.2).

The results show that, generally, welfare increases when a toll is applied to the network. Notice that the vehicle flow in the links between fixed toll scenario and optimal toll scenario produce a similar result, which is expected in the small network example. The network is small and thus it has limited alternative route in which the CV demand can detour. However, a closer look to the result reveals that the total demand for each OD pair is different since the minimum travel time for each OD pair changes meaning the different toll impacts the distribution of the CV demand. This redistribution evokes different welfare value for each scenario.

The optimal toll obtains better welfare gains compared to the fixed toll scenario. The fixed toll scenario gains 25 welfare units which is below the gain obtained by the optimal toll scenario for which the gain is 113 welfare units. Further, the result revealed the optimal toll to be 1.62 cost units, a significantly lower value than the 5 cost units in the fixed toll scenario. The result implies, in this numerical set up, the effect of over tolling for CV demand will result in sub-optimal conditions. This result emphasises the significance of finding the optimal toll.

**Table 7-6. Results of Experiment 3**

| Scenario | OD pair | Demand | Percentage | Welfare gain |
|---|---|---|---|---|
| No toll | R-S1 | 371.5 | 74.3% | N/A |
| | R-S2 | 128.5 | 25.7% | |
| Fixed toll | R-S1 | 372.4 | 74.5% | 25 |
| | R-S2 | 127.6 | 25.5% | |
| Optimal toll | R-S1 | 367.4 | 73.5% | 113 |
| | R-S2 | 132.6 | 26.5% | |

### 7.7.5 Remarks on the software used and algorithm to solve the optimisation process

Initially, the author runs the numerical example using MS excel 2016. The author uses the GRG nonlinear algorithm provided within the program to solve the minimisation problem of the MPEC problem provided in this chapter. The author then builds the numerical problem using MATLAB 2016b. The numerical example in the excel then acts as a tool to check the result produced by MATLAB. It is an important step since the MATLAB code depicting the numerical example will be used to carry out the experiment in the real-world network presented in the next chapter.

## 7.8 Chapter summary

In this chapter, we use bilevel programming to represent the local authority's objective and retailer behaviour. The local authority's objective is to gain optimal welfare whilst incorporating road users' behaviours particularly independent retailers' restocking activities.

The bilevel programming consists of two level problems. In the model, the upper level of the bilevel program is a non-linear minimisation problem, with the objective function reflecting the goal of the local authority to minimise the total system cost of the urban road network. At the lower level, the user equilibrium traffic assignment problem is represented as variational inequality. In this chapter, the variational inequality is formulated accounting for route choice and another choice dimensions. Yet another issue is to formulate the variational inequality accounting for mixed traffic conditions in which there are two user classes in the network, namely commercial vehicles and private vehicles. By formulating the user equilibrium as variational inequality, the commercial vehicle behaviour and the private vehicle behaviour are presented in the model as a constraint. Yet another novelty of this work is that the choice decision model is subsumed as a constraint to the lower level rather than solving retailer choices in an iterative manner. We specified the demand functions that were used in the model. We use the multinomial logit function to depict the decisions made by the independent retailers regarding the location of their supplier. Meanwhile for the private vehicle demand, we depict their behaviour using the power function. To illustrate the working of the model, this chapter provided a numerical example including three experiments using a simple small network.

Next, to provide a wider perspective of the modelling framework, in the next chapter, we applied the modelling framework to the real-world cases of Bandung city centre.

# Chapter 8 Road pricing policy considering independent retailers' restocking activities

This chapter provides a real-world case application for the model formulation discussed in previous chapters. In this chapter, we use the models and the modelling framework we discussed and implement them in a real-world case. The aim of this application is threefold:

(i) To illustrate the working of the models in a real-world case that includes the application of the demand model and the implementation of the bilevel problem in a real-world medium size network;
(ii) To seek the optimal toll value to meet the local authority objective of improving overall welfare; and
(iii) To understand the dynamics of benefit values for different user classes due to different pricing and demand scenarios.

This chapter is arranged as follows: Section 8.1 describes the context of the problem that is being modelled. Next the and demand and network specification are discussed in Section 8.2 and Section 8.3. Section 8.4 deals with the validation of the model for the current condition/do-nothing scenario. The rest of the chapter discusses the implementation of city logistics policies. Firstly, we consider the optimal toll charge for CV demand in various predetermined links in Section 8.5. Next, in Section 8.6, we discuss the results considering the scenario in which a combination of city logistics policies other than toll is considered by the local authorities. Section 8.7 explores the modelling result implications for UGM transport planning. A remark on the computational effort is made in Section 8.8, and finally, this chapter closes with a summary in Section 8.9.

## 8.1 Context of the problem

The modelling procedure presented in the previous section was applied to the case of Bandung city centre (BCC) in Indonesia. Most retailers in Bandung are independent retailers making their own restocking decisions as opposed to centrally managed chain retailers. Generally, the main restocking decision by independent retailers is to select the suppliers (Russo and Comi, 2010). The decision to select a supplier also implies a decision regarding the supplier location.

To meet the purpose of this research, an independent survey was conducted to capture the restocking decisions of independent retailers located in BCC. In Chapter 5, the survey revealed that independent retailers have high vehicle ownership and mostly use their own vehicle for restocking. The survey also revealed that restocking trips usually take place from 06:00-09:00 AM during the morning peak hour.

Thus, we model the morning peak hour condition in which the interaction of private vehicles and commercial vehicles is more relevant as the working day begins between 08:00 and 09:00. Although the commercial vehicle trips can start both from the supplier location (i.e. delivery services) and the retailer location, in this research we consider the retailers‘ commercial vehicle starting the journey from the retailer node to supplier node as this is the most significant mode of restocking as shown by the survey results. The retailers restocking trips in this case is very similar to the shopping trips conduct by end-consumers.

The bilevel programming framework to depict the UGM activity above is depicted as follow:

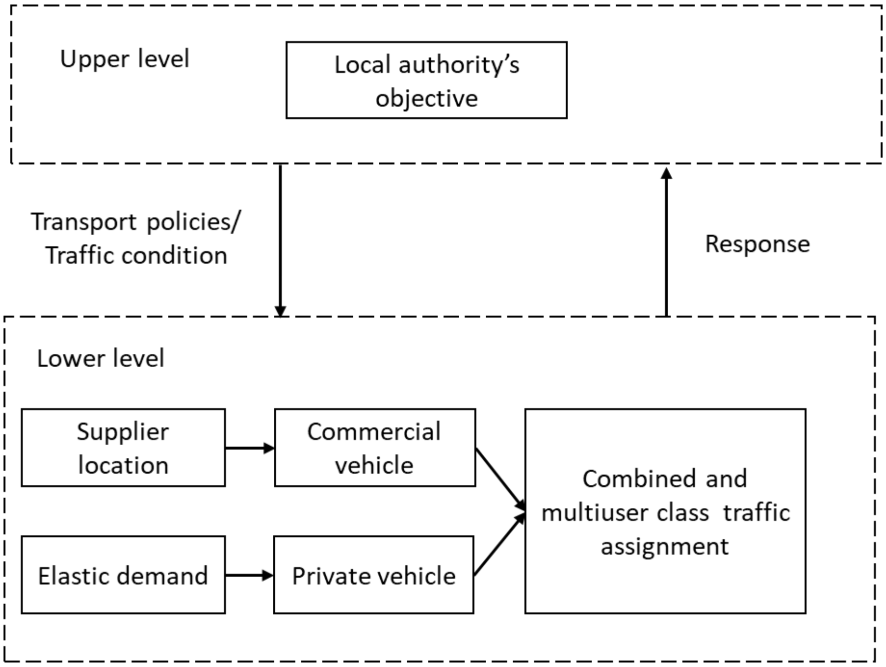



**Figure 8-1. Proposed model for local authorities – UGM interaction in the study area**

The bilevel programming model formulates the interaction between local authorities and road users namely commercial vehicle and private vehicle. In this modelling framework, the commercial vehicle demand (CV) choose the supplier location based on the traffic condition. This decision implies the destination choice for the CV demand. Meanwhile, the private vehicle demand (PV) choose wether to take the journey or not which implies that the PV demand is elastic. In this model, both CV and PV demands are able to choose the route choice which follows the user equilibrium condition. The local authorities control the CV's and PV's behavior by applying transport policies that may change the traffic condition.

## 8.2 Demand specification

The traffic demand in this simulation consists of commercial vehicle (CV) demand and private vehicle (PV) demand. The demand is for peak hour from 08.00-09.00. The initial demand is represented by the OD matrices namely:

(i) OD matrices representing private vehicle (PV) demand with 14 x 14 dimensions; and

(ii) Commercial vehicle (CV) demand for each r node with 11 x 1 dimensions (note that the CV destinations are unknown and will be worked out by the destination choice cum assignment model).

The overall demand during the period 08:00-09:00 for PV for all OD pairs is 30989 PCUs. The PV demand is obtained from previous study (Farda and Balijepalli, 2018). As for the demand for the CV demand for each zone is worked out from the generation model we estimated in Chapter 6. We use Model 6 presented in Table 6-3 as follows:

$$y = 1.59 + 0.19\, x_3 + 16.84\, x_4 - 31.18\, x_5 + 0.58\, x_7 + 0.16\, x_9 + 0.06\, x_{10}$$

where; $y$ : Number of weekly trips
$x_3$ : Number of persons employed
$x_4$ : Weekly goods demand (tonnes)
$x_5$ : Average shipment weight (tonnes)
$x_7$ : Dummy for two-wheeler ownership,1 if the retailer has a two-wheeler, otherwise 0
$x_9$: Dummy for the presence of a traditional market, 1 if the retailer is located <= 3 km from the traditional market, otherwise 0
$x_{10}$: Product of $x_7$ and $x_9$

To get the aggregate demand in the form of total weekly trips for each zone, we put the average number for each independent variable in the model equation and then multiply it by the number of retailers in each zone. Notice that the generation model produces the number of trips on a weekly basis. And thus, to make it into typical daily restocking trips, we assume that the number of trips is distributed evenly across the week, meaning the demand results are then divided by five days. Additionally, to make the daily trips to represent the peak hour condition, we used the factor 0.49 to be multiplied by the daily demand as our survey suggests that 0.49% of the daily restocking activities by retailers' own vehicles are done from 06.00-9.00 AM.

Further, in this application, we focus on the restocking activities that use *own vehicles* transport service, meaning we only consider the trips that originate from the retailer zones. The reasons are two folds: firstly, the origin for vehicle trips from the delivery service is unknown. In a delivery service, the suppliers are the decisions maker in terms of transport delivery service choice and can opt to use their own vehicles or order third party carriers to deliver the goods, and thus the origin of the vehicle trips is unknown to us. Secondly, the survey suggests most of the restocking activities by independent retailers in peak hour time are done using their own vehicles. Given the above condition, the restocking trips by own vehicles can then be calculated by multiplying the total trips for each zone that are obtained from the generation model with the proportion of restocking by own vehicle. Based on the survey, the proportion of own vehicle restocking activities is 79%.

With all those considerations from the demand model, we calculate the initial demand for CV user class from all instances of zone r, which is OD matrices with 11x1 dimensions see Table 8-1. Notice that the destination of the CV vehicle is worked out with the destination choice model embedded in the bilevel programming problem.

**Table 8-1. Number of initial CV demands ($D_r$) for all the zones**

| Origin zone | Number of trips | Origin zone | Number of trips |
|---|---|---|---|
| Balong Gede (BG) | 671 | Kebon Jati (KJ) | 496 |
| Braga (BR) | 411 | Kebon pisang (KP) | 442 |
| Ciateul (CA) | 562 | Nyenseret (NY) | 979 |
| Cibadak (CB) | 1369 | Paledang (PA) | 340 |
| Cikawao (CK) | 708 | Pungkur (PU) | 1321 |
| Karang Anyar (KA) | 899 | Total | 8189 |

## 8.2.1 Specific demand function

In this numerical example, we use different demand functions for CV and PV demand. To address the supplier location choice, we incorporate a multinomial logit model for CV demand and power function for PV demand as discussed in section 7.5.1.

For CV demand, the choice model follows the multinomial logit model as follow

$$d_w^1(\mu_w^1) = D_r \frac{e^{-\alpha(u_s)}}{\sum_{s\in S} e^{-\alpha(u_s)}}; \qquad w \in W$$

$$u_s = \beta * \mu_w^1 + \alpha_{s_n} * z_{s_n} + \delta$$

$\alpha$ is scale factor, in which in the MNL model the value is equal to 1. The utility function for supplier location choice follows Model 1 presented in chapter 6. (see Table 6-4).

$$u_s = -0.295\, x_8 + 0.042\, x_9 + 0.547 x_{10}$$

where; $u_s$ : Utility to choose supplier location $s$
$x_8$ : Travel time between OD pairs (in hours)
$x_9$ : Number of establishment in supplier zones
$x_{10}$ : Dummy for traditional market presence in supplier zones, 1 if there is a traditional market in the zone, otherwise 0

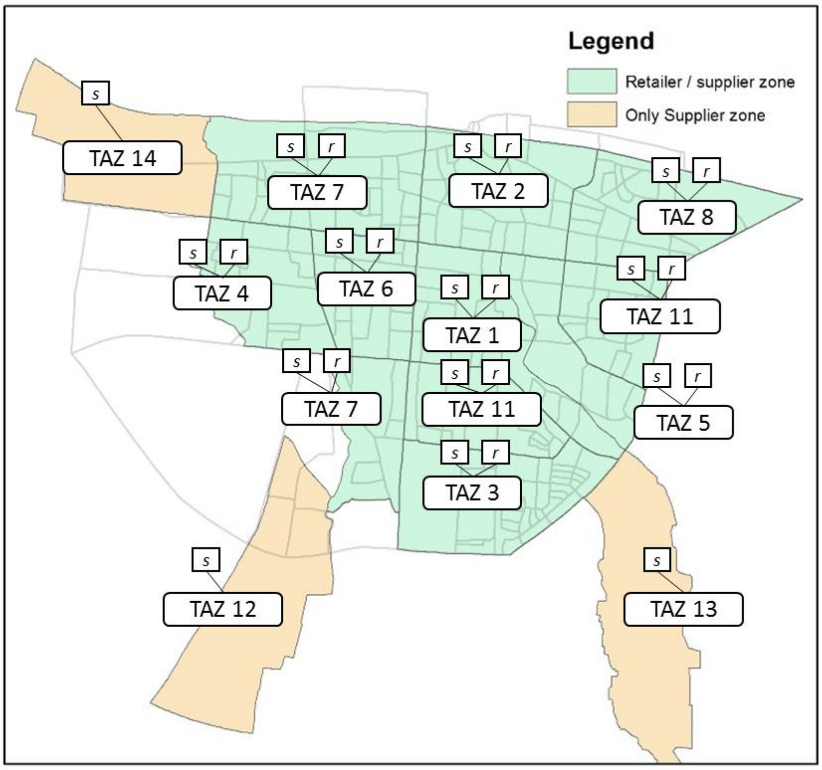
As for PV demand, the model follows power function formulated as

$$D_w^2 = \breve{D}_w^2 \left(\frac{\mu_w^2}{\breve{\mu}_w^2}\right)^{-0.57}$$

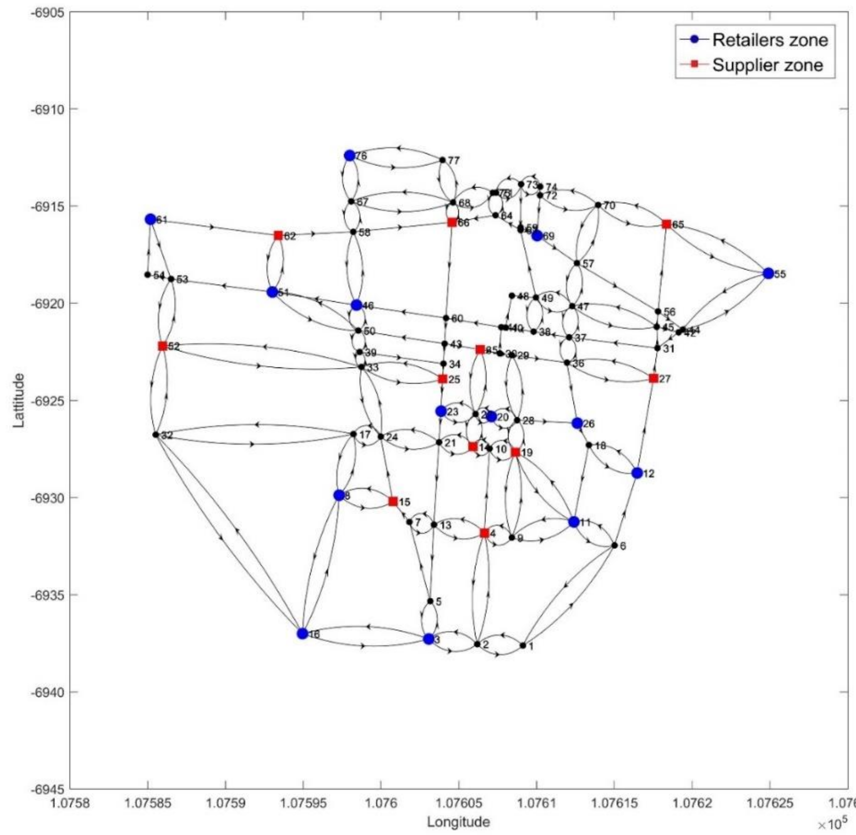
## 8.3 Network specification

The network specification follows the general architecture of the model discussed in Chapter 4 in which the sub-districts of the study area are treated as traffic analysis zones (TAZs). Thus, each TAZ is an administrative area defined by the local authority. To accommodate commercial vehicle traffic assignment, each TAZ consists of two different nodes: retailer (*r*), supplier (*s*) nodes – see Figure Figure 8-2.a. For commercial vehicle user class (*i* = 1) the origin nodes are the retailer nodes (*r*) and the destination nodes are the supplier nodes (*s*). Therefore, valid OD pairs are formed by combining retailer and supplier nodes for the commercial vehicle user class. Meanwhile the private vehicle user class does not distinguish zones between *r* and *s* nodes, and hence each TAZ acts as an origin and a destination for private user vehicles. Therefore, in this setup, the path followed by commercial vehicles and private vehicles need not necessarily be the same for a pair of TAZs since we define origins in a different way for different user classes. The network (see. Figure 8-2.b) and travel demand comprise the following:

- 119 junction nodes. This numerical example accounts for the travel cost on links only, and thus the junction nodes represent a meeting place between links without specifying the cost associated with the junction itself.
- 189 links represent the actual streets. The characteristics of the links (e.g. free flow time, capacity, etc.) follow the SATURN model of Bandung as depicted in Farda and Balijepalli (2018).
- 11 retailer nodes and 14 supplier nodes are identified within 119 junction nodes.




- (a)




(b)

**Figure 8-2. Modelled Bandung city centre zoning and network**

To convert the link travel times into costs, we need values of time (*VOT*) and vehicle operating cost (*VOC*) values. Previous studies in Indonesia reveal a typical private passenger *VOT* of 13900 IDR (Sugiyanto, 2012). We update the *VOT* value using an average inflation rate of 4% to arrive at the value of 16100 IDR for 2016 for passenger vehicles. As for *VOT* for the commercial vehicle, a study by Nugroho (2015) reveals a value of 30400 IDR although it is the *VOT* for containerized freight which is nearly twice the passenger *VOT* value. However, we deal with urban freight movements typically carried by two-wheelers, thus we factored in the private vehicle *VOT* by 1.3 giving 20900 IDR as the *VOT* for commercial vehicles. The factor is well below the 1.75 indicated by Holguín-Veras and Cetin (2009) for reasons stated. As for *VOC*, Nugroho (2015) reveals the average *VOC* for a typical private vehicle is 5720 IDR/ km. Intuitively, the *VOC* for a commercial vehicle should be higher than that of a private vehicle since the former is heavier and slower than the latter. Thus, we assume the *VOC* for a commercial vehicle to be 1.5 times higher and thus the *VOC* for commercial vehicles is 6310 IDR/km. Table 4.1 summarises the *VOT* and *VOC* values used in the research.

**Table 8-2. Value of time and vehicle operating cost for each user class (IDR)**

| User class | *VOT* $(\lambda_i)$ | *VOC* $(\theta_i)$ |
|---|---|---|
| Private vehicle (PV) | 16100 | 5720 |
| Commercial vehicle (CV) | 20900 | 6310 |

Note: 1 USD = ~14,500 IDR

This section describes the results of traffic assignment for various scenarios. Firstly, we validate the current conditions in the do-nothing scenario by comparing with observed choices in terms of the distribution of supplier locations in Bandung. Subsequently, this section describes the optimal toll charge to maximise overall welfare. In this numerical setting, to reflect the fact that tolling is seen as a demand management tool to regulate CVs, the toll charge is applied only to CV demand on the two most congested road links in the city. Finally, this section extends the analysis by undertaking testing of a typical city logistic policy of restricting the CVs in combination with toll charging by considering a series of what-if scenarios involving different levels of demand in combination with varying toll charges.

## 8.4 The bilevel programming specification

Given the discussion in the previous chapter on the proposed bilevel programming, in this section we adopt the proposed model to be applied into the case study. Firstly, we define the objective function / upper level problem as to maximize the economic benefit:

$$Z = \sum_{w \in W} \sum_{i \in I} \int_{0}^{D_w^i} {d_w^i}^{-1}(\omega) - \sum_{i \in I} \sum_{a \in A} c_a^i \, v_a^i \qquad 8\text{-}1$$

Next, we define the lower level problem as a *combined and multi user class traffic assignment* following user equilibrium. Note that we need to consider the toll pricing in the lower level program. Mathematically, the problem can be written as a variational inequality as follow:

$$\boldsymbol{c}\,(\boldsymbol{v}^*, \tau)^{\boldsymbol{T}}(\boldsymbol{v}^* - \boldsymbol{v}) - \boldsymbol{d}^{-\mathbf{1}}(\boldsymbol{d}^*, \tau)^{\boldsymbol{T}}(\boldsymbol{d}^* - \boldsymbol{d}) \le \mathbf{0}, \quad \forall \boldsymbol{v}, \boldsymbol{d} \in \Omega \qquad 8\text{-}2$$

Given equation 8-2 and equation 8-3, then the bilevel programming can be written as

$$\min_{\boldsymbol{v}, \boldsymbol{d}, \tau} -Z\,(\boldsymbol{v}, \boldsymbol{d}, \tau) \qquad 8\text{-}3$$

$$s.t$$

$$0 \le \tau_a^i \le \varepsilon_a \, \overline{\tau_a^i}$$

$$\boldsymbol{c}\,(\boldsymbol{v}^*, \tau)^{\boldsymbol{T}}(\boldsymbol{v}^* - \boldsymbol{v}) - \boldsymbol{d}^{-\mathbf{1}}(\boldsymbol{d}^*, \tau)^{\boldsymbol{T}}(\boldsymbol{d}^* - \boldsymbol{d}) \le 0 \;\; \forall\, \boldsymbol{v}, \boldsymbol{d} \in \Omega$$

Notice that in the above formulation, we change the maximization problem into the minimization problem to fit the tools we use to solve the problem (see section 8.8). The first constraint formulates the toll lower bound and upper bound. Finally, the second constraint formulates the traffic assignment as a variational inequality problem. In our specific application, the VI for the lower level problem needs to consider two types of demand, i.e. logit-based function for commercial vehicles and a power-law based function for private vehicles. Therefore, the VI constraint can be expanded as below:

$$\left\{\sum_{a \in A} c_a^1\,(\lambda_1, t_a(v_a^*), \tau_a^1)\left(v_a^{1^*} - v_a^1\right) - \sum_{w \in W} \frac{1}{\beta} \ln\left(\frac{d_w^1}{D_r - \sum_{s \neq w_S} d_w}\right)\left(d_w^{1^*} - d_w^1\right)\right\} + \left\{\sum_{a \in A} c_a^2(\lambda_2, t_a(v_a^*), \tau_a^2)\left(v_a^{2^*} - v_a^2\right) - \sum_{w \in W} {\mu_w^2}^0 \left(\frac{d_w^2}{{d_w^2}^0}\right)^{-1.75}\left(d_w^{2^*} - d_w^2\right)\right\} \le 0; \qquad \textbf{8-4}$$

$$\forall (v_a^i, d_w^i) \in \Omega$$

$$\Omega = \left\{ \begin{array}{c} \mathbf{v},\, \mathbf{d} \mid \sum_{p_w} d_{p_w}^i = d_w^i,\, v_a^i = \sum_{w} \sum_{p \in P_w} \delta_p^a f_p^i,\, v_a = \sum_{i \in I} v_a^i,\, d_{p_w} \ge 0 \\ D_r = \sum_{w} d_w^1(\mu_w^1);\; \forall\, w \in W,\; a \in A, i \in I \end{array} \right\}$$

## 8.5 Validating the model and the model convergence

In this section, we validate the model and discuss the model convergence. The model validation involves the do-nothing scenario. As we run several numbers of what-if scenarios, the convergence of the model will be shown for each individual model.

### 8.5.1 Validating the modelled supplier locations chosen

The do-nothing scenario corresponds to the current condition where there are 30989 trips of private vehicles and 8198 trips of commercial vehicles (i.e. CVs = 26% of PVs). In this model, we first look at the basic output of the model (see Table 8-3). The aim is to show the do-nothing scenario, and see if we produce a reasonable output from our model or not. The results can also be used to determine if the values for VOT and VOC we have taken are reasonable.

**Table 8-3. Basic results for do-nothing scenario**

| Variable | Unit | User class | Value |
|---|---|---|---|
| Economic Benefit | 1000 IDR / Hour | All | 328377 |
| User benefit | 1000 IDR / Hour | CV | 123708 |
| | | PV | 136616 |
| | | All | 260324 |
| Total cost | 1000 IDR | CV | -18718 |
| | | PV | -49336 |
| | | All | -68054 |
| Total travel time | Trips hour | CV | 1020 |
| | | PV | 3064 |
| | | All | 4084 |
| Total travel Km | Trips Km | CV | 17764 |
| | | PV | 63067 |
| | | All | 80831 |
| Average travel time | Hour / trips | CV | 0.12 |
| | | PV | 0.13 |
| | | All | 0.13 |
| Average travel Km | Km / trips | CV | 2.17 |
| | | PV | 2.63 |
| | | All | 2.51 |
| Average travel speed | Km / hour | CV | 17.4 |
| | | PV | 20.5 |
| | | All | 19.79 |

The results show a reasonable value for speed in Bandung city centre which is 19.79 km/hour for all vehicle types. Since we do not have the speed or traffic flow data to validate the model, we validate the model through the retailers' supplier location choice. In the do-nothing scenario, the supplier location choice represents the retailer behaviour and acts as a trip distribution model. Thus, the input for the model constitutes CV origins and the outputs include their trip distribution along with the routing.

The supplier location choice is a multinomial logit model and the utility function comprises measurable characteristics, namely: the travel time between retailer and supplier zones, number of establishments in supplier zones, and the presence of traditional markets in supplier zones. The results from the supplier location choice model is the trip distribution as a proportion of demand from each retailer node.

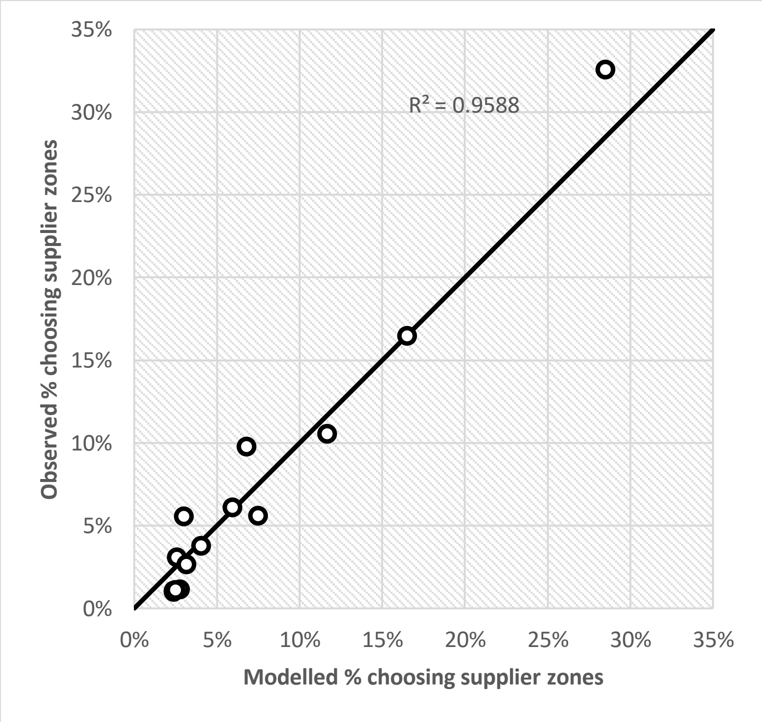



**Figure 8-3. Modelled and observed proportions choosing various supplier zones**

Figure 8-3 compares the modelled destinations data for each supplier node with observed proportions gathered from the survey. These two data are independent. The observation data (Y-axis) for retailer trips distribution are known from the survey results. Meanwhile the modelling data for retailer trips distribution (X-Axis) are the result from the model simulation which is largely dependent on the simulated traffic condition. The traffic condition in the model is the result of the simulation and not from the survey, hence, the result of the simulation can be considered valid when it is able to reasonably duplicate the traffic conditions in the real world.

The model performs well with a high $R^2$-value, thus the do-nothing model is considered to represent the current conditions sufficiently well.

### 8.5.2 Model convergence

In this chapter, we run several models based on the scenario we want to test. Generally, the models can be classified into two groups:

- Optimal toll models: a set of models which aims to search for optimal toll values depending on the location of the toll being charged (3 scenarios)
- Fixed toll models: a set of models which aims to evaluate the various CV demand and toll values, once the location of the toll is set. The scenarios include 5 different CV demands and 9 different toll scenarios (in total the author ran 45 scenarios). Note that the tolls are only applied to the CV demand.

Regarding the convergence of the models, all models eventually converge based on the convergence criteria (see Appendix B). However, the number of iterations needed for the model to eventually converge differs from 4 to 20 iteration (see Figure 8-4).

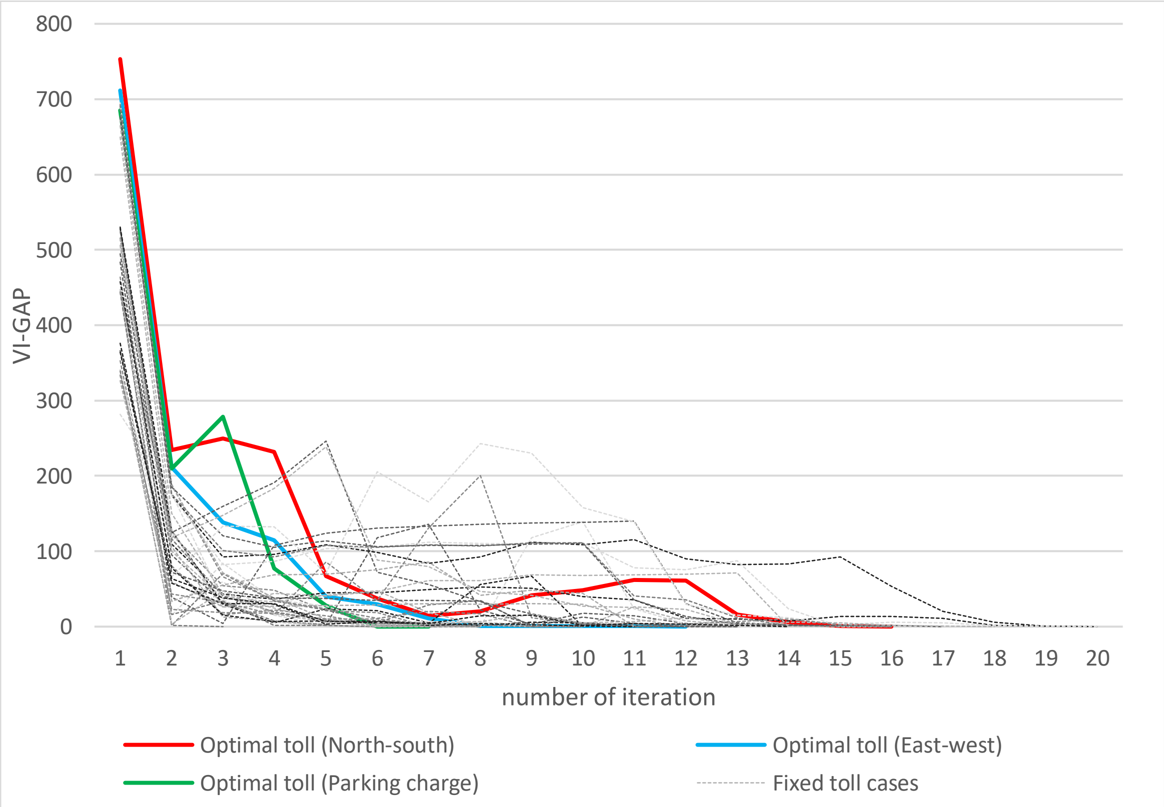
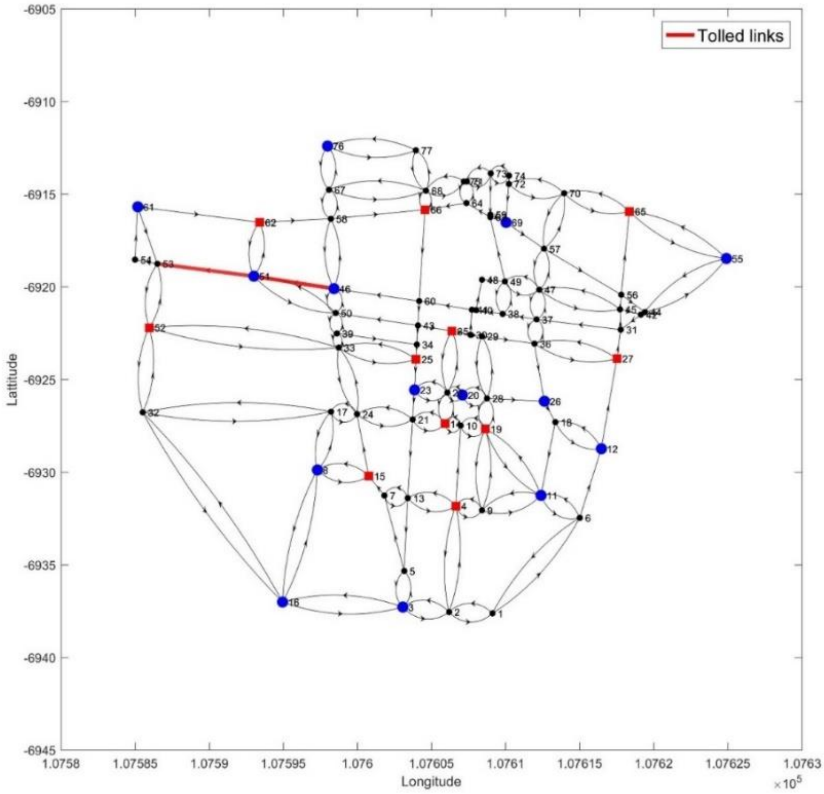


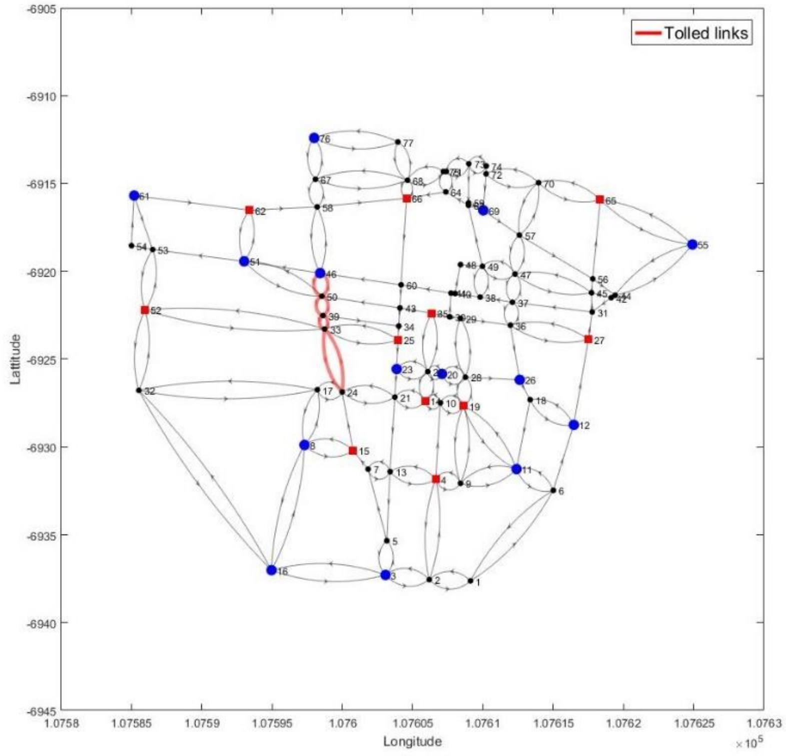

**Figure 8-4. VI-GAP value for all scenarios**

## 8.6 Optimal toll charge for different tolled link scenarios

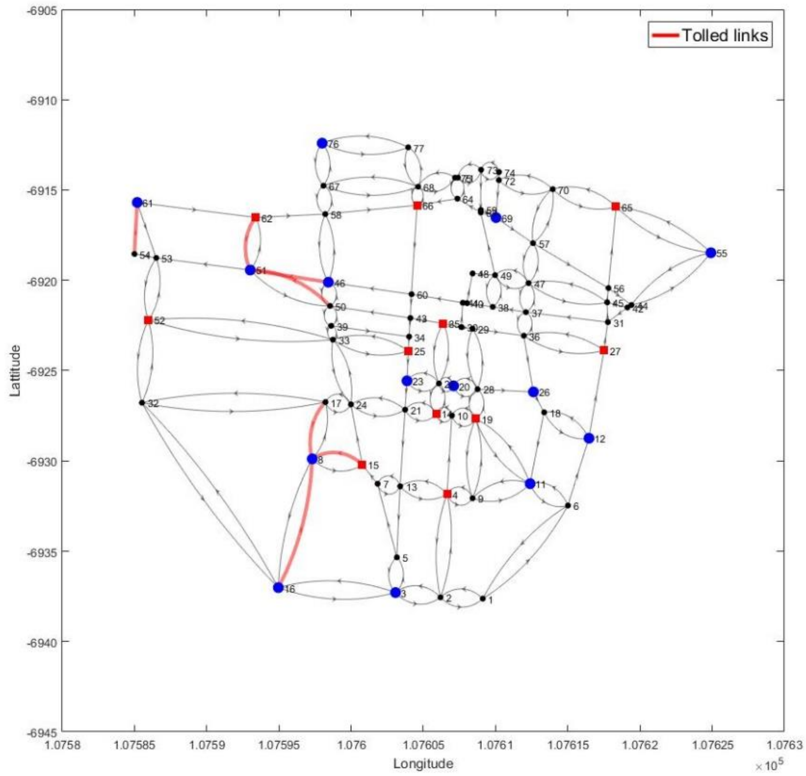
We now consider the possibility of improving the overall welfare over and above the current levels of welfare by managing the CV demand. In this experiment, we test three different scenarios of applying the toll in predetermined links: east-west link toll, north-south link toll and parking charge link toll (see Figure 8-5). The selection of the predetermined links to be tolled is based on the most congested links in the current conditions. As for parking charge, the parking charge is applied for CV demand for the top three visited supplier location zones.




(a) East-west link toll




(b) North-south link toll

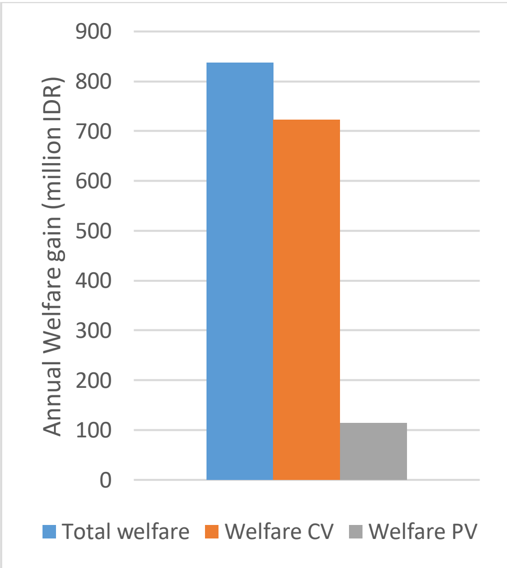



(c) Parking charge

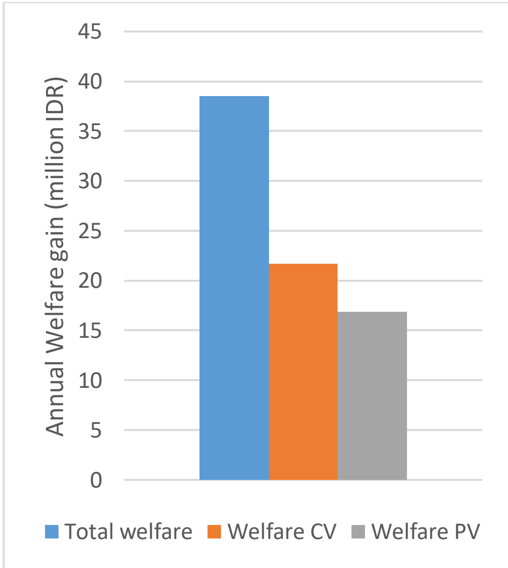
**Figure 8-5. Tolled links for CV demand**

We ran the bilevel model to find out the optimal toll charge that maximises the overall welfare for CV and PV demand. By identifying the optimal toll charge, the local authority will have the ability to make a positive influence on society by anticipating the response of both PV and CV user classes.

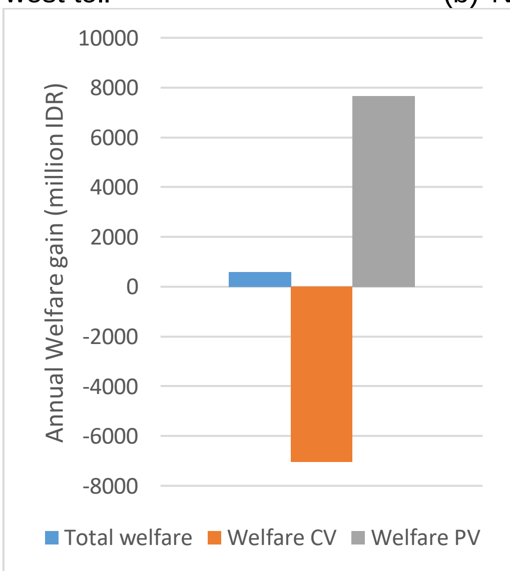
The do-nothing results become the benchmark to calculate the welfare gain for any scenario. The welfare gain is the difference between the absolute welfare value from a given scenario (do-something) and that of the do-nothing scenario. Figure 8-6 shows the annual welfare gain over the do-nothing scenario split by user class for all scenarios. Note that the welfare gain is worked out per annum from the peak hour model by multiplying the welfare by a typical number of working days of 225.




(a) East-west toll




(b) North-south toll




(c) Parking charge toll

**Figure 8-6. Annual welfare gain for optimal toll scenario**

The results indicate that for all scenarios, the introduction of the toll indeed improves the overall welfare. The biggest welfare gain is achieved when the toll is applied to the east-west scenario. In this scenario, overall welfare for society gains 835 million IDR by charging the CVs a toll of 19800 IDR per trip for each link. It also shows that the CVs are the main beneficiary though the PVs too will benefit from a reduction in congestion. The north-south scenario gives minimal welfare gain, just 38 million IDR annually by charging 1700 IDR per trip for each link. In this scenario, both CV and PV gain benefit. The parking charge scenario also gains overall benefit (593 million IDR annually), yet at a closer look at the impact of the policies on the different user classes, the parking charge actually causes a loss for the CV user class whilst the PV user class gains significant benefit.

It is interesting to see where the benefits arise for each user class in order to understand why each scenario gives a different result. Based on the welfare formulation in Chapter 7 (see equation 7-10) , there are two components that determine the value of welfare: the user benefit, and the social cost. The user benefit of CV demand is determined by the distribution of CVs, while the PV demand is determined by the total number of PV trips generated; both are determined by the congestion level of each OD pair.

Further analysis of the east-west toll scenario indicates that the majority of benefits arise from the redistribution of the CV demand which, in turn, affects their routing and hence lowers the congestion levels. The total social cost in the network is reduced by 164 hour trips. Figure 8-9 shows that tolling will result in many CV destinations shifting from the west to central and eastern parts of Bandung city centre which will then produce a first order gain for CVs (723 million IDR annually) and then a second order gain for PVs (115 million IDR annually). Thus, it is concluded that there is a clear benefit of regulating CVs by applying a toll charge for the east-west scenario.

For the north-south scenario, further analysis reveals that the majority of the benefits arise from reducing the total cost of CVs rather than redistribution of CVs. Redistribution happens but unlike for the east-west scenario, the CV distribution results in reducing welfare (-12 million IDR annually). However, in this scenario both CV and PV total costs reduce compared to the do-nothing scenario. CV total costs reduce by 34 million IDR annually and thus the scenario still gives positive benefit for CV demand (22 million IDR annually). Thus, it is concluded that there is a benefit by implementing an optimal toll for the north-south scenarios; however, the benefit is not as significant as for the east-west scenario.

The parking charge scenario applied a parking charge to 3 supplier location zones (Nyengseret, Cibadak, and Ciroyom). The analysis shows that the optimal toll charge for this scenario is IDR 8800. It is clear from Figure 8-6-c that this scenario results in shortcomings for CV demand (-7061 million IDR annually). Further analysis shows that the parking scenario reduces CV user benefit and increases CV total cost. The total cost for CVs increases by 176 million IDR annually whilst the redistribution caused by the parking charge makes the CV user class lose 6885 million IDR annually. However, this scenario increases the welfare for PV (7655 million IDR annually), and overall the parking charge scenario still results in welfare gains by 593 million IDR annually. This scenario shows that the planning for charging a toll for CV demand must be conducted carefully. The policies may lead to disadvantages to the CV demand compared to the PV demand, which then creates tension between the local authorities and the UGM industries as the local authorities can be perceived as ignoring the UGM industry.

## 8.7 City logistics policy testing

In this section, there are two main policies that will be tested. One is related to the optimal toll (Section 8.5). Further, the impact of different toll charges combined with the more restricted vehicle ban is also examined. In this testing we use the east-west toll scenario since the scenario gives the best results for the optimal toll experiment.

One of the most commonly used city logistics policies is to allow CVs in specific time windows – e.g. no entry for goods vehicles during a particular period. This will, in effect, limit the number of CVs in an area, the extent of which will depend on the type of restriction in place. The restrictions could come in any form, e.g. traffic management methods for banning goods vehicles weighing over a certain limit (e.g. 3.5 tonnes) to a complete ban of CVs during a period of the day. This method of restricting goods vehicles is commonly known as 'time-windows'. This policy can be tested by limiting the CV demand to a pre-specified level within the bilevel model. Secondly, independent to the above, city authorities can implement a charge on CVs to limit their numbers in the city centre. The charge applied may serve multiple aims such as improving the environment, efficiency, safety etc. In general, we refer to this as a toll charge, which, in this paper, is aimed at improving efficiency. Finally, a toll charge can also be applied in combination with time windows, thus the ensuing numerical tests are aimed at addressing the following key questions:

(i) Would time windows be an effective method for improving overall welfare?
(ii) To what extent would the toll charging method improve welfare?
(iii) Would the combination of time windows and toll charge be more effective than either of the two alone?

### 8.7.1 Impact of limiting the demand through time windows

As the east-west scenario produced the best solution for the optimal toll scenario, we then continued the analysis to include the analysis of the different levels of CV demand. Reducing the CV demand could be implemented in any form, e.g. weight restriction, height restriction etc.

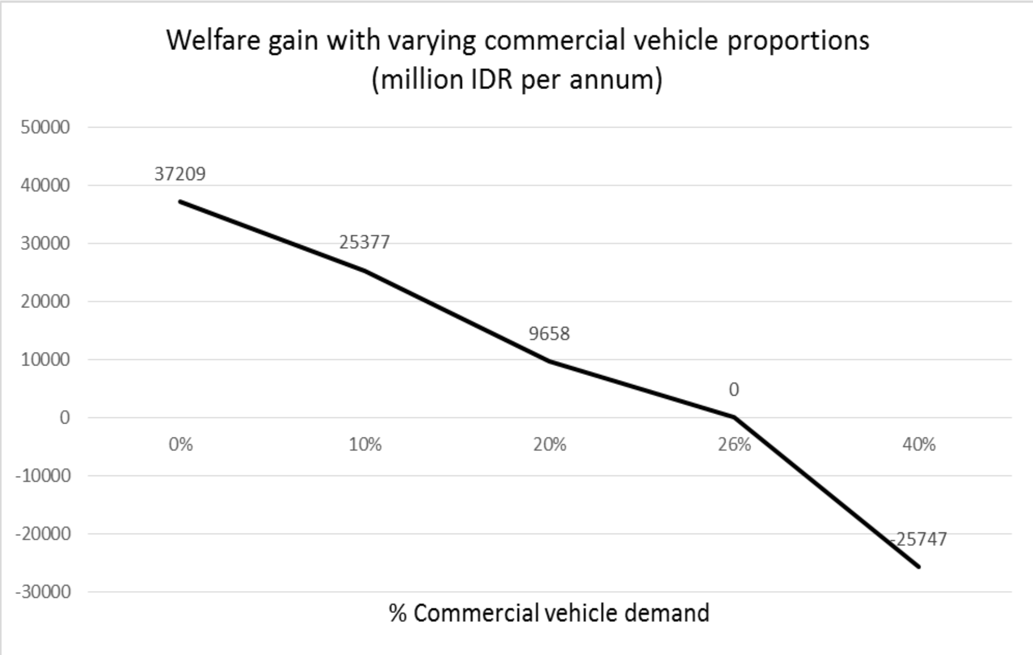



**Figure 8-7. Sensitivity of welfare gain to commercial vehicle proportions**

We ran the bilevel model with a series of CV demand levels varying from 0%, 10%, ..., 40% to assess the impact on welfare gain. Figure 8-7 shows that reducing the CV demand would clearly improve the overall welfare relative to the current situation. This confirms that time windows are an effective logistics policy in cities especially during peak hours, resulting in large benefits. Such a policy of partially/fully banning CVs will help relieve traffic congestion by a significant margin. Reducing the CVs from the current level of 26% to 20% will reduce traffic congestion by 7% and a complete restriction would benefit road users through a 29% reduction in congestion. Thus, a time windows policy would be very effective for dealing with city centre congestion in Bandung but may require careful planning as it may affect the shoulder periods either side of the peak due to potential rescheduling of CV movements.

### 8.7.2 Impact of toll charging on East West Scenario

Toll charging is seen as a less restrictive policy than time windows as it would allow the retailers to use the particular links charged if they are prepared to pay the toll; if not they will have to choose alternative routes. Thus, we ran the bilevel model with a series of varying toll charges from no toll to 40000 IDR based on the east-west scenario as before when working out the optimal toll at the current level of CV demand.

Figure 8-8 shows that there is a benefit to be gained from charging CVs relative to the current situation where there is no charging done. The welfare level increases quite steeply with toll charge up to 20000 IDR after which welfare starts falling indicating the optimal toll to charge (exact optimal value worked out to 19800 IDR, see Section 8.6).

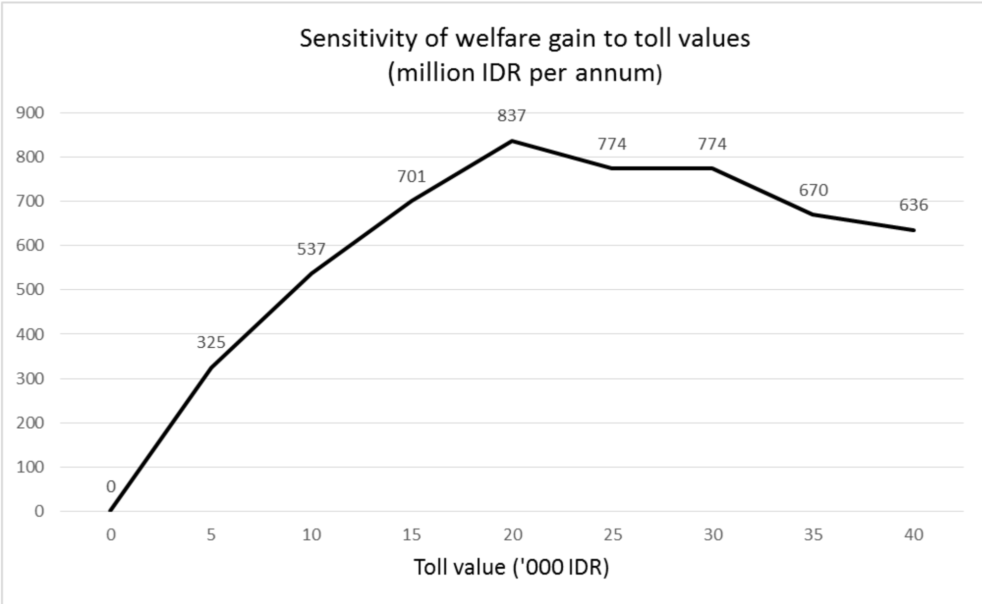
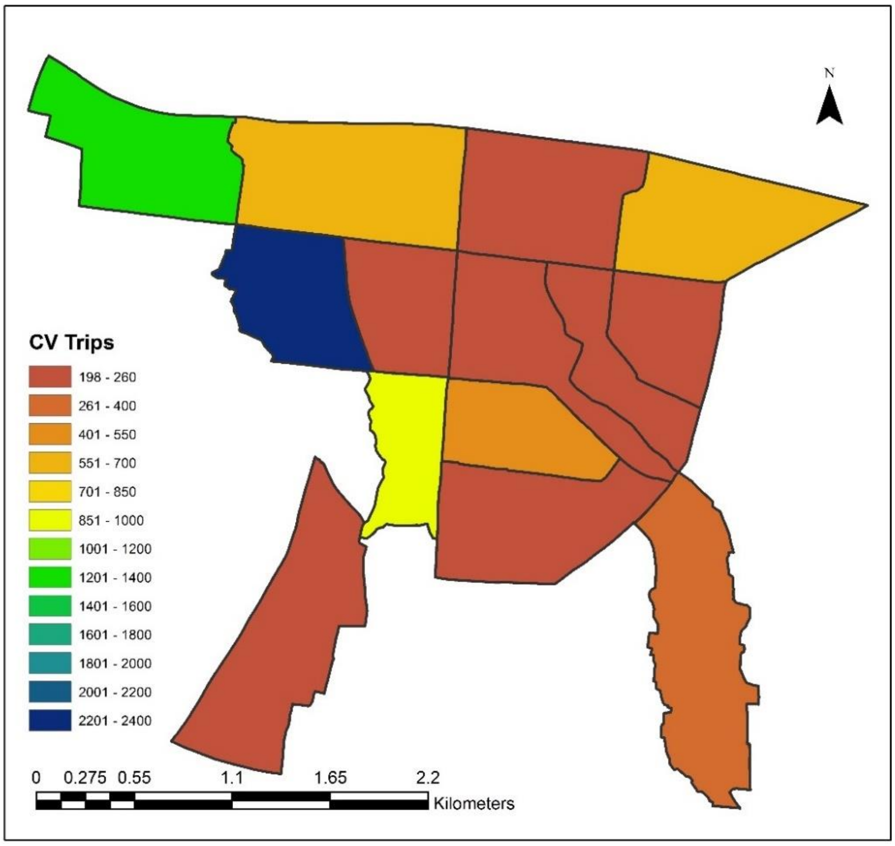
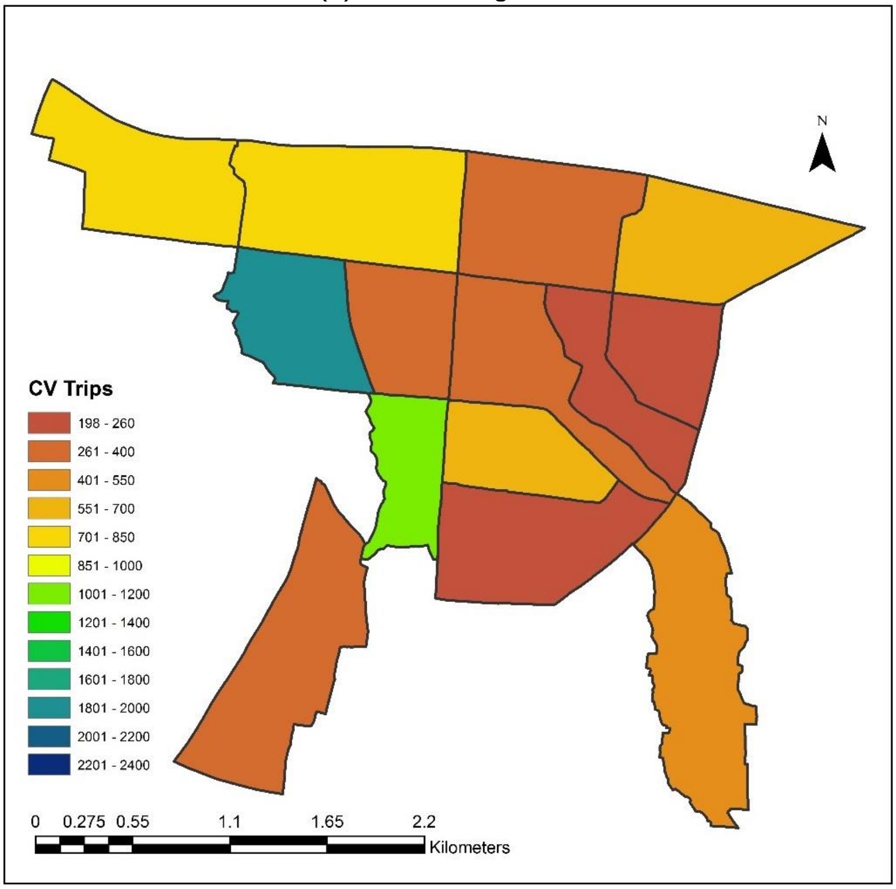



**Figure 8-8. Sensitivity of welfare gain to toll charges**

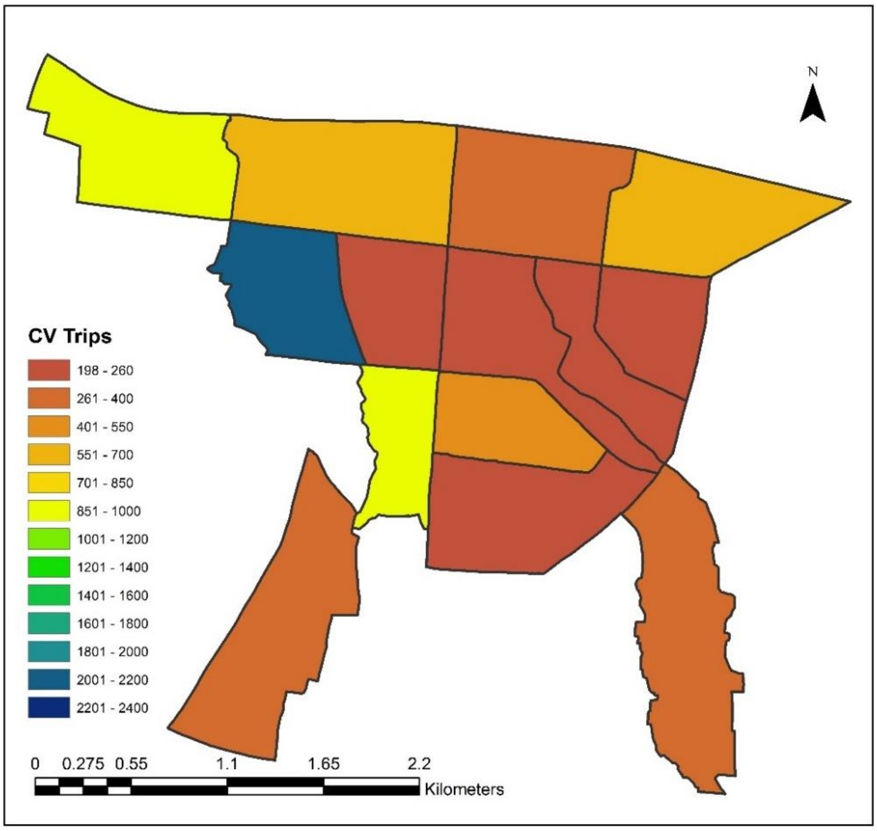
Compared to the time windows policy, welfare gains from toll charging are an order of magnitude smaller. A notable point is that almost all of the welfare is gained from the redistribution effect rather than congestion reduction. For example, a toll charge of 20000 IDR would make the retailers seek to restock from nearby suppliers rather than thronging to the wholesalers located to the west of the city centre. Figure 8-9 shows the redistribution of the CV demand for various scenarios. From the figure, it is evident that a higher toll (i.e. 40000 IDR) caused a higher redistribution of CV demand. This outcome has a major implication for city logistics policy in Bandung. A toll charge is likely to redistribute the CV destinations effectively through the city indicating the need to develop alternative wholesaling market yards and driving the retailers to procure from new locations.



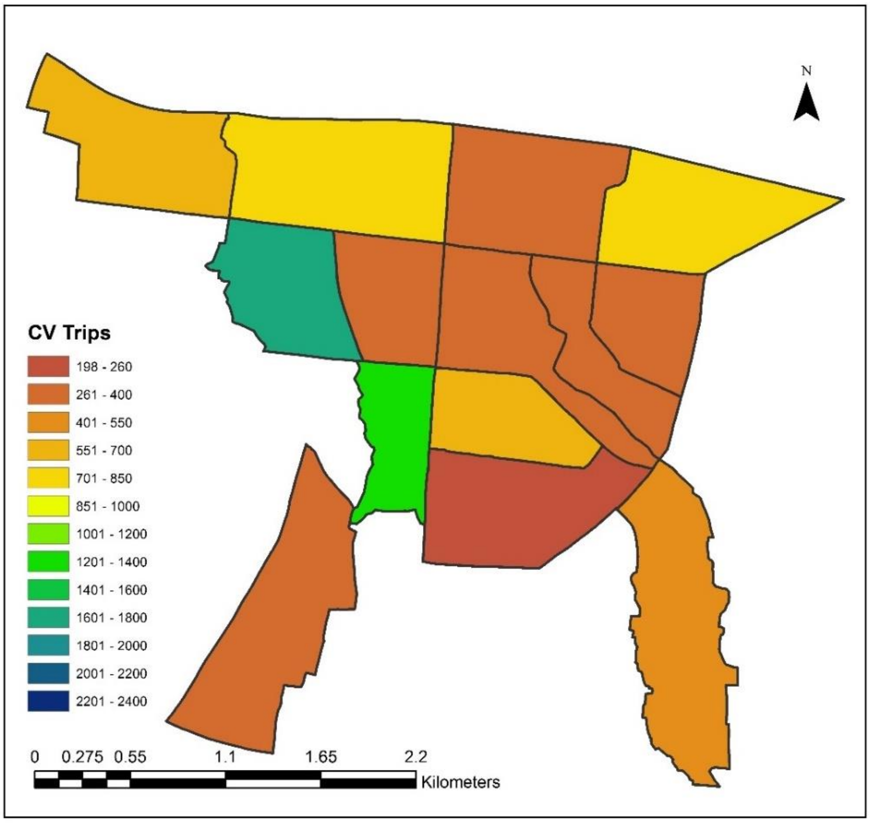

(a) Do-nothing scenario




(b) Optimal toll scenario




(c) IDR 5000 toll scenario




(d) IDR 40000 toll scenario

**Figure 8-9. Number of trips attracted to each zone for different scenarios**

### 8.7.3 Impact of combination of limiting the demand and toll charging

Finally, we analyse the impact of restricting the demand through time windows in combination with various toll levels with the help of the model created. The bilevel model was run over a series of nine levels of toll (no toll, 5000 IDR, 10000 IDR, so on up to 40000 IDR) in combination with five levels of demand for commercial vehicle (0%, 10%, so on up to 40%), thus a total of 45 instances were simulated in all. Figure 8-10 plots the surface of welfare gains relative to the current situation.

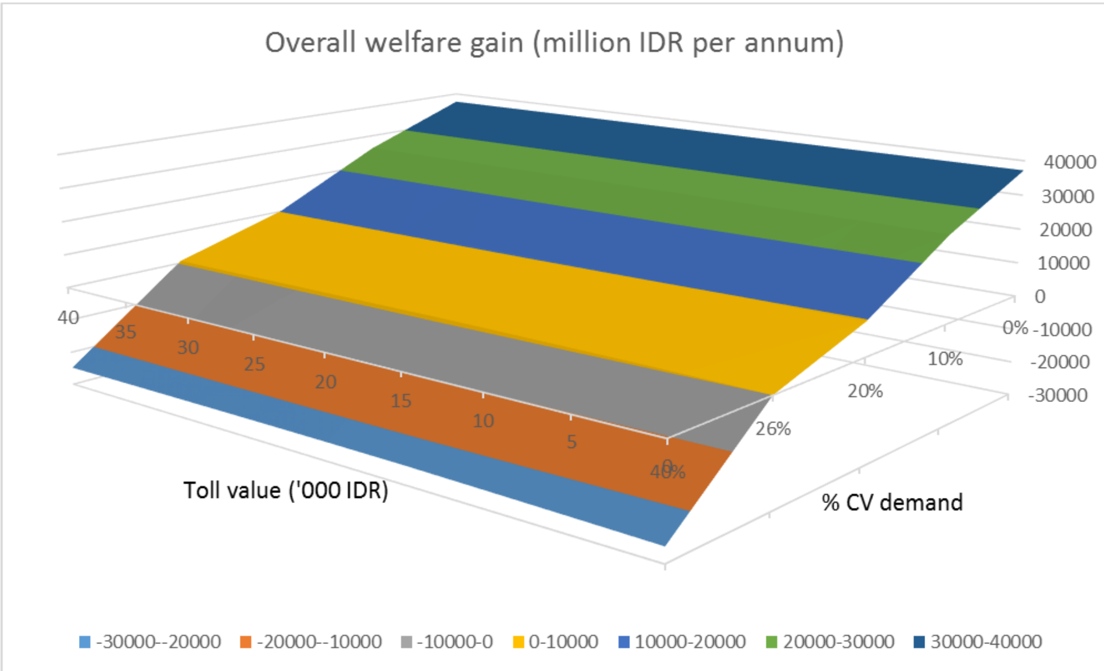



**Figure 8-10. Surface of welfare gain**

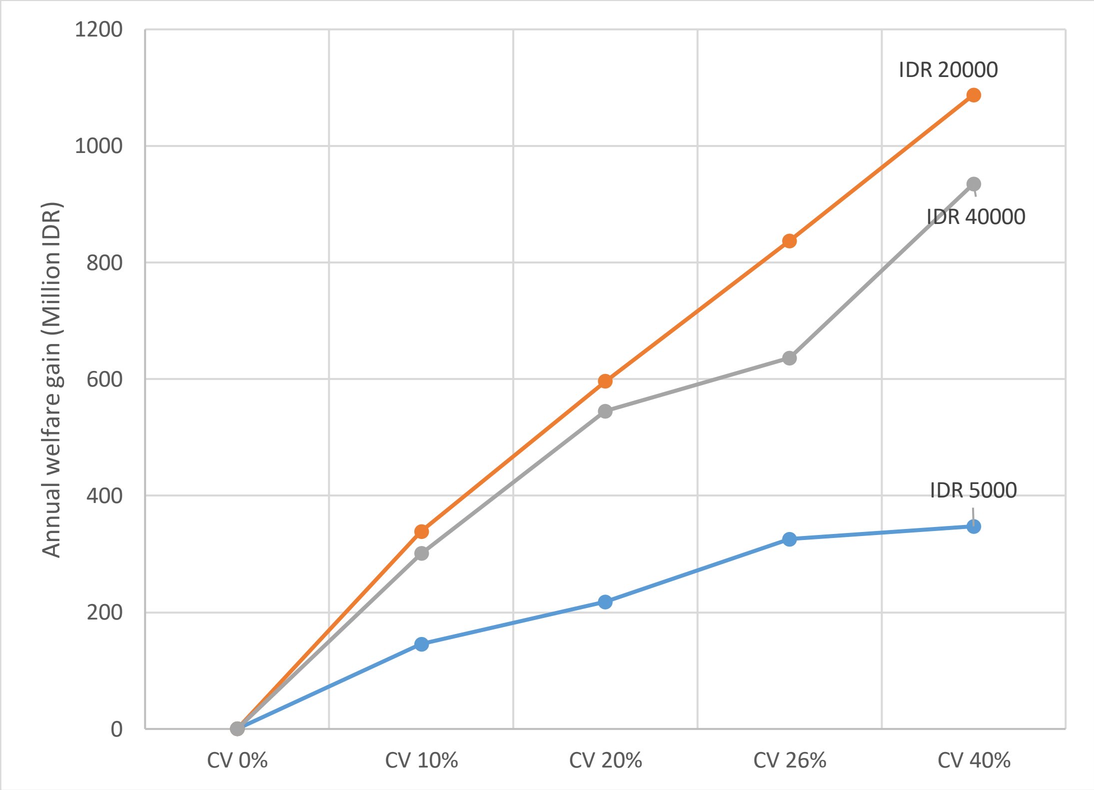
Figure 8-10 shows that the proportion of CV demand driven by the time windows policy is far more effective than the toll charging method. The welfare gains are much higher with varying CV demand levels whilst the toll charging appears to deliver rather smaller variations in welfare levels with respect to varying tolls.

## 8.8 Implications for city logistics policy planning

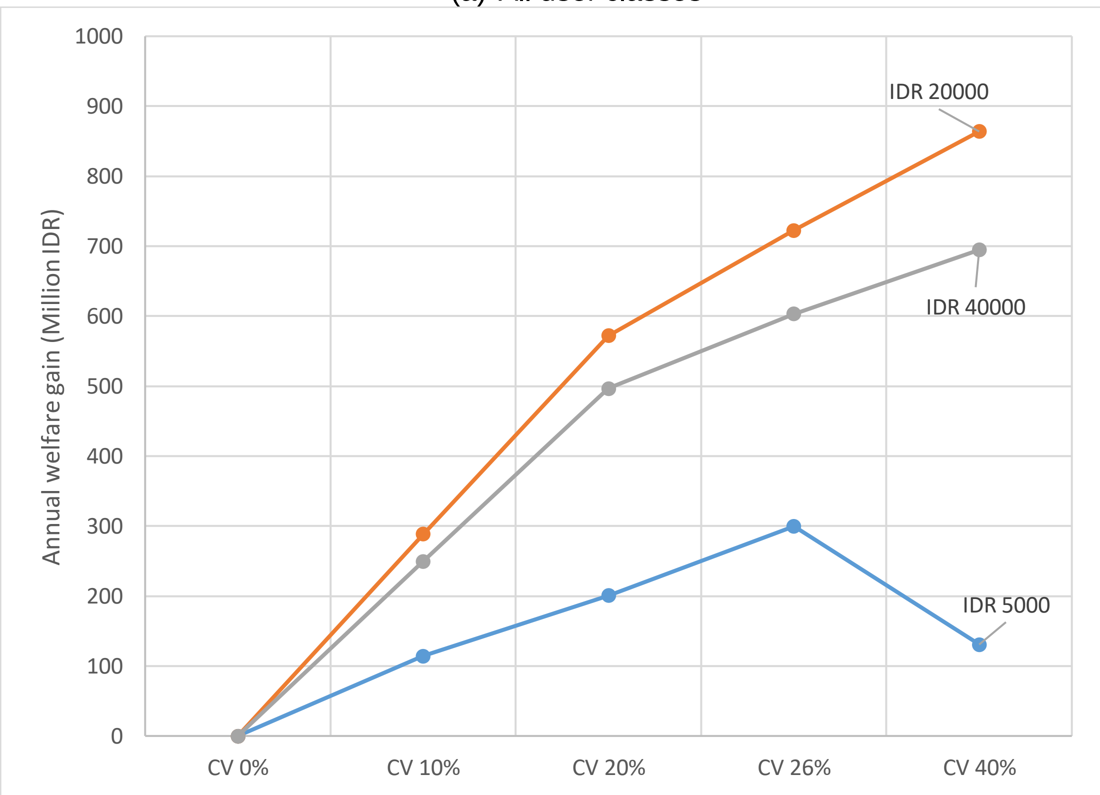
In this research, we tested two key city logistics policies viz., time windows and charging the CVs both of which promised substantial benefits to gain. Between the two policies, the time windows policy seems to deliver potentially much larger benefits compared to the toll charging. The policy of time window-based deliveries is relatively easy to implement too. However, local authorities may face criticism from the retailer/wholesaler associations depending on the extent of restrictions envisaged. Local authorities may also need to consider the impact of time windows affecting the shoulder periods before/after the restrictions are in place.

Alternatively, local authorities may resort to charging the CVs for using parts of the network though they will need to gain support from user groups. Such a charging system may be implemented as a simple paper-based one (less flexible) or through electronic pricing (expensive but flexible to extend to other locations). Although the model indicates the optimal toll to charge, local authorities may wish to consider lower/higher charges depending on the public support and political will. Figure 8-11 plots the impact of different toll charges on welfare for three levels of charges: 5000 IDR, 20000 IDR, and 40000 IDR.

Firstly, the local authority may wish to apply a soft pricing scenario, i.e. charging less than the optimal toll. With a softer charging level such as 5000 IDR, local authorities will still be able to obtain welfare gain (Figure 9a). However, if the total number of CVs increases, the pricing policy will be less effective, since the welfare gain rates will reduce significantly. Figure 8-11.b showing welfare gain of CVs indicates that applying a soft pricing policy will eventually reduce the CV welfare when the CV demand increases. It is noted that the welfare gain is largely obtained from redistributing the CV demand to other wholesalers within the city. As the soft pricing is not strong enough to push the CV demand to redistribute, higher CV demands increase the total travel costs (more congested) and thus decrease the overall CV welfare. Alternatively, if the local authority wishes to apply a steep charge, such as 40000 IDR, they can gain higher welfare than with the soft pricing policy. However, the overall welfare is still less than that for the optimal pricing policy. Furthermore, with higher charging, the resistance from the UGM operators and users will be even higher.




(a) All user classes




(b) CV user class

**Figure 8-11. Annual welfare gain with varying CV demand**

## 8.9 Computational effort

We wrote the code to solve the bilevel problem using MATLAB R2016b. Note that the solution technique of cutting constraint algorithm (CCA) involves a two-stage iteration process. The application of this iteration in the MATLAB code can be elaborated in MATLAB pseudo code below (the complete MATLAB code can be seen in appendix C):

**MATLAB 2016b pseudo code**

a. Define the number of links *a* and link characteristics e.g. free flow time ($t_0$), and capacity ($k_a$)
b. Define the number of O-D pairs *w*
c. Define the number of user classes *i*
d. Define the value of time for each class $\lambda_i$
e. Define the number of feasible paths $P_w$ connecting the O-D pairs, $P_w \in P$
f. Define the demand vector $D_r^i$ for each origin *r*
g. Define the link-path incidence matrix ($\delta_p^a$ ) for each O-D pair *w*. Each O-D pair has $P_w$ feasible paths.
h. Define the number of iteration *n*
i. Define the convergence criteria $\varepsilon^i$ as VI gap for each UC *i*

$$\sum_w \sum_p x_{p_w}^i * c_{p_w}^i - \sum_w D_w^i \ \mu_w^i \leq \varepsilon^i$$

j. Initizialize path flow vector for each user class $x_p^i$ by dividing the trips demand for each OD equally for every possible paths.

Iteration *n* = 0

k. Calculate link flow vector by $v_a^i = \sum_{w \in W} \sum_{p \in P_w} \delta_p^a \ x_p^i$
l. Calculate the link travel cost vector $c_a^i = \mu_i \ t_a(v_a)$; where $t_a(v_a)$ is the relationship between travel time and link flow for e.g. BPR function
m. Calculate path travel cost vector for each O-D pair *w* $C_p^i \ = \sum_{a \in A} \delta_p^a \ c_a^i$
n. Calculate the value inverse demand function for each user class *i* at current path cost; ${d_w^i}^{-1}(\omega)$
o. Identify the shortest path ($SP^i$) vector for each user class *i* within the feasible paths $P_w$, in which $SP^i$ is the shortest path based on travel cost for a particular user class *i*
p. Perform the all-or-nothing (AON) assignment to get the AON link flow (${v_a}^*$)for each UC *i* by assign the demand vector $D_w^i$ according to $SP^i$ vector; ${v_a}^* = D_w^i \ SP^i$
q. Calculate the total demand based on path flow vector $D_w^{i^*} = \sum_{p \in P_w} x_p^i$
r. Calculate the scalar variational inequailty

$$VI = \sum_i \left[ \sum_a \check{c}_a^i (t_a(v_a^*, \tau_a^i)) \ (v_a^* - v_a) - \sum_w {d_w^i}^{-1} (D_w^i)(D_w^{i^*} - D_w^i) \right]$$

s. Calculate objective function - Z

$$-\mathrm{Z} = \sum_{w \in W} \sum_{i \in I} \int_{0}^{D_w^i} d^{-1}(\omega) + \sum_{a \in A} t_a(v_a) v_a$$

t. Solve the minimization problem of $-\mathrm{Z}$ using *fmincon* by varying $x_p^i$, s.t. $x_p^i \geq 0,\ D_w^{i^*} = D_w^i, VI \leq 0$.
u. Update the demand $D_w^i$, using demand function $d^i(\omega)$
v. Calculate convergence criteria

Iteration *n* = *n* + 1

Iterate until number of iteration meets maximum iteration or the result meets the convergence criteria. In this paper, $n_{max}$ = 20, and $\varepsilon^i$= 0.1.

The first stage iteration involves the process of finding the shortest path for each OD pair. This iteration is represented by the number of all or nothing assignments needed generating one extreme point at a time each of which cuts away the part of the region not feasible for the problem defined. In the pseudo code above this step is represented by step *o* and *p*.

Another iteration process is also needed but at the upper level to solve the minimisation problem of the objective function. In this case, we use the *sequential quadratic programming* (SQP) algorithm to solve the problem provided by the *fmincon* solver from MATLAB. The method uses Newton's method for constrained and unconstrained optimisation. At each iteration, a Hessian or Lagrangian function is approximated using a quasi-Newton method. This is then used to generate quadratic programming subproblem. The solution can be used in the line search and trust-region framework. In the pseudo code this step is represented by step *t*.

As we run a range of scenarios from do-nothing to optimal toll and several what-if scenarios, the number of iterations required to solve the problems varies hugely from as low as four to about twenty iterations. All models run eventually converged and met the convergence criteria satisfactorily (see Appendix B). As for computational effort, we ran the program using supercomputing facilities available at the University of Leeds (https://arc.leeds.ac.uk/). The standard number of nodes for this facility is 24 cores with 128 GB of memory. The CPU clock rate is 2.2 GHz with a turbo system where possible. With this particular facility, the MATLAB code on average needed 9.4 hours for each model run to be completed, involving about 14 iterations.

## 8.10 Chapter summary

In this chapter, we provide a real-world case for implementing the model formulation. The modelling work involves the inclusion of the demand model estimated in Chapter 6 and the bilevel programming problem set up in Chapter 7.

The validation of the model shows that the model can capture the current situation quite well. The policy results show that the optimal toll can be obtained depending on the tolled link in the network. Nevertheless, local authorities need to be careful to select the links that will be tolled since tolling particular links randomly will cause disbenefit for particular user classes (e.g. the parking charge scenario in this chapter improves the welfare of the PV user class but decreases the CV demand welfare significantly).

This chapter also tests some city logistics policies namely: the impact of limiting the CV demand, and various toll charging. A city logistics policy of allowing goods pick up/deliveries only during particular hours of the day would be extremely effective. This would reduce CVs significantly during the restricted hours, and the overall welfare would increase substantially due to the high disutility associated with their movement (though it is assumed that the goods would be delivered at a different hour of the day). Secondly, the time windows policy would increase the welfare for other road users due to the reduced congestion on the streets. A time windows policy may, however, be seen as highly restrictive by the retailers/wholesalers in the city.

This chapter provides the end of the thesis analysis. The next chapter will summarise and conclude the thesis and presents the limitations and future research direction.

# Chapter 9 Summary and conclusions

This chapter provides a summary of the study and gives concluding remarks on the entire study. This chapter is divided into 4 sections starting with Section 8.1 that summarises the research activities and findings. Section 8.2. specifically states the fulfilment of the research aim stated in Chapter 1. Then general conclusions are outlined in Section 8.4. Finally, the limitation of this study and the recommendations for further studies are presented in Section 8.4.

## 9.1 Summary

### 9.1.1 Urban goods movement and independent retailer activities

After doing the literature review of urban goods movement activities and in particular independent retailer activities, the results can be summarised as follows:

- There are at least three identified actors shaping UGM activities and city logistics policies: the local authority, private/UGM industry actors (e.g. retailers / carriers / wholesalers), and the end consumers / other road users.
- The local authority is the actor most interested in implementing city logistics measures. However, it is important to consider the interests of UGM industry actors while planning the policies to improve UGM activities.
- The literature reveals that in general most city logistics measures tried to reduce the negative impact of UGM activities by placing some restriction on commercial vehicles. The restriction, while it may alleviate the perceived problems may not be harmful to UGM activities. Therefore, it is essential for the authorities to address *optimal* city logistics measures that take account of the interest of actors involved and affected by UGM activities.
- This thesis focuses on the activities of independent retailers. Independent retailers are generally small family businesses that sell everyday essential goods; and are usually owned by a family and operated by the owner. Independent retailers, prevalent in developing countries, play an important role in distributing goods within the city.
- According to the presentation of the current urban goods movement policies and independent retailers' restocking activities, this thesis attempts to investigate the *optimal* city logistics policies by building a modelling framework that can assess city logistics policies whilst taking into account the behaviour of independent retailers as well as other road users. This thesis specified the

problem in the context of independent retailers prevalent in developing countries.

### 9.1.2 Findings from the review of methodologies

Reviewing the related literature on UGM modelling attempts and optimisation models to address city logistics policies, some findings can be elaborated as follows:

- A UGM model should be able to depict the behaviour of the actors shaping the activities since UGM movements involve many stakeholders. Unlike in passenger movements in which the decision maker is the traveller him/herself, in UGM activities, each stakeholder has decisions to make. The decisions affect the way goods are transported. Further, the unit of the goods transported changes throughout the decision-making process.
- The most common approach found in the literature to model UGM activities is through a typical four-step model profound in passenger movements: generation model, distribution model, mode choice model, and traffic assignment model.
- The first three models (generation, distribution, and mode choice models) deal with the demand side of UGM activities, while the traffic assignment model deals with the interaction between supply and demand. Regarding UGM activities, there are two phenomena that need to be considered when applying traffic assignment methods: (i) *incorporating the decisions of UGM actors;* (ii) *incorporating mixed traffic conditions*.
- This thesis aimed to address how to impose an *optimal* city logistics policy considering the behaviour of road users. The literature shows that it can be approached using a bilevel programming method.

### 9.1.3 Summary of data collection and data description

As part of this research, this study conducted a data collection process to understand the revealed preference of independent retailers regarding their restocking activities. The data collection process can be summarised as follows:

- The survey began with the questionnaire design. The questionnaire was designed to be retrospective by including questions exploring the independent retailer decisions and the attributes that can affect the decisions.
- The survey was conducted over 4 weeks. We used face-to-face interviews and a paper-based questionnaire to conduct the interview. We hired 6 enumerators from local universities to help us to conduct the survey.

- We successfully gathered 235 questionnaires out of 265. The overall response rate was 88%. However out of 235 questionnaires that were completed, only 224 were deemed to be valid and suitable for detailed analysis.

From the data we collected, we summarise some of the characteristics of the retailers and their restocking activities.

- The majority of independent retailer shops occupy areas less than 30 $m^2$ and more than 80% of them hire less than or equal to two employees. However, the majority of them own their own vehicles in the form of two-wheelers that are used to restock their shops.
- Regarding restocking activities, the majority of them choose to restock from suppliers that reside inside the Bandung city centre (BBC) area. Interestingly, 41% of them choose suppliers in traditional markets implying the importance of traditional markets in the supply chain of independent retailers.
- As expected from the high value of vehicle ownership, the majority of restocking activities are done using their own vehicles. In terms of time for deliveries, morning time from 06.00-09.00 AM is still the prime time for independent retailers to restock their shops.

### 9.1.4 Demand model estimation

The demand models are estimated to examine the significant attributes using the data gathered from the surveys. Three models are estimated: (i) the generation models; (ii) the supplier location choice models; (iii) the transport service choice model. The summary of the estimation results are as follows:

- The generation model was estimated using a regression model. The estimation resulted in a good $R^2$ value indicating the data fit quite well with the models. In the estimation process we included dummy variables and interaction variables within the dummy variables.
- As expected, the models showed that the ownership of two-wheelers has a positive influence on the number of trips. Further, the interaction variable between two-wheeler ownership and the proximity of traditional markets revealed that two-wheeler ownership and proximity to the traditional market encourages retailers to take more trips.
- The supplier location choice model and transport choice model were modelled using multinomial logit models. We also investigated the combined supplier location and transport service using multinomial logit models and nested logit models.

- The estimation for *restocking choice model* revealed that the retailers are more likely to go to the zone that has traditional markets given the retailers have their own vehicles. As for the *transport choice model*, the model revealed that retailers who possess a vehicle and easily access the traditional market tend to use their own vehicle.

### 9.1.5 Bilevel programming formulation and numerical example

This thesis aims to aid the local authority with a modelling framework that can suggest city logistics policies that result in optimal output. This thesis utilises bilevel programming to formulate local authority objectives, and retailers'/other road users' behaviours. The formulation process can be summarised as follows:

- The local authority objective is formulated as the upper level problem. The objective of the local authorities is to maximise welfare economics for all user classes. The welfare value is obtained by calculating the difference between user benefit and total social cost. By calculating the area under the demand function, we then obtained the user benefit whilst the social cost was obtained by summing up all the travel costs generated within the network.
- Traffic user equilibrium formulation was used to depict the condition in the lower level problem. The lower level captured retailer behaviour in terms of minimising the cost of procuring goods from the wholesalers. The model accounted for retailer choice decisions while also accounting for the general road user responses in aiming at minimising their own travel costs. Two problems were addressed in the user equilibrium formulation: (i) the problem of involving decisions other than route choice in the user equilibrium formulation; (ii) the problem of depicting mixed traffic conditions in which there are two user classes in the user equilibrium formulation: commercial vehicles and private vehicles.
- To solve the bilevel programming problem we utilised the cutting constraint algorithm (CCA). The key to the CCA algorithm is to generate extreme points to cut the unfeasible region from the solution. Nevertheless, since we deal with multiple user class problems, we modified the CCA algorithm by generating the necessary extreme points for each class separately.

### 9.1.6 Model implementation and policy testing

The bilevel programming that has been formulated was implemented in two examples: (i) the small network numerical example, and (ii) the case of a medium sized network in the case of Bandung city centre (BCC). In the example using the Bandung city centre network, some city logistics policies (i.e. time window restrictions, and toll charge) were investigated. The summary can be given as follows:

- The main aim of the small network of numerical examples was to test the working of the bilevel formulation. After running three different experiments, we concluded that the formulation works and reaches an acceptable convergence level. The model can capture various traffic conditions as well as the introduction of city logistics policies and act accordingly.
- The model was also implemented in a real-world case. In this implementation, the demand models in the previous chapter were used as the input into the bilevel programming.
- The validation process, comparing the observed data from the survey and the simulation data in the do-nothing scenario, showed a good result ($R^2$ = 0.95).
- In the policies testing, we focused on two city logistics policies tests: toll charges and commercial vehicle restriction trough time window policies. The toll is charged only to the commercial vehicle (CV) user class, since in this study context, it is the CV user class we want to manage.

Regarding policies testing, there were some interesting findings:

- The optimal toll scenario tests the impact of tolled links in different locations against the welfare of each user class. The results showed all scenarios increase the overall welfare. However, the local authorities need to be careful in their planning approach since a particular toll scenario (in this case, the parking charge) can significantly decrease CV welfare though improving PV welfare.
- Regarding time window policies, the policies are very effective in decreasing congestion in BCC but may require further planning as it may affect other periods of the day, in particular the shoulder time, due to the rescheduling of retailers' restocking activities.
- The toll charge can be seen as a less restrictive policy than time windows. The results show that the toll increases the value of overall welfare, and further analysis shows that the welfare mainly gains from the redistribution of CV demand.
- Finally, we also analysed the impact of restricting the demand in combination with various toll levels. The results showed that a restriction in CV demand is far more effective for improving overall welfare compared to toll charging methods.

## 9.2 Concluding remarks

The results obtained from the thesis provide interesting insights into how city logistics policies need to be applied by local authorities. This thesis investigates urban goods movement (UGM) in the cities in which independent retailers as opposed to chain retailers are predominant retailers in the city. Independent retailers, prevalent in the cities in developing countries, have a different decision-making process and tend to be less consolidated.  Relatively few studies have addressed restocking activities addressing the independent retailer context. To the best of the authors' knowledge, this thesis is the first to investigate restocking activities by independent retailers particularly in the context of a developing country.

The demand modelling analysis provides important pointers for policymakers requiring a better understanding of the trip characteristics of independent retailers in respect of their restocking activities. The ensuing freight trip generation models can be used in many ways. The most obvious use is to quantify trips generated by retail establishments in the study area. Since every city has a different context and different needs, freight trip generation patterns in each city will also differ. Our approach to restocking choice modelling can be used to identify the more attractive TAZs based on characteristics of the zones, allowing planners and policy makers to determine appropriate policies, for example, in terms of determining delivery restrictions in order to improve local traffic conditions and environmental conditions. Meanwhile, the transport service choice model provides important insights into whether trips are made by own vehicle (production trips from retailers to suppliers) or by delivery vehicle (attraction trips from supplier to retailers). The result of the models is useful in generating an OD matrix of trips for retailer restocking activities. Furthermore, as the demand model specifically quantifies the effect of traditional market presence, the model can be used to assess any changes in restocking trip patterns resulting from changes in market locations or the establishment of a new market.

In summary, therefore, the demand models provided in this thesis can be used by the local authorities in three ways: (i) to predict the trips generated and the distribution of trips by independent retailer restocking activities; (ii) to assess the performance of freight-specific transport policies; and (iii) to analyse the impacts of changing market locations in the study area.

We now turn our attention to the problem of local authorities who wants to address *optimal* city logistics policies. The modelling framework, to the best of the author's knowledge, is the first model that combines three key stakeholders viz., local authorities, retailers/wholesalers and private vehicle road users in the UGM studies.

The modelling framework involved needed extensions to both when computing welfare and when distributing/assigning traffic to the road network. Thus, the resulting model is robust and considers each stakeholder's decisions and explicitly models the interactions between them. The main output of the model is an optimal solution to UGM activities besides also generating standard outputs such as traffic flows/costs on road links by type of vehicle. The model facilitates testing of popular city logistics policies such as time windows and road user charging too.

The results of our numerical example for Bandung city centre show that a city logistics policy of allowing goods pick ups/deliveries during particular hours of the day would be extremely effective. As they reduce the CVs during the restricted hours, the overall welfare would increase substantially due to the high disutility associated with their movement (though it is assumed that the goods will be delivered at a different hour of the day). Secondly, the time windows policy will increase the welfare for other road users due to reduced congestion on the streets. A time windows policy may, however, be seen as highly restrictive by the retailers/wholesalers in the city.

Another less restrictive policy of city logistics would be to manage the demand by charging CVs. This policy could be a simple paper-based easy to implement method or, alternatively, it could rely on an electronic method of detecting/charging CVs. In the case of Bandung, it is noted that the charging system with appropriate levels of tolls, could push retailers to distribute away from the congested wholesaling area to other parts of the city resulting in substantial welfare gains. There would also be some congestion reduction benefits from this policy, though with the limited city centre network modelled within the research. A wider network is likely to offer even larger benefits due to the availability of alternative routes.

This studyhas developed a model that specifically address the cases of independent restocking activities which are prevalent in developing countries. Nevertheless, we believe that, the method proposed is sufficiently general as the assumptions are not too restrictive and the model can be easily adopted for different planning contexts,including to assess UGM activities in developed countries. For example, we assume the significant decision by retailers is to choose their supplier location. This is the case since the majority of retailers in our case are independent retailers. This can be generalised by assuming different decisions by retailers, e.g. to choose shipment size, or the type of vehicles, in which these decisions are more relevant in the case of chain retailers in order to effectively restock their outlets. In summary, this thesis proposes a general modelling framework for UGM activities, that can consider the logistic choice dimension to be considered when assessing UGM trips and their interactions with other road user and local authority's city logistic measurements.

In terms of different planning contexts, the general framework can be used to consider a different externality. For example, we might consider extending our method to investigate the optimal toll to address another objective, e.g. minimising emissions in the city centre. In this respect, the assumption we choose can be seen as just one of the many possibilities.

## 9.3 Fulfilment of the research aims

As mentioned in Chapter 1, this thesis has two main objectives: (i) to understand independent retailers' restocking activities, and (ii) to build a modelling framework that can find optimal policies in line with the local authority objective whilst considering the interaction between local authorities, retailers, and end consumers/ other road users.

The first objective of this study is centred on the understanding of independent retailers' restocking activities particularly in a developing country context. The aim has been fulfilled by conducting several activities. Firstly, a literature review was done to understand the independent retailers' restocking activities (presented in Chapter 2). Further to quantitatively be able to investigate independent retailers' restocking activities, the author conducted a literature review on general UGM modelling (presented in Chapter 3). Estimation of demand models including generation and distribution models for independent retailers' restocking activities have been done and reported in the thesis (Chapter 6). The estimation results revealed the significant factors that affect the logistics decisions of independent retailers.

This research conducted several activities to fulfil the second objective. We began by reviewing the related literature on the possible methods of approaching the problem. The related review of UGM modelling methods was presented in Chapter 3. Then the study continued by building a modelling framework based on the bilevel programming approach. The formulation of bilevel programming and the subsequent numerical example that was able to address the research aim was presented in Chapter 7. Then using the previous demand models as one of the inputs into the model, we applied the bilevel formulation using Bandung city centre as a real-world case study. Further we also tested several city logistics measures to show how the model can be a tool to aid the authorities to put in place better city logistics policies. The results of these applications were presented in Chapter 8.

## 9.4 Limitations and recommendations

### 9.4.1 Limitations of the research

This research is the first study that develops the optimisation approach for the UGM problem particularly in the independent retailer context. However, some aspects should be mentioned as limitations of the research:

- This study focuses on the trips generated by independent retailers. It is known that UGM activities consist of various activities other than retailer activities. Nevertheless, in the case of Bandung city centre, the trips by independent retailers still contribute to the majority of trips generated by goods movements.
- The RP data for this study was only limited to the data gathered in the survey. Thus, for some zones with numerous retailers, the data may not give a good representative sample of the entire population. Nevertheless, for the purpose of building the demand modelling estimation, the data was sufficient and the estimation results for the choice modelling were statistically significant.
- The data collection process did not investigate the precise trading relationship between suppliers and retailers. Further, this thesis focused more on the trips generated by independent retailers and not on the range of commodities carried on such trips.
- This study has restricted the implementation of the proposed model into a small geographical region and specifically addresses restocking trips that are originated from retailers locations (i.e. retailers use their own vehicle when conducting the trips). In this case the model implementation may lose the actual trips that occur in the cities. Nevertheless we concentrate our studies in the city centre area where the majority of restocking trips are taking place and in the case of independent retailers, the majority of them are using their own vehicle to restock their shops.
- The upper level problem of the bilevel programming focuses on the overall economic welfare as the only objective by local authorities. In reality, the objective of the local authorities can be wider than this, including for example the development of a particular area in the city centre or the transport equity between the suppliers, etc. Nevertheless, this study is relevant because the UGM related problem is often associated with congestion, which is fully considered in this approach.

### 9.4.2 Recommendations for future studies

From the findings elaborated in this chapter, some further investigation could be carried out in future studies:

- Regarding the demand models, a future demand model could focus on more explicit consideration of the types of products being purchased during restocking activities.
- The formulation of the local authority objective may include multi objective criteria such as including an environmental objective, and therefore the policy implication for city logistics measures could be assessed from a wider perspective.
- Future research could elaborate another approach to solve the bilevel programming problem and compare the results with the CCA algorithm used in this thesis. Exploring another approach like simulated annealing, genetic algorithm, or another metaheuristics approach should be an aim of future study.

## Bibliography

Abdulaal, M., LeBlanc, L.J., 1979. Methods for Combining Modal Split and Equilibrium Assignment Models. Transp. Sci. 13, 292–314. https://doi.org/10.1287/trsc.13.4.292

Ade Ogunsanya, A., 1984. ESTIMATING INTRA-URBAN FREIGHT GENERATION AND ATTRACTION. Transp. Res. Part A Gen. 8, 181–189.

Alho, A.R., de Abreu e Silva, J., 2017. Modeling retail establishments' freight trip generation: a comparison of methodologies to predict total weekly deliveries. Transportation (Amst). 44, 1195–1212. https://doi.org/10.1007/s11116-016-9700-z

Alho, A.R., de Abreu e Silva, J., 2015. Lisbon's Establishment-based Freight Survey: revealing retail establishments' characteristics, goods ordering and delivery processes. Eur. Transp. Res. Rev. 7. https://doi.org/10.1007/s12544-015-0163-7

Allen, J., Browne, M., Cherrett, T., 2012. Survey techniques in urban freight transport studies. Transp. Rev. 32, 287–311. https://doi.org/10.1080/01441647.2012.665949

Anand, N., van Duin, R., Quak, H., Tavasszy, L., 2015. Relevance of City Logistics Modelling Efforts: A Review. Transp. Rev. 35, 701–719. https://doi.org/10.1080/01441647.2015.1052112

Anderson, S., Allen, J., Browne, M., 2005. Urban logistics - How can it meet policy makers' sustainability objectives? J. Transp. Geogr. 13, 71–81. https://doi.org/10.1016/j.jtrangeo.2004.11.002

Arencibia, A.I., Feo-Valero, M., García-Menéndez, L., Román, C., 2015. Modelling mode choice for freight transport using advanced choice experiments. Transp. Res. Part A Policy Pract. 75, 252–267.

Arnold, F., Cardenas, I., Sörensen, K., Dewulf, W., 2018. Simulation of B2C e-commerce distribution in Antwerp using cargo bikes and delivery points. Eur. Transp. Res. Rev. https://doi.org/10.1007/s12544-017-0272-6

Ballantyne, E.E.F., Lindholm, M., Whiteing, A., 2013. A comparative study of urban freight transport planning: Addressing stakeholder needs. J. Transp. Geogr. https://doi.org/10.1016/j.jtrangeo.2013.08.013

Barnard, P.O., 1987. Modelling shopping destination choice behaviour using the basic multinomial logit model and some of its extensions. Transp. Rev. 7, 17–51. https://doi.org/10.1080/01441648708716642

Bastida, C., Holguín-Veras, J., 2009. Freight Generation Models. Transp. Res. Rec. J. Transp. Res. Board 2097, 51–61. https://doi.org/10.3141/2097-07

Bazaraa, M.S., Sherali, H.D., Shetty, C.., 2006. Nonlinier programming Theory and Algorithms, 3rd Editio. ed. John Wiley and Sons, NewJersey.

Beckmann, M., McGuire, C.., B.Winsten, C., 1956. Studies in the Economics of Search. Yale University Press, New Heaven.

Behrends, S., Lindholm, M., Woxenius, J., 2008. The impact of urban freight transport: A definition of sustainability from an actor's perspective. Transp. Plan. Technol. 31, 693–713. https://doi.org/10.1080/03081060802493247

Ben-Akiva, M., Lerman, S.R., 1985. Discrete Choice Analysis: Theory and Application to Travel Demand. MIT Press, Cambridge.

Bierlaire, M., 2003. BIOGEME: A free package for the estimation of discrete choice models. Swiss Transp. Res. Conf. 1–27.

Boerkamps, J.H.K., van Binsbergen, A.J., Bovy, P.H.L., 2000. Modeling behavioral aspects of urban freight movements in supply chains. Transp. Res. Rec. 1725, 17–25.

BPS, 2015. Establishment Listing: the 2014 Economic Sensus Result. Badan Pusat Statistik Indonesia / Statistics Indonesia, Jakarta.

Browne, M., 1997. REPORT OF THE HUNDRED AND NINTH ROUND TABLE ON TRANSPORT ECONOMICS (Eds.) Freight Transport and the City European Conference of Ministers of Transport. Paris, France.

Bureau, B., Glachant, M., 2011. Distributional effects of public transport policies in the Paris Region. Transp. Policy 18, 745–754. https://doi.org/10.1016/j.tranpol.2011.01.010

Cadilhon, J.-J., Moustier, P., Poole, N.D., Tam, P.T.G., Fearne, A.P., 2006. Traditional vs. Modern Food Systems? Insights from Vegetable Supply Chains to Ho Chi Minh City (Vietnam). Dev. Policy Rev. 24, 31–49. https://doi.org/10.1111/j.1467-7679.2006.00312.x

Cantarella, G.E., De Luca, S., Di Gangi, M., Di Pace, R., 2013. Stochastic equilibrium assignment with variable demand: literature review, comparisons and research needs, in: WIT Transactions on the Built Environment. pp. 349–364. https://doi.org/10.2495/UT130271

Cherrett, T., Allen, J., McLeod, F., Maynard, S., Hickford, A., Browne, M., 2012. Understanding urban freight activity – key issues for freight planning. J. Transp. Geogr. 24, 22–32. https://doi.org/10.1016/j.jtrangeo.2012.05.008

Clark, A., Sumalee, A., Shepherd, S., Connors, R., 2009. On the existence and uniqueness of first best tolls in networks with multiple user classes and elastic demand. Transportmetrica 5, 141–157. https://doi.org/10.1080/18128600802673281

Clegg, J., Smith, M., Xiang, Y., Yarrow, R., 2001. Bilevel programming applied to optimising urban transportation. Transp. Res. Part B Methodol. 35.

Colson, B., Marcotte, P., Savard, G., 2007. An overview of bilevel optimization. Ann. Oper. Res. 153, 235–256. https://doi.org/10.1007/s10479-007-0176-2

Comi, A., Donnelly, R., Russo, F., 2014. Urban Freight Models, in: Modelling Freight Transport. Elsevier, Amsterdam, pp. 163–200.

Comi, A., Nuzzolo, A., 2014. Simulating Urban Freight Flows with Combined Shopping and Restocking Demand Models. Procedia - Soc. Behav. Sci. 125, 49–61. https://doi.org/10.1016/j.sbspro.2014.01.1455

Comi, A., Site, P.D., Filippi, F., 2012. Urban Freight Transport Demand Modelling : a State of the Art. Eur. Transp. 7, 1–17.

Cordeiro, F.G., Bezerra, B.S., Peixoto, A.S.P., Ramos, R.A.R., 2016. Methodological aspects for modeling the environmental risk of transporting hazardous materials by road. Transp. Res. Part D Transp. Environ. https://doi.org/10.1016/j.trd.2016.02.008

Crainic, T.G., Gendreau, M., Potvin, J.Y., 2009a. Intelligent freight-transportation systems: Assessment and the contribution of operations research. Transp. Res. Part C Emerg. Technol. 17, 541–557. https://doi.org/10.1016/j.trc.2008.07.002

Crainic, T.G., Ricciardi, N., Storchi, G., 2009b. Models for Evaluating and Planning City Logistics Systems. Transp. Sci. 43, 432–454. https://doi.org/10.1287/trsc.1090.0279

Crainic, T.G., Ricciardi, N., Storchi, G., 2004. Advanced freight transportation systems for congested urban areas. Transp. Res. Part C Emerg. Technol. 12, 119–137. https://doi.org/10.1016/j.trc.2004.07.002

Cui, J., Dodson, J., Hall, P. V, 2015. Planning for Urban Freight Transport: An Overview. Transp. Rev. 35, 593–598. https://doi.org/10.1080/01441647.2015.1038666

Dablanc, L., 2009. Urban Freight Toolkit. Washington DC.

Dablanc, L., 2007. Goods transport in large European cities: Difficult to organize, difficult to modernize. Transp. Res. Part A Policy Pract. 41, 280–285. https://doi.org/10.1016/j.tra.2006.05.005

Dablanc, L., Ogilvie, S., Goodchild, A., 2014. Logistics Sprawl. Transp. Res. Rec. J. Transp. Res. Board. https://doi.org/10.3141/2410-12

Dafermos, S.C., 1980. Traffic Equilibrium and Variational Inequalities. Transp. Sci. 14, 42–54. https://doi.org/10.1287/trsc.14.1.42

Dafermos, S.C., 1972. The Traffic Assignment Problem for Multiclass-User Transportation Networks. Transp. Sci. 6, 73–87.

Daly, A., Hess, S., 2010. Simple approaches for random utility modelling with panel data, in: European Transport Conference 2010. pp. 1–21.

de Abreu e Silva, J., Alho, A.R., 2017. Using Structural Equations Modeling to explore perceived urban freight deliveries parking issues. Transp. Res. Part A Policy Pract. 102, 18–32. https://doi.org/10.1016/j.tra.2016.08.022

de Cea, J., Fernández, J.E., Dekock, V., Soto, A., 2005. Solving network equilibrium problems on multimodal urban transportation networks with multiple user classes. Transp. Rev. 25, 293–317. https://doi.org/10.1080/0144164042000335805

De Magalhães, D.J.A.V., 2010. Urban freight transport in a metropolitan context: The Belo Horizonte city case study. Procedia - Soc. Behav. Sci. 2, 6076–6086. https://doi.org/10.1016/j.sbspro.2010.04.020

de Palma, A., Lindsey, R., 2011. Traffic congestion pricing methodologies and technologies. Transp. Res. Part C Emerg. Technol. 19, 1377–1399. https://doi.org/10.1016/j.trc.2011.02.010

Dell'Olio, L., Moura, J.L., Ibeas, A., Cordera, R., Holguin-Veras, J., 2017. Receivers' willingness-to-adopt novel urban goods distribution practices. Transp. Res. Part A Policy Pract. 102, 130–141. https://doi.org/10.1016/j.tra.2016.10.026

DfT, 2010. Freight Modal Choice Study : Addressable Markets. London.

Dharmowijoyo, D.B.E., Susilo, Y.O., Karlström, A., 2017. Analysing the complexity of day-to-day individual activity-travel patterns using a multidimensional sequence alignment model: A case study in the Bandung Metropolitan Area, Indonesia. J. Transp. Geogr. 64, 1–12. https://doi.org/10.1016/j.jtrangeo.2017.08.001

Drezner, Z., Wesolowsky, G.O., 1997. Selecting an Optimum Configuration of One-Way and Two-Way Routes. Transp. Sci. 31, 386–394. https://doi.org/10.1287/trsc.31.4.386

Ellison, R.B., Teye, C., Hensher, D.A., 2017. Modelling Sydney's light commercial service vehicles. Transp. Res. Part A Policy Pract. 96, 79–89. https://doi.org/10.1016/j.tra.2016.12.002

Elspeth, E., Ballantyne, F., 2013. The benefit of integrating freight logistics into urban transport demand management measures and policies. University of Leeds.

Eriksson, J.R., 1995. Urban freight transport forecasting - an empirical approach. Swedish Natl. Road Transp. Res. Inst. 8, 359–369.

Farahani, R.Z., Miandoabchi, E., Szeto, W.Y., Rashidi, H., 2013. A review of urban transportation network design problems. Eur. J. Oper. Res. 229, 281–302. https://doi.org/10.1016/j.ejor.2013.01.001

Farda, M., Balijepalli, C., 2018. Exploring the effectiveness of demand management policy in reducing traffic congestion and environmental pollution: Car-free day and odd-even plate measures for Bandung city in Indonesia. Case Stud. Transp. Policy. https://doi.org/10.1016/j.cstp.2018.07.008

Fernie, J., Sparks, L., McKinnon, A.C., 2010. Retail logistics in the UK: past, present and future. Int. J. Retail Distrib. Manag. 38, 894–914. https://doi.org/10.1108/09590551011085975

Figliozzi, M.A., 2007. Analysis of the efficiency of urban commercial vehicle tours: Data collection, methodology, and policy implications. Transp. Res. Part B Methodol. 41, 1014–1032. https://doi.org/10.1016/j.trb.2007.04.006

Fisk, C.S., Boyce, D.E., 1983. Alternative Variational Inequality Formulations of the Network Equilibrium-Travel Choice Problem. Transp. Sci. 17, 454–463. https://doi.org/10.1287/trsc.17.4.454

Friesz, T.L., Cho, H., Mehta, N.J., Tobin, R.L., Anandalingam, G., 1992. A Simulated Annealing Approach to the Network Design Problem with Variational Inequality Constraints. Transp. Sci. 26, 18–26. https://doi.org/10.1287/trsc.26.1.18

Gatta, V., Marcucci, E., 2016. Behavioural implications of non-linear effects on urban freight transport policies: The case of retailers and transport providers in Rome. Case Stud. Transp. Policy. https://doi.org/10.1016/j.cstp.2015.08.001

Gentile, G., Vigo, D., 2013. Movement generation and trip distribution for freight demand modelling applied to city logistics. Eur. Transp. - Trasp. Eur. 1–27.

Giuliano, G., Kang, S., 2018. Spatial dynamics of the logistics industry: Evidence from California. J. Transp. Geogr. https://doi.org/10.1016/j.jtrangeo.2017.11.013

Golhar, D.Y., Banerjee, S., 2013. An optimal ordering strategy for a third-party managed supply chain. Int. J. Prod. Res. 51, 2969–2980. https://doi.org/10.1080/00207543.2012.751512

Gonzalez-Feliu, J., Ambrosini, C., Pluvinet, P., Toilier, F., Routhier, J.L., 2012. A simulation framework for evaluating the impacts of urban goods transport in terms of road occupancy. J. Comput. Sci. 3, 206–215. https://doi.org/10.1016/j.jocs.2012.04.003

Gromsen, E., 1981. The Role of Marketplace in Developing Countries, in: Agricultural Markets in the Semi-Arid Tropics. p. 121.

Grosso, R., Muñuzuri, J., Palero, M.R., Aparicio, P., 2012. Estimating the effects of access time windows in the management of urban delivery fleets, in: WIT Transactions on the Built Environment. pp. 335–346. https://doi.org/10.2495/UT120291

Harris, R.I.D., Liu, A., 1998. Input-Output Modelling of the Urban and Regional Economy: The Importance of External Trade. Reg. Stud. 32, 851–862. https://doi.org/10.1080/00343409850118004

Hearn, D.W., Yildirim, M.B., Ramana, M. V, Bai, L.H., 2001. Computational Methods for Congestion Toll Pricing Models, in: Proc. of IEEE Intelligent Transportation System. Okland, pp. 1–6.

Hedges, C.A., 1971. Demand forecasting and development of a framework for analysis of urban commodity flow: Statement of the problem., in: Special Report 120: Urban Commodity Flow. pp. 145–148.

Heitz, A., Dablanc, L., Olsson, J., Sanchez-Diaz, I., Woxenius, J., 2018. Spatial patterns of logistics facilities in Gothenburg, Sweden. J. Transp. Geogr. https://doi.org/10.1016/j.jtrangeo.2018.03.005

Hensher, D.A., Puckett, S.M., 2005. Refocusing the Modelling of Freight Distribution: Development of an Economic-Based Framework to Evaluate Supply Chain Behaviour in Response to Congestion Charging. Transportation (Amst). 32, 573–602. https://doi.org/10.1007/s11116-004-7615-6

Herzog, B.O., 2009. Urban Freight In Developing Cities. Bonn.

Hicks, S.., 1977. Urban Freight, in: Hensher, D.A. (Ed.), Urban Transport Economics.

Cambridge University Press, Cambridge.

Ho, H.W., Wong, S.C., Sumalee, A., 2013. A congestion-pricing problem with a polycentric region and multi-class users: A continuum modelling approach. Transp. A Transp. Sci. 9, 514–545. https://doi.org/10.1080/18128602.2011.621652

Hole, A.R., 2007. Fitting mixed logit models by using maximum simulated likelihood. Stata J. 7, 388–401. https://doi.org/10.1177/1536867x0700700306

Holguín-Veras, J., 2010. The truth, the myths and the possible in freight road pricing in congested urban areas. Procedia - Soc. Behav. Sci. 2, 6366–6377. https://doi.org/10.1016/j.sbspro.2010.04.045

Holguín-Veras, J., Cetin, M., 2009. Optimal tolls for multi-class traffic: Analytical formulations and policy implications. Transp. Res. Part A Policy Pract. 43, 445–467. https://doi.org/10.1016/j.tra.2008.11.012

Holguín-Veras, J., Gonzalez-Calderon, C., Sanchez-Diaz, I., Jalller, M., Campbell, S., 2014a. Vehicle Trip Estimation Models, in: Tavasszy, L.A., Jong, G. de (Eds.), Modelling Freight Transport. Elsevier, Amsterdam, pp. 143–162.

Holguín-Veras, J., Jaller, M., Destro, L., Ban, X. (Jeff), Lawson, C., Levinson, H.S., 2011. Freight Generation, Freight Trip Generation, and Perils of Using Constant Trip Rates. Transp. Res. Rec. J. Transp. Res. Board 2224, 68–81. https://doi.org/10.3141/2224-09

Holguín-Veras, J., Jaller, M., Sanchez-Diaz, I., Campbell, S., Lawson, C., 2014b. Freight Generation and Freight Trip Generation Models, in: Tavasszy, L.A., Jong, G. de (Eds.), Modelling Freight Transport. Elsevier, Amsterdam, pp. 43–63.

Holguín-Veras, J., Patil, G.R., 2008. A Multicommodity Integrated Freight Origin–destination Synthesis Model. Networks Spat. Econ. https://doi.org/10.1007/s11067-007-9053-4

Holguín-Veras, J., Silas, M., Polimeni, J., Cruz, B., 2008. An investigation on the effectiveness of joint receiver-carrier policies to increase truck traffic in the off-peak hours. Part II: The behavior of carriers. Networks Spat. Econ. 8, 327–354. https://doi.org/10.1007/s11067-006-9011-6

Kato, H., Sato, J., 2006. Urban Freight Transportation Analysis in Developing Countries: Case Study in Medan, Indonesia. Tokyo, Japan: Department of Civil Engineering, University of Tokyo.

Kirkpatrick, S., Gelatt, C.D., Vecchi, M.P., 1983. Optimization by Simulated Annealing. Science (80-. ). 220.

Koç, Ç., Bektaş, T., Jabali, O., Laporte, G., 2016. The impact of depot location, fleet composition and routing on emissions in city logistics. Transp. Res. Part B Methodol. 84, 81–102. https://doi.org/10.1016/j.trb.2015.12.010

Koh, A., Shepherd, S., Sumalee, A., 2009. Second best toll and capacity optimisation in networks: Solution algorithm and policy implications. Transportation (Amst). 36, 147–165. https://doi.org/10.1007/s11116-009-9187-y

Koppelman, F.S., Bhat, C., 2006. A Self Instructing Course in Mode Choice Modeling : Multinomial and Nested Logit Models by with technical support from Table of Contents.

Kroes, E.P., Sheldon, R.J., 1988. Stated Preference Methods: An Introduction. J. Transp. Econ. Policy 22, 756–757. https://doi.org/10.1007/978-1-349-95810-8_1173

Lam, W.H.K., Huang, H.-J., 1992. A combined trip distribution and assignment model for multiple user classes. Transp. Res. Part B Methodol. 26, 275–287. https://doi.org/10.1016/0191-2615(92)90038-X

Lawphongpanich, S., Hearn, D.W., 2004. An MPEC approach to second-best toll pricing. Math. Program. 101. https://doi.org/10.1007/s10107-004-0536-5

Leblanc, L.J., 1975. An Algorithm for the Discrete Network Design Problem. Transp. Sci. 9, 183–199. https://doi.org/10.1287/trsc.9.3.183

LeBlanc, L.J., Boyce, D.E., 1986. A Bilevel Programming Algorithm for Exact Solution of the Network Design Problem with User Optimal Flows. Transp. Res. Part B Methodol. 20B, 259–265.

Lee, C.-K., Yang, K.-I., 2005. NETWORK DESIGN OF ONE-WAY STREETS WITH SIMULATED ANNEALING. Pap. Reg. Sci. 73, 119–134. https://doi.org/10.1111/j.1435-5597.1994.tb00606.x

Liang, K.Y., Zeger, S.L., 1986. Longitudinal data analysis using generalized linear models. Biometrika 73, 13–22. https://doi.org/10.1093/biomet/73.1.13

Lindholm, M., 2013. Urban freight transport from a local authority perspective – a literature review. Eur. Transp. \ Trasp. Eur. 1–37.

Lindholm, M., 2012. How Local Authority Decision Makers Address Freight Transport in the Urban Area. Procedia - Soc. Behav. Sci. 39, 134–145. https://doi.org/10.1016/j.sbspro.2012.03.096

McDermott, D.R., 1980. Urban Goods Movement: State of the Art and Future Possibilities. Transportation (Amst). 20, 34–40.

Mei, B., 2013. Destination Choice Model for Commercial Vehicle Movements in Metropolitan Area. Transp. Res. Rec. J. Transp. Res. Board 2344, 126–134. https://doi.org/10.3141/2344-14

Mera, A.P., Balijepalli, C., 2019. Towards improving resilience of cities: an optimisation approach to minimising vulnerability to disruption due to natural disasters under budgetary constraints. Transportation (Amst). https://doi.org/10.1007/s11116-019-09984-8

Meyer, M.D., 1999. Demand management as an element of transportation policy: using carrots and sticks to influence travel behavior. Transp. Res. Part A Policy Pract. 33, 575–599. https://doi.org/10.1016/S0965-8564(99)00008-7

Migdalas, A., 1995. Bilevel programming in traffic planning: Models, methods and challenge. J. Glob. Optim. https://doi.org/10.1007/BF01099649

Morganti, E., Gonzalez-feliu, J., 2015. Case Studies on Transport Policy City logistics for perishable products . The case of the Parma ' s Food Hub. Case Stud. Transp. Policy 3, 120–128. https://doi.org/10.1016/j.cstp.2014.08.003

Muñuzuri, J., Cortes, P., Onieva, L., Guadix, J., 2010. Modelling peak-hour urban freight movements with limited data availability. Comput. Ind. Eng. 59, 34–44. https://doi.org/10.1016/j.cie.2010.02.013

Muñuzuri, J., Cortés, P., Onieva, L., Guadix, J., 2012. Estimation of Daily Vehicle Flows for Urban Freight Deliveries. J. Urban Plan. Dev. 138, 43–52. https://doi.org/10.1061/(ASCE)UP.1943-5444.0000099

Muñuzuri, J., Larrañeta, J., Onieva, L., Cortés, P., 2005. Solutions applicable by local administrations for urban logistics improvement. Cities 22, 15–28. https://doi.org/10.1016/j.cities.2004.10.003

Nagurney, A.B., 2000. A multiclass, multicriteria traffic network equilibrium model. Math. Comput. Model. 7177, 393–411.

Nash, J., 1951. Non-cooperative games. Ann. Math. 286-295.

Nielsen, 2015. Maximizing tradition - The shop, shopper, and shopkeeper. Singapore.

Nugroho, M.T., 2015. Stated Preference Study of Port and Inland Mode Choice for Containerized Exports from Java. University of Leeds.

Nuzzolo, A., Comi, A., 2014a. Urban freight transport policies in Rome: lessons learned and the road ahead. J. Urban. Int. Res. Placemaking Urban Sustain. 8, 1–15. https://doi.org/10.1080/17549175.2014.884976

Nuzzolo, A., Comi, A., 2014b. Urban freight demand forecasting: A mixed quantity/delivery/vehicle-based model. Transp. Res. Part E Logist. Transp. Rev. 65, 84–98. https://doi.org/10.1016/j.tre.2013.12.014

Nuzzolo, A., Comi, A., Crisalli, U., Galuppi, S., 2010. Demand models for the estimation of urban goods movements: an application to the city of Rome, in: 12th World Conference on Transportation Research. Lisbon.

OECD, 2003. Delivering the Goods. Paris, France.

Ofori, D., 2013. Hierarchy of market centres along the Volta Lake in Ghana: A regional development framework. J. Geogr. Reg. Plan. 6, 280–293. https://doi.org/10.5897/JGRP2013.0353

Ogden, K.W., 1992. Urban goods movement : a guide to policy and planning. Ashgate, Aldershot, Hants, England; Brookfield, Vt., USA.

Oppenheim, N., 1993a. Equilibrium trip distribution/assignment with variable destination costs. Transp. Res. Part B Methodol. 27, 207–217. https://doi.org/10.1016/0191-2615(93)90030-E

Oppenheim, N., 1993b. A Combined, Equilibrium Model of Urban Personal Travel and Goods Movements. Transp. Sci. 27, 161–173. https://doi.org/10.1287/trsc.27.2.161

Ortuzar, J. de D., Willumsen, L.G., 2011. Modelling Transport, Modelling Transport. https://doi.org/10.1002/9781119993308

Paddeu, D., 2017. The Bristol-Bath Urban freight Consolidation Centre from the perspective of its users. Case Stud. Transp. Policy 5, 483–491. https://doi.org/10.1016/j.cstp.2017.06.001

Pani, A., Sahu, P.K., Patil, G.R., Sarkar, A.K., 2018. Modelling urban freight generation: A case study of seven cities in Kerala, India. Transp. Policy 69, 49–64. https://doi.org/10.1016/j.tranpol.2018.05.013

Pigou, A., 1920. The Economic of Welfare. Palgrave Macmillan, London.

Pourabdollahi, Z., Karimi, B., Mohammadian, A. (Kouros), 2013. Joint Model of Freight Mode and Shipment Size Choice. Transp. Res. Rec. J. Transp. Res. Board 2378, 84–91. https://doi.org/10.3141/2378-09

Prasetyo, I., Fukuda, D., Yoshino, H., Yai, T., 2003. Analysis of Travel Time Saving Benefit by Understanding Individual Needs and Value of Activity Time: Case Study of Tokyo and Jakarta. Transp. Res. Rec. J. Transp. Res. Board 1854, 12–21. https://doi.org/10.3141/1854-02

Quak, H., 2008. Sustainability of urban freight transport - Retail Distribution and Local Regulations in Cities., Erasmus Research Institute of Management (ERIM).

Quak, H., de Koster, M. (René) B.M., 2006a. Urban distribution: The impacts of different governmental time-window schemes, ERIM Report Series Ref No. ERS-2006-053-LIS.

Quak, H., de Koster, M. (René) B.M., 2006b. The Impacts of Time Access Restrictions and Vehicle Weight Restrictions on Food Retailers and the Environment. Eur. J. Transp. Infrastruct. Res. 6, 131–150. https://doi.org/https://doi.org/10.18757/ejtir.2006.6.2.3430.

Qureshi, A.G., Taniguchi, E., Thompson, R.G., Teo, J.S.E., 2014. Application of exact route optimization for the evaluation of a city logistics truck ban scheme. Int. J. Urban Sci. 18, 117–132. https://doi.org/10.1080/12265934.2014.930672

Revelt, D., Train, K., 1998. Mixed logit with repeated choices: Households’ choices of appliance efficiency level. Rev. Econ. Stat. 80, 647–657. https://doi.org/10.1162/003465398557735

Roghanian, E., Sadjadi, S.J., Aryanezhad, M.B., 2007. A probabilistic bi-level linear multi-objective programming problem to supply chain planning. Appl. Math. Comput. 188, 786–800. https://doi.org/10.1016/j.amc.2006.10.032

Routhier, J., Toilier, F., 2007. FRETURB V3 , A Policy Oriented Software of Modelling Urban Goods Movement. 11th WCTR 23.

Ruesch, M., 2004. Road pricing and urban freight transport: Practices and developments from the BESTUFS project, Advances in Transport.

Russo, F., Comi, A., 2012. City Characteristics and Urban Goods Movements: A Way to Environmental Transportation System in a Sustainable City. Procedia - Soc. Behav. Sci. https://doi.org/10.1016/j.sbspro.2012.03.091

Russo, F., Comi, A., 2011. A model system for the ex-ante assessment of city logistics measures. Res. Transp. Econ. 31, 81–87. https://doi.org/10.1016/j.retrec.2010.11.011

Russo, F., Comi, A., 2010. A modelling system to simulate goods movements at an urban scale. Transportation (Amst). 37, 987–1009. https://doi.org/10.1007/s11116-010-9276-y

Russo, F., Polimeni, A., Comi, A., 2008. Urban freight transport and logistics: retailer's choices., in: Taniguchi, E., Thompson, R.G. (Eds.), Innovations in City Logistics. Nova Science Publisher, Haippauge, NY, p. 401414.

Ryu, J.-H., Dua, V., Pistikopoulos, E.N., 2004. A bilevel programming framework for enterprise-wide process networks under uncertainty. Comput. Chem. Eng. 28, 1121–1129. https://doi.org/10.1016/j.compchemeng.2003.09.021

Sakai, T., Kawamura, K., Hyodo, T., 2015. Locational dynamics of logistics facilities: Evidence from Tokyo. J. Transp. Geogr. https://doi.org/10.1016/j.jtrangeo.2015.05.003

Saragih, N.I., Bahagia, S.N., Suprayogi, Syabri, I., 2015. City logistics for mega city: A conceptual model (Case study: DKI Jakarta). Proc. Jt. Int. Conf. Electr. Veh. Technol. Ind. Mech. Electr. Chem. Eng. (ICEVT IMECE) 178–182. https://doi.org/10.1109/ICEVTIMECE.2015.7496660

Shaw, S. a., Gibbs, J., 1999. Procurement strategies of small retailers faced with uncertainty: an analysis of channel choice and behaviour. Int. Rev. Retail. Distrib. Consum. Res. 9, 93–109. https://doi.org/10.1080/095939699342705

Sheffi, Y., 1985. Urban transportation networks. Prentice Hall, New Jersey. https://doi.org/10.1016/0191-2607(86)90023-3

Smith, M.J., 1979. The existence, uniqueness and stability of traffic equilibria. Transp. Res. Part B Methodol. 13, 295–304. https://doi.org/10.1016/0191-2615(79)90022-5

Stackelberg, H. Von, 1952. The Theory of Market Economy. Oxford University Press, Oxford.

Stathopoulos, A., Valeri, E., Marcucci, E., 2012. Stakeholder reactions to urban freight policy innovation. J. Transp. Geogr. 22, 34–45. https://doi.org/10.1016/j.jtrangeo.2011.11.017

Steenbrink, P.., 1974. Optimization of Transport Networks. John Wiley & Sons, London, UK.

Sugiyanto, G., 2012. Permodelan Biaya Kemacetan Pengguna Mobil Pribadi Dengan Variasi Nilai Kecepatan Aktual Kendaraan. J. Transp. 12, 123–132.

Sumalee, A., 2004. OPTIMAL ROAD PRICING SCHEME DESIGN. University of Leeds.

Taniguchi, E., Noritake, M., Yamada, T., Izumitani, T., 1999. Optimal size and location planning of public logistics terminals. Transp. Res. Part E Logist. Transp. Rev. 35, 207–222. https://doi.org/10.1016/S1366-5545(99)00009-5

Taniguchi, E., Shimamoto, H., 2004. Intelligent transportation system based dynamic vehicle routing and scheduling with variable travel times. Transp. Res. Part C Emerg. Technol. 12, 235–250. https://doi.org/10.1016/j.trc.2004.07.007

Taniguchi, E., Thompson, R.G., Yamada, T., 2016. New Opportunities and Challenges for City Logistics. Transp. Res. Procedia 12, 5–13. https://doi.org/10.1016/j.trpro.2016.02.004

Taniguchi, E., Thompson, R.G., Yamada, T., 2008. Modelling the behaviour of stakeholders in city logistics, in: Taniguchi, E., Thompson, R.G. (Eds.), Innovations in City Logistics. Nova Science Publisher, Haippauge, New York, pp. 1–16.

Taniguchi, E., Thompson, R.G., Yamada, T., 2003. Predicting the effects of city logistics schemes. Transp. Rev. 23, 489–515. https://doi.org/10.1080/01441640210163999

Toilier, F., Serouge, M., Routhier, J.-L., Patier, D., Gardrat, M., 2016. How can Urban Goods Movements be Surveyed in a Megacity? The Case of the Paris Region. Transp. Res. Procedia 12, 570–583. https://doi.org/10.1016/j.trpro.2016.02.012

Train, K., 2009. Discrete Choice Methods with Simulation, Cambrige University Press.

UN-Habitat, 2013. Global Report on Human Settlements 2013 - Planning and Design for Sustainable Urban Mobility. Nairobi.

Van Vliet, D., Bergman, T., Scheltes, W.H., 1986. Equilibrium Traffic Assignment with Multiple User Classes, in: Planning and Transport Research and Computation Annual Meeting. England, pp. 111–122.

Verhoef, E.T., 2002. Second-best congestion pricing in general networks. Heuristic algorithms for finding second-best optimal toll levels and toll points. Transp. Res. Part B Methodol. 36, 707–729. https://doi.org/10.1016/S0191-2615(01)00025-X

Verhoef, E.T., 1996. The Economics of Regulating Road Transport. Edward Elgar, Cheltenham.

Vidal Vieira, J.G., Fransoo, J.C., 2015. How logistics performance of freight operators is affected by urban freight distribution issues. Transp. Policy 44, 37–47. https://doi.org/10.1016/j.tranpol.2015.06.007

Visser, J., Nemoto, T., Browne, M., 2014. Home Delivery and the Impacts on Urban Freight Transport: A Review. Procedia - Soc. Behav. Sci. 125, 15–27. https://doi.org/10.1016/j.sbspro.2014.01.1452

Visser, J., van Binsbergen, A., 1999. Urban freight transport policy and planning Review, in: Taniguchi, E., Thompson, R.G. (Eds.), First International Symposium on City Logistics. Institute of System Science Research, Kyoto Japan, pp. 39–69.

Wang, G.M., Gao, Z.Y., Xu, M., 2014. An MPEC formulation and its cutting constraint algorithm for continuous network design problem with multi-user classes. Appl. Math. Model. 38, 1846–1858. https://doi.org/10.1016/j.apm.2013.10.003

Wang, Q., Hu, J., 2012. Behavioral Analysis of Decisions in Choice of Commercial Vehicular Mode in Urban Areas. Transp. Res. Rec. J. Transp. Res. Board 2269, 58–64. https://doi.org/10.3141/2269-07

Wang, X., Zhang, D., 2017. Truck freight demand elasticity with respect to tolls in New York State. Transp. Res. Part A Policy Pract. 101, 51–60. https://doi.org/10.1016/j.tra.2017.04.035

Wardrop, J.G., 1952. ROAD PAPER. SOME THEORETICAL ASPECTS OF ROAD TRAFFIC RESEARCH. Proc. Inst. Civ. Eng. 1, 325–362. https://doi.org/10.1680/ipeds.1952.11259

Williams, H.C.W.L., 1977. On the Formation of Travel Demand Models and Economic Evaluation Measures of User Benefit. Environ. Plan. A 9, 285–344. https://doi.org/10.1068/a090285

Wisetjindawat, W., Sano, K., Matsumoto, S., 2007. Micro-Simulation Model, for Modelling freight agents interactions in Urban Freight Movement, in: 86th Annual Meeting of the Transportation Research Board. Washington DC January 21-25.

Wisetjindawat, W., Sano, K., Matsumoto, S., 2006. Commodity Distribution Model Incorporating Spatial Interactions for Urban Freight Movement. Transp. Res. Rec. J. Transp. Res. Board 1966, 41–50. https://doi.org/10.3141/1966-06

Xiong, Y., Schneider, J.B., 1992. Transportation network design using a cumulative genetic algorithm and neural network. Transp. Res. Rec. 1364, 37–44.

Yamada, T., Russ, B.F., Castro, J., 2007. Optimal Planning of Multimodal Freight Transport Network - Modelling With Ga-Based Procedures and Its Application in Indonesia -. Doboku Gakkai Ronbunshuu 63, 103–109.

Yáñez, M.F., Cherchi, E., Heydecker, B.G., Ortúzar, J. de D., 2011. On the Treatment of Repeated Observations in Panel Data: Efficiency of Mixed Logit Parameter Estimates. Networks Spat. Econ. 11, 393–418. https://doi.org/10.1007/s11067-010-9143-6

Yang, H., 1999. System Optimum, Stochastic User Equilibrium, and Optimal Link Tolls. Transp. Sci. 33, 354–360. https://doi.org/10.1287/trsc.33.4.354

Yang, H., Huang, H.J., 2004. The multi-class, multi-criteria traffic network equilibrium and systems optimum problem. Transp. Res. Part B Methodol. 38, 1–15. https://doi.org/10.1016/S0191-2615(02)00074-7

Yang, H., Huang, H.J., 1998. Principle of marginal-cost pricing: How does it work in a general road network? Transp. Res. Part A Policy Pract. 32, 45–54. https://doi.org/10.1016/S0965-8564(97)00018-9

## Appendix A. Survey Questionnaire

# SURVEY OF INDEPENDENT RETAILER ACTIVITY AT BANDUNG CITY CENTER

| Surveyor's name: | Contact:<br>Phone : +6287xxxxxxxx<br>Email : |
|---|---|

| **Section A: Retailer Attribute** | | |
|---|---|---|
| Retailer Name: | | |
| Address: | | |
| Shop total area: | | |
| number of employee: | | |
| Own Vehicle : | ☐ Van | ☐ two-wheeler / TW |

| **Section B: Goods and Supplier Attribute** | | | | | | | |
|---|---|---|---|---|---|---|---|
| No | Core Goods | Sell / Not Sell | Supplier | Supplier Location | Average Goods Price / Unit | | Travel Time (minutes) |
| 1 | Stationaries | ☐Yes ☐No | | | | Box | |
| 2 | Grocery | | | | | | |
| | Rice | ☐Yes ☐No | | | | Kg | |
| | Flour | ☐Yes ☐No | | | | Kg | |
| | Sugar | ☐Yes ☐No | | | | Kg | |
| | Vegetable oil | ☐Yes ☐No | | | | Liter | |
| | Eggs | ☐Yes ☐No | | | | Kg | |
| | Salt | ☐Yes ☐No | | | | Box | |
| | Vegetable / Fruit | ☐Yes ☐No | | | | Kg | |
| | Dairy Product | ☐Yes ☐No | | | | Box | |
| 3 | Food and Beverage | ☐Yes ☐No | | | | Box | |
| 4 | Canned Drinks | ☐Yes ☐No | | | | Box | |
| 5 | Tobacco | ☐Yes ☐No | | | | Box | |
| 6 | Drugs and Pharmacy | ☐Yes ☐No | | | | Unit | |
| 7 | Kitchen Utensil | ☐Yes ☐No | | | | Unit | |
| 8 | Household items | ☐Yes ☐No | | | | Box | |
| 9 | Baby and kids Product | ☐Yes ☐No | | | | Unit | |
| 10 | Gas Cylinder | ☐Yes ☐No | | | | Unit | |
| 11 | Electronics | ☐Yes ☐No | | | | Box | |
| 12 | Home Appliances | ☐Yes ☐No | | | | Unit | |

**Section C: Delivery/Collection Survey**

1. **In this section, please fill the delivery collection form that indicates your restocking activity on a weekly basis.**

| No | Goods | Quantity | | | | Restocking method | | |
|---|---|---|---|---|---|---|---|---|
| 1 | Stationery | < 5 | 5-10 | >10 | Box | ☐ Own vehicle | Van/TW | ☐ Delivery |
| 2 | Grocery | | | | | | | |
| | Rice | < 10 | 10-50 | >50 | Kg | ☐ Own vehicle | Van/TW | ☐ Delivery |
| | Flour | < 5 | 5-10 | >10 | Kg | ☐ Own vehicle | Van/TW | ☐ Delivery |
| | Sugar | < 10 | 10-50 | >50 | Kg | ☐ Own vehicle | Van/TW | ☐ Delivery |
| | Vegetable oil | < 5 | 5-10 | >10 | Liter | ☐ Own vehicle | Van/TW | ☐ Delivery |
| | Eggs | < 5 | 5-10 | >10 | Kg | ☐ Own vehicle | Van/TW | ☐ Delivery |
| | Salt | < 5 | 5-10 | >10 | Box | ☐ Own vehicle | Van/TW | ☐ Delivery |
| | Vegetable / Fruit | < 5 | 5-10 | >10 | Kg | ☐ Own vehicle | Van/TW | ☐ Delivery |
| | Dairy Product | < 10 | 10-50 | >50 | Box | ☐ Own vehicle | Van/TW | ☐ Delivery |
| 3 | Food and Beverage | < 20 | 20-100 | >100 | Box | ☐ Own vehicle | Van/TW | ☐ Delivery |
| 4 | Canned Drinks | < 5 | 5-10 | >10 | Box | ☐ Own vehicle | Van/TW | ☐ Delivery |
| 5 | Tobacco | < 10 | 10-20 | >20 | Box | ☐ Own vehicle | Van/TW | ☐ Delivery |
| 6 | Drugs and Pharmacy | < 5 | 5-10 | >10 | Unit | ☐ Own vehicle | Van/TW | ☐ Delivery |
| 7 | Kitchen Utensil | < 5 | 5-10 | >10 | Unit | ☐ Own vehicle | Van/TW | ☐ Delivery |
| 8 | Household items | < 5 | 5-10 | >10 | Box | ☐ Own vehicle | Van/TW | ☐ Delivery |
| 9 | Baby, Toddler, Kids Product | < 5 | 5-10 | >10 | Unit | ☐ Own vehicle | Van/TW | ☐ Delivery |
| 10 | Gas Cylinder | < 10 | 10-30 | >30 | Unit | ☐ Own vehicle | Van/TW | ☐ Delivery |
| 11 | Electronics | < 10 | 10-30 | >30 | Box | ☐ Own vehicle | Van/TW | ☐ Delivery |
| 12 | Home Appliances | < 10 | 10-30 | >30 | Unit | ☐ Own vehicle | Van/TW | ☐ Delivery |

| | Own vehicle: | | Delivery: |
|---|---|---|---|
| **1. Number of restocking activities *in a typical week*?** | Van | TW | |
| | | | |
| **2. How much transportation cost you spend for restocking activity?** | | | |
| **3. On what day you usually do your restocking activities ?** | | | |

**4. What time of the day do you usually restock by your own vehicle or majority of deliveries come to your shop?**

| | Own Vehicle | Delivery |
|---|---|---|
| Early morning (6.00 – 9.00) | ☐ | ☐ |
| During the morning (9.00 – 12.00) | ☐ | ☐ |
| During the afternoon (12.00 – 15.00) | ☐ | ☐ |
| During the afternoon (15.00 - 18.00) | ☐ | ☐ |
| During the evening (18.00-21.00) | ☐ | ☐ |
| Overnight (21.00-6.00) | ☐ | ☐ |

| Section D: Parking and Loading/Unloading Activity | | | |
|---|---|---|---|
| **1. Do you have loading/unloading bay in front of your shop:** | | | Yes / No |
| **2. Do you have dedicated unloading facilities at** | a. *Rear* or *side* your shop<br>**b.** *Front* of your shop | | Yes / No<br>Yes / No |
| **3. Is there any parking restriction in front of your shop?** | | | Yes / No |
| **4. If yes, at what time the parking restriction applied?** | | | |
| Early morning (6.00 – 9.00) | ☐ | | |
| During the morning (9.00 – 12.00) | ☐ | | |
| During the afternoon (12.00 – 15.00) | ☐ | | |
| During the afternoon (15.00 - 18.00) | ☐ | | |
| During the evening (18.00-21.00) | ☐ | | |
| Overnight (21.00-6.00) | ☐ | | |
| | Own Vehicle | Delivery | |
| **5. How long does it usually take to transfer goods from vehicle to your shop?** | ☐ < 15 Minutes<br>☐ 15-29 Minutes<br>☐ 30-45 Minutes<br>☐ >45 Minutes | ☐ < 15 Minutes<br>☐ 15-29 Minutes<br>☐ 30-45 Minutes<br>☐ >45 Minutes | |
| **6. Where do vehicles park when unloading is taking place?** | ☐ On the shop premises<br>☐ On the public road<br>☐ away from shop premises | ☐ On the shop premises<br>☐ On the public road<br>☐ away from shop premises | |

| **Section E: Respondent Identity (optional)** |
|---|
| Thank you for your cooperation in the survey. Please write your contact detail below:<br><br>Name:<br>Phone:<br>Email: |

# Appendix B. Example of BIOGEME syntax and estimation result

## Example of syntax for supplier location choice (MODEL 1) using python BIOGEME

```
########################################
#
# @file logitsupplierchoice.py
# @author: Taufiq S Nugroho, UoL
# @date: Wed Oct 13:23:27 2018
#
########################################

from biogeme import *
from headers import *
from loglikelihood import *
from statistics import *

#Parameters to be estimated
# Arguments:
#   - 1  Name for report; Typically, the same as the variable.
#   - 2  Starting value.
#   - 3  Lower bound.
#   - 4  Upper bound.
#   - 5  0: estimate the parameter, 1: keep it fixed.
#   - 6  description ti be used in LATEX report

B_NR = Beta('B_NR',0,-10,10,0,'B_NR')
B_TT = Beta('B_TT',0,-10,10,0,'B_TT')
B_MT = Beta('B_MT',0,-10,10,0,'B_MT')

# Utility functions
V1 = B_TT * (BG_TT/60) + B_NR * (BG_NR/100) + B_MT* BG_MT
V2 = B_TT * (BR_TT/60) + B_NR * (BR_NR/100) + B_MT* BR_MT
V3 = B_TT * (CA_TT/60) + B_NR * (CA_NR/100) + B_MT* CA_MT
V4 = B_TT * (CB_TT/60) + B_NR * (CB_NR/100) + B_MT* CB_MT
V5 = B_TT * (CK_TT/60) + B_NR * (CK_NR/100) + B_MT* CK_MT
V6 = B_TT * (KA_TT/60) + B_NR * (KA_NR/100) + B_MT* KA_MT
V7 = B_TT * (KJ_TT/60) + B_NR * (KJ_NR/100) + B_MT* KJ_MT
V8 = B_TT * (KP_TT/60) + B_NR * (KP_NR/100) + B_MT* KP_MT
V9 = B_TT * (NY_TT/60) + B_NR * (NY_NR/100) + B_MT* NY_MT
V10 = B_TT * (PA_TT/60) + B_NR * (PA_NR/100) + B_MT* PA_MT
V11 = B_TT * (PU_TT/60) + B_NR * (PU_NR/100) + B_MT* PU_MT
V12 = B_TT * (S_AN_TT/60) + B_NR * (S_AN_NR/100) + B_MT* S_AN_MT
V13 = B_TT * (S_ST_TT/60) + B_NR * (S_ST_NR/100) + B_MT* S_ST_MT
V14 = B_TT * (S_CR_TT/60) + B_NR * (S_CR_NR/100) + B_MT* S_CR_MT

# Associate utility functions with the numbering of alternatives
V = {1: V1,
    2: V2,
    3: V3,
    4: V4,
    5: V5,
    6: V6,
    7: V7,
    8: V8,
    9: V9,
   10: V10,
   11: V11,
   12: V12,
   13: V13,
   14: V14}

# Associate the availability conditions with the alternative
av = {1: BG_NR,
     2: BR_NR,
```

```
   3: CA_NR,
   4: CB_NR,
   5: CK_NR,
   6: KA_NR,
   7: KJ_NR,
   8: KP_NR,
   9: NY_NR,
  10: PA_NR,
  11: PU_NR,
  12: S_AN_NR,
  13: S_ST_NR,
  14: S_CR_NR}

# The choice model is a logit, with availability conditions
logprob = bioLogLogit(V,av,CHOICE)

# Defines an itertor on the data
rowIterator('obsIter')

# DEfine the likelihood function for the estimation
BIOGEME_OBJECT.ESTIMATE = Sum(logprob,'obsIter')

# Statistics
nullLoglikelihood(av,'obsIter')
choiceSet = [1,2,3,4,5,6,7,8,9,10,11,12,13,14]
cteLoglikelihood(choiceSet,CHOICE,'obsIter')
availabilityStatistics(av,'obsIter')

BIOGEME_OBJECT.PARAMETERS['optimizationAlgorithm'] = "BIO"
BIOGEME_OBJECT.FORMULAS['Balong Gede utility'] = V1
BIOGEME_OBJECT.FORMULAS['Braga utility'] = V2
BIOGEME_OBJECT.FORMULAS['Ciateul utility'] = V3
BIOGEME_OBJECT.FORMULAS['Cibadak utility'] = V4
BIOGEME_OBJECT.FORMULAS['Cikawao utility'] = V5
BIOGEME_OBJECT.FORMULAS['Karang Anyar utility'] = V6
BIOGEME_OBJECT.FORMULAS['Kebon Jeruk utility'] = V7
BIOGEME_OBJECT.FORMULAS['Kebon Pisang utility'] = V8
BIOGEME_OBJECT.FORMULAS['Nyengseret utility'] = V9
BIOGEME_OBJECT.FORMULAS['Paledang utility'] = V10
BIOGEME_OBJECT.FORMULAS['Pungkur utility'] = V11
BIOGEME_OBJECT.FORMULAS['S_Ancol utility'] = V12
BIOGEME_OBJECT.FORMULAS['S_Situsaeur utility'] = V13
BIOGEME_OBJECT.FORMULAS['S_Ciroyom utility'] = V14
```

### Estimation result for MODEL 1

biogeme 2.5 [Wed, Jul 27, 2016 1:52:51 PM]

Home page: http://biogeme.epfl.ch
Submit questions to http://groups.yahoo.com/group/biogeme
Michel Bierlaire, Transport and Mobility Laboratory, Ecole Polytechnique Fédérale de Lausanne (EPFL)

This file has automatically been generated on 10/31/18 18:29:32
If you drag this HTML file into the Calc application of OpenOffice, or the spreadsheet of LibreOffice, you will be able to perform additional calculations.

**Report file:** `Supplier_Choice_VEOMT.html`
**Sample file:** `__bin_ALL.dat`

## Formulas

| | |
|---|---|
| ***Balong Gede utility:*** | *( B_TT * BG_TT ) / ( 60 ) + ( B_NR * BG_NR ) / ( 100 ) + B_MT * BG_MT* |
| ***Braga utility:*** | *( B_TT * BR_TT ) / ( 60 ) + ( B_NR * BR_NR ) / ( 100 ) + B_MT * BR_MT* |
| ***Ciateul utility:*** | *( B_TT * CA_TT ) / ( 60 ) + ( B_NR * CA_NR ) / ( 100 ) + B_MT * CA_MT* |
| ***Cibadak utility:*** | *( B_TT * CB_TT ) / ( 60 ) + ( B_NR * CB_NR ) / ( 100 ) + B_MT * CB_MT* |
| ***Cikawao utility:*** | *( B_TT * CK_TT ) / ( 60 ) + ( B_NR * CK_NR ) / ( 100 ) + B_MT * CK_MT* |
| ***Karang Anyar utility:*** | *( B_TT * KA_TT ) / ( 60 ) + ( B_NR * KA_NR ) / ( 100 ) + B_MT * KA_MT* |
| ***Kebon Jeruk utility:*** | *( B_TT * KJ_TT ) / ( 60 ) + ( B_NR * KJ_NR ) / ( 100 ) + B_MT * KJ_MT* |
| ***Kebon Pisang utility:*** | *( B_TT * KP_TT ) / ( 60 ) + ( B_NR * KP_NR ) / ( 100 ) + B_MT * KP_MT* |
| ***Nyengseret utility:*** | *( B_TT * NY_TT ) / ( 60 ) + ( B_NR * NY_NR ) / ( 100 ) + B_MT * NY_MT* |
| ***Paledang utility:*** | *( B_TT * PA_TT ) / ( 60 ) + ( B_NR * PA_NR ) / ( 100 ) + B_MT * PA_MT* |
| ***Pungkur utility:*** | *( B_TT * PU_TT ) / ( 60 ) + ( B_NR * PU_NR ) / ( 100 ) + B_MT * PU_MT* |
| ***S_Ancol utility:*** | *( B_TT * S_AN_TT ) / ( 60 ) + ( B_NR * S_AN_NR ) / ( 100 ) + B_MT * S_AN_MT* |
| ***S_Ciroyom utility:*** | *( B_TT * S_CR_TT ) / ( 60 ) + ( B_NR * S_CR_NR ) / ( 100 ) + B_MT * S_CR_MT* |
| ***S_Situsaeur utility:*** | *( B_TT * S_ST_TT ) / ( 60 ) + ( B_NR * S_ST_NR ) / ( 100 ) + B_MT * S_ST_MT* |

### Statistics

| | |
|---|---|
| ***Alt. 1 available:*** | *303* |
| ***Alt. 1 chosen:*** | *13* |
| ***Alt. 10 available:*** | *303* |
| ***Alt. 10 chosen:*** | *3* |
| ***Alt. 11 available:*** | *303* |
| ***Alt. 11 chosen:*** | *13* |
| ***Alt. 12 available:*** | *303* |
| ***Alt. 12 chosen:*** | *15* |
| ***Alt. 13 available:*** | *303* |
| ***Alt. 13 chosen:*** | *6* |
| ***Alt. 14 available:*** | *303* |
| ***Alt. 14 chosen:*** | *54* |
| ***Alt. 2 available:*** | *303* |
| ***Alt. 2 chosen:*** | *7* |
| ***Alt. 3 available:*** | *303* |
| ***Alt. 3 chosen:*** | *0* |
| ***Alt. 4 available:*** | *303* |
| ***Alt. 4 chosen:*** | *100* |
| ***Alt. 5 available:*** | *303* |
| ***Alt. 5 chosen:*** | *1* |
| ***Alt. 6 available:*** | *303* |
| ***Alt. 6 chosen:*** | *2* |
| ***Alt. 7 available:*** | *303* |
| ***Alt. 7 chosen:*** | *33* |
| ***Alt. 8 available:*** | *303* |
| ***Alt. 8 chosen:*** | *18* |
| ***Alt. 9 available:*** | *303* |
| ***Alt. 9 chosen:*** | *38* |
| ***Cte loglikelihood (only for full choice sets):*** | *-613.336* |
| ***Null loglikelihood:*** | *-799.634* |

### Estimation report

**Number of estimated parameters:** 3

**Sample size:** 303
**Excluded observations:** 0
**Init log likelihood:** -799.634
**Final log likelihood:** -596.938
**Likelihood ratio test for the init. model:** 405.392
**Rho-square for the init. model:** 0.253
**Rho-square-bar for the init. model:** 0.250
**Final gradient norm:** +1.704e-004
**Diagnostic:** Convergence reached...
**Iterations:** 7
**Data processing time:** 00:00
**Run time:** 00:00
**Nbr of threads:** 2

## Estimated parameters

Click on the headers of the columns to sort the table [Credits]

| Name | Value | Std err | t-test | p-value | | Robust Std err | Robust t-test | p-value | |
|---|---|---|---|---|---|---|---|---|---|
| B_MT | 0.547 | 0.190 | 1.71 | 0.09 | * | 0.194 | 1.68 | 0.09 | * |
| B_NR | 0.042 | 0.00446 | 11.40 | 0.00 | | 0.00425 | 11.95 | 0.00 | |
| B_TT | -0.295 | 0.0272 | -10.90 | 0.00 | | 0.0267 | -11.10 | 0.00 | |

## Correlation of coefficients

Click on the headers of the columns to sort the table [Credits]

| Coefficient1 | Coefficient2 | Covariance | Correlation | t-test | p-value | | Rob. cov. | Rob. corr. | Rob. t-test | p-value | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| B_MT | B_NR | -0.000579 | -0.681 | 1.42 | 0.16 | * | -0.000574 | -0.695 | 1.39 | 0.16 | * |
| B_MT | B_TT | 0.000259 | 0.0500 | 3.26 | 0.00 | | -0.000449 | -0.0865 | 3.14 | 0.00 | |
| B_NR | B_TT | -2.51e-005 | -0.207 | 12.20 | 0.00 | | -3.91e-006 | -0.0344 | 12.77 | 0.00 | |

Smallest singular value: 6.95166e-310

# Appendix C. Matlab Code for Bilevel programming problem

This is the code for master program. The master program call the functions which are coded separately

```
%---- initialize network
load digraph_G.mat;
ca = [digraph_G.Edges.Ca]';
t0 = [digraph_G.Edges.T_0]';
Da = [digraph_G.Edges.Length]'./1000;
links = [digraph_G.Edges.EndNodes];
N_adj = adjacency (digraph_G);
N = link2mat (t0, links, N_adj);
N(N==0) = inf;
%----------------------%
%%%--Initialization--%%%
%----------------------%

%---- initialize retailers/supplier/zone nodes
r = [35 66 4 46 19 25 58 56 15 27 14]';
s = [29 72 1 52 11 60 77 55 8 26 9 6 3 61]';

%---- Initialize path flow value
paths_OD_r = 5 .* ones (size(r,1) .* size(s,1),1);
paths_OD_c = 5 .* ones (size(s,1) .* size(s,1),1);
a = size(s,1);
paths_OD_c ((a*a)-a +1 : a*a) = []; %minus the same 14 zones equal to 0.

%---- Initialize path link incidence ----
load('paths_links_incidence_c_5.mat') %14 x 14 = 196 ODs. then 196 x 3
paths = 588 [] 189 links
paths_links_indicence_c_sum = sum (paths_links_incidence_c,2);
null_index = find (~paths_links_indicence_c_sum);
paths_links_incidence_c (null_index',:) = [];
load('paths_links_incidence_r_5.mat') %11+3dummy x 14 = 196 ODs then 196
x 3 paths = 588 [] 189 links
%index of path with dummy [496,497,498] [541 542 543] [586 587 588]

%---- Inititialize the initial value ---
load('od_c_196.mat');% 14 x 14 = 196 ODs
od_c_196 (od_c_196 == 0) = []; % remove zeros value
od_c_182 = od_c_196;
load('od_r_11_30.mat');% 11 R zones
load('va_pt_189.mat'); % 189 links
vop_c = 5.72; % 1000 IDR hour / km --> operational cost
vop_r = 6.31; % 1000 IDR hour / km --> operational cost
vot_c = 16.1; % 1000 IDR / hour
vot_r = 20.8; % 1000 IDR / hour

%---- split the demand evenly between OD pair and its path ----

%initial demand
pf_toll = d_split(od_r_11, od_c_182,
r,s,paths_links_incidence_r,paths_links_incidence_c);
pf_toll
(size(paths_links_incidence_r,1)+size(paths_links_incidence_c,1)+1,1)= 0;
%toll value
```

```
% --- OD according to r and s size
od_c_182 = od_c_182 (1:(a*a)-a,1);
od_r_11 = od_r_11 (1:size(r),1);

%---- initialize initial demand for dr
[va_sum_0,~,~] =
Va(paths_links_incidence_r,paths_links_incidence_c,pf_toll,links,va_pt_18
9);
va_hand =
@(pf_toll)Va(paths_links_incidence_r,paths_links_incidence_c,pf_toll,link
s,va_pt_189);
ta_hand = @(pf_toll)Ta(va_hand,pf_toll,t0,ca);
paths_ct_hand =
@(pf_toll)Paths_ct_linktoll(paths_links_incidence_r,paths_links_incidence
_c,paths_OD_r,paths_OD_c,ta_hand,Da,pf_toll,vot_c,vop_c,vot_r,vop_r);
[od_r_154] = Od_r(pf_toll,od_r_11,r,s,paths_ct_hand,vot_r);
od_r_hand = @(pf_toll)Od_r(pf_toll,od_r_11,r,s,paths_ct_hand,vot_r);

%-initialize cp_min_c_0
%load cp_min_c_0.mat;
load cp_min_c_0_1.mat;
cp_min_c_0 = cp_min_c_0 (1:(a*a)-a,1);

%initial veh.km;veh.minute;and velocity
ta = ta_hand(pf_toll);
va_sum_tripshour_0 = sum(va_sum_0 .* ta);
va_sum_tripskm_0 = sum(va_sum_0 .* Da);
velocity_0 = va_sum_tripskm_0 ./ va_sum_tripshour_0;

%---- initial value
No_iter = 20;
q_aux_r = zeros (size(paths_OD_r,1),No_iter+1);
q_aux_c = zeros (size(paths_OD_c,1),No_iter+1);
va_ext_r_iter = zeros (No_iter,size(links,1));
va_ext_c_iter = zeros (No_iter,size(links,1));
vi_r = zeros (No_iter,1);
vi_c = zeros (No_iter,1);
vi_tot = zeros (No_iter,1);
q_aux_r(:,1) = od_r_154;
q_aux_c(:,1) = od_c_182;
ub = inf (size (pf_toll,1),1);
ub (size (pf_toll,1),1) = 0; % maximum toll value
lb = zeros(size(pf_toll,1),1);
lb (size (pf_toll,1),1) = 0; % minimum toll value


%----- store the result
A_obj_func = zeros (No_iter,1);
A_toll = zeros (No_iter,1);

A_vi_gap_r_iter = zeros (No_iter,1);
A_vi_gap_c_iter = zeros (No_iter,1);
A_vi_gap_tot_iter = zeros (No_iter,1);

A_va_r_iter = zeros (No_iter,size(links,1));
A_va_r_tripshour_iter = zeros (No_iter,1);
A_va_r_tripskm_iter = zeros (No_iter,1);
A_va_r_velocity_iter = zeros (No_iter,1);
```

```
A_va_c_iter = zeros (No_iter,size(links,1));
A_va_c_tripshour_iter = zeros (No_iter,1);
A_va_c_tripskm_iter = zeros (No_iter,1);
A_va_c_velocity_iter = zeros (No_iter,1);

A_va_sum_iter = zeros (No_iter,size(links,1));
A_va_sum_tripshour_iter = zeros (No_iter,1);
A_va_sum_tripskm_iter = zeros (No_iter,1);
A_va_sum_velocity_iter = zeros (No_iter,1);

B_benefit_c = zeros (No_iter,1);
B_benefit_r = zeros (No_iter,1);
B_tot_travel_cost_r = zeros (No_iter,1);
B_tot_travel_cost_c = zeros (No_iter,1);
B_tot_travel_cost = zeros (No_iter,1);

C_links_vcr_iter = zeros (No_iter,size(links,1));

vi_gap_r = 1;
vi_gap_c = 1;
vi_gap_tot = 1;
iter = 1;

te_iter = zeros (No_iter,1);
%%
%------------------------------%
%%%---- Bi level program  ---%%%
%------------------------------%

while or (vi_gap_r < 0.01,vi_gap_c < 0.01)

%---- va function for all UC----
[~,~,~] =
Va(paths_links_incidence_r,paths_links_incidence_c,pf_toll,links,va_pt_18
9);
va_hand =
@(pf_toll)Va(paths_links_incidence_r,paths_links_incidence_c,pf_toll,link
s,va_pt_189);

%---- ta function for all UC----
[ta] = Ta(va_hand,pf_toll,t0,ca);
ta_hand = @(pf_toll)Ta(va_hand,pf_toll,t0,ca);

%---- path and link cost function for all UC ---
[cp_r,cp_c,cp_min_r,cp_min_c,~,~,~] =
Paths_ct_linktoll(paths_links_incidence_r,paths_links_incidence_c,paths_O
D_r,paths_OD_c,ta_hand,Da,pf_toll,vot_c,vop_c,vot_r,vop_r);
paths_ct_hand =
@(pf_toll)Paths_ct_linktoll(paths_links_incidence_r,paths_links_incidence
_c,paths_OD_r,paths_OD_c,ta_hand,Da,pf_toll,vot_c,vop_c,vot_r,vop_r);

%---- va_ext function ---- generates extreme point for each user class
[va_ext_r, va_ext_c] = Va_ext (pf_toll,paths_links_incidence_r,
paths_links_incidence_c, paths_OD_r, paths_OD_c, paths_ct_hand,
q_aux_r(:,iter),q_aux_c(:,iter));
va_ext_r_iter (iter,:) = va_ext_r;
va_ext_c_iter (iter,:) = va_ext_c;

%---- sum path flow function ----
```

```
[sum_path_flow_r, sum_path_flow_c] =
Sum_path_flow(pf_toll,paths_OD_r,paths_OD_c,paths_links_incidence_r);
sum_path_flow_hand = @(pf_toll)
Sum_path_flow(pf_toll,paths_OD_r,paths_OD_c,paths_links_incidence_r);

%---- inv var demand function ----
[inv_demand_r] = Inv_demand_r(pf_toll,od_r_hand,paths_OD_r,od_r_11,r,s);
inv_demand_r_hand = @(pf_toll)
Inv_demand_r(pf_toll,od_r_hand,paths_OD_r,od_r_11,r,s);

[inv_demand_c] =
Inv_demand_c(pf_toll,od_c_182,paths_OD_c,paths_ct_hand,cp_min_c_0);
inv_demand_c_hand = @(pf_toll)
Inv_demand_c(pf_toll,od_c_182,paths_OD_c,paths_ct_hand,cp_min_c_0);

%---- VI function----
[vi_r,vi_c,vi_tot] =
Vi(pf_toll,va_hand,paths_ct_hand,inv_demand_r_hand,inv_demand_c_hand,sum_
path_flow_hand,q_aux_r,q_aux_c,va_ext_r_iter,va_ext_c_iter,vi_r,vi_c,vi_t
ot,iter);
vi_hand =
@(pf_toll)Vi(pf_toll,va_hand,paths_ct_hand,inv_demand_r_hand,inv_demand_c
_hand,sum_path_flow_hand,q_aux_r,q_aux_c,va_ext_r_iter,va_ext_c_iter,vi_r
,vi_c,vi_tot,iter);

%---- benefit function ----
[benefit_c] =
Ben_function_c(pf_toll,od_c_182,paths_OD_c,paths_ct_hand,cp_min_c_0);
ben_function_c_hand = @(pf_toll)
Ben_function_c(pf_toll,od_c_182,paths_OD_c,paths_ct_hand,cp_min_c_0);

[benefit_r] =
Ben_function_r(pf_toll,sum_path_flow_hand,paths_OD_r,vot_r);
ben_function_r_hand = @(pf_toll)
Ben_function_r(pf_toll,sum_path_flow_hand,paths_OD_r,vot_r);

%---- create and solve the minimization problem ---
objective_fun = @(pf_toll)
param_obj_fun(pf_toll,va_hand,ta_hand,ben_function_c_hand,ben_function_r_
hand,vot_c,vot_r);
options = optimoptions
('fmincon','Display','iter','Algorithm','sqp','ConstraintTolerance',1);
A = [];
b = [];
Aeq = [];
beq = [];
lb = lb;
ub = ub;
nonlcon = @(pf_toll)
constraints(pf_toll,vi_hand,sum_path_flow_hand,q_aux_r,q_aux_c,iter);
x0 = pf_toll;
tic
%solving the master problem using fmincon
pf_toll = fmincon(objective_fun,x0,A,b,Aeq,beq,lb,ub,nonlcon,options);

%%
%update value after minimization
[va_sum,va_r,va_c] = feval (va_hand,pf_toll);
[cp_r,cp_c,cp_min_r,cp_min_c,ca_r,ca_r_toll,ca_c]=
feval(paths_ct_hand,pf_toll);
```

```
[sum_path_flow_r, sum_path_flow_c] = feval (sum_path_flow_hand,pf_toll);
[ta,ta_r]= feval(ta_hand,pf_toll);
[benefit_c] = feval (ben_function_c_hand, pf_toll);
[benefit_r] = feval (ben_function_r_hand, pf_toll);
tot_cost_r = vot_r .* ta .* va_r;
tot_cost_c = vot_c .* ta .* va_c;

%---- calcualte va_r and va_c demand function ----
[od_r_154] = Od_r(pf_toll,od_r_11,r,s,paths_ct_hand,vot_r);
[od_c_var] = Od_c(pf_toll,paths_ct_hand,paths_OD_c,od_c_182,cp_min_c_0);

q_aux_r(:,iter+1) = od_r_154;
q_aux_c(:,iter+1) = od_c_var;
%%
%flow convergence measures
pf_toll_r = pf_toll (1:size(paths_links_incidence_r,1),1);
pf_toll_c = pf_toll
(size(paths_links_incidence_r,1)+1:size(paths_links_incidence_r,1)+size(p
aths_links_incidence_c,1),1);

%CV VI Gap
%calculate cost including toll
Paths_Counter=0;
temp_conv = zeros (size(pf_toll_r));
for od = 1 : size (paths_OD_r,1)
    for pf = Paths_Counter+1 : Paths_Counter+paths_OD_r(od,1)
        temp_conv (pf,1)= pf_toll_r (pf,1)*(cp_r (pf,1));
    end
    Paths_Counter = Paths_Counter + paths_OD_r(od,1);
end
tot_cost_toll_r = sum (temp_conv);
%calculate cost for minimal shortest path
tot_cost_shortest_r = sum (cp_min_r .* sum_path_flow_r);
%calculate VI_gap
vi_gap_r = tot_cost_toll_r - tot_cost_shortest_r;

% PV VI Gap
Paths_Counter=0;
temp_conv = zeros (size(pf_toll_c));
for od = 1 : size (paths_OD_c,1)
    for pf = Paths_Counter+1 : Paths_Counter+paths_OD_c(od,1)
        temp_conv (pf,1)= pf_toll_c (pf,1)*(cp_c (pf,1));
    end
    Paths_Counter = Paths_Counter + paths_OD_c(od,1);
end
tot_cost_toll_c = sum (temp_conv);
%calculate cost for minimal shortest path
tot_cost_shortest_c = sum (cp_min_c .* sum_path_flow_c);
%calculate VI_gap
vi_gap_c = tot_cost_toll_c - tot_cost_shortest_c;

%store each iteration result
A_obj_func (iter,1) =
param_obj_fun(pf_toll,va_hand,ta_hand,ben_function_c_hand,ben_function_r_
hand,vot_c,vot_r);
A_toll(iter,1)= pf_toll
(size(paths_links_incidence_r,1)+size(paths_links_incidence_c,1) +1,1);
A_vi_gap_r_iter(iter,1)= vi_gap_r;
A_vi_gap_c_iter (iter,1)= vi_gap_c;
A_va_r_iter(iter,1:size(links,1))= va_r ;
```

```
A_va_r_tripshour_iter(iter,1) = sum (va_r .* ta_r);
A_va_r_tripskm_iter(iter,1) = sum (va_r .* Da);
A_va_r_velocity_iter (iter,1) = A_va_r_tripskm_iter(iter,1) ./
A_va_r_tripshour_iter(iter,1);
A_va_c_iter(iter,1:size(links,1))= va_c ;
A_va_c_tripshour_iter(iter,1) = sum (va_c .* ta);
A_va_c_tripskm_iter(iter,1) = sum (va_c .* Da);
A_va_c_velocity_iter (iter,1) = A_va_c_tripskm_iter(iter,1) ./
A_va_c_tripshour_iter(iter,1);
A_va_sum_iter(iter,1:size(links,1))= va_sum ;
A_va_sum_tripshour_iter(iter,1) = sum (va_sum .* ta);
A_va_sum_tripskm_iter(iter,1) = sum (va_sum .* Da);
A_va_sum_velocity_iter (iter,1) = A_va_sum_tripskm_iter(iter,1) ./
A_va_sum_tripshour_iter(iter,1);

B_benefit_c (iter,1)= benefit_c - sum (tot_cost_c);
B_benefit_r (iter,1)= benefit_r - sum (tot_cost_r);
B_tot_travel_cost_r (iter,1) = sum (tot_cost_r);
B_tot_travel_cost_c (iter,1) = sum (tot_cost_c);
B_tot_travel_cost (iter,1) = sum (tot_cost_r + tot_cost_c);

C_links_vcr_iter(iter,1:size(links,1)) = va_sum ./ca;

toc
te= toc;
te_iter(iter,1)= te;
toll = pf_toll
(size(paths_links_incidence_r,1)+size(paths_links_incidence_c,1) +1,1);

iter = iter + 1;

if iter-1 == No_iter
break
end

end

%%
save ('1.iter20_DN_30.mat')
quit;
```

Traffic flow (va), link travel time (ta), path travel costs (cp), Traffic flow extreme (va_ext), user benefit (ub), inverse demand($d^{-1}$), and objective function (-z) functions are coded below:

```
%va function

function [va_sum,va_r,va_c] =
Va(paths_links_incidence_r,paths_links_incidence_c,pf_toll, links,va_pt)
%Flow on the link function
% Input: Network mat, paths links, path_flow, links
% output : Va for each link in matrice format
temp_va_r = zeros (1,1);
temp_va_c = zeros (1,1);
va_r = zeros (1,size(links,1));
va_c = zeros (1,size(links,1));

%commercial vehicle
for lk=1 : size(links,1)
    for pt = 1: (size(paths_links_incidence_r,1))
        temp_va_r(pt)= paths_links_incidence_r(pt,lk) * pf_toll(pt,1);
    end
    va_r(1,lk)= sum(temp_va_r(1,:));
end

c_index = size(paths_links_incidence_r,1);

% private vehicle
for lk=1 : size(links,1)
    for pt = 1 : (size(paths_links_incidence_c,1))
        temp_va_c(pt)= paths_links_incidence_c(pt,lk) *
pf_toll(pt+c_index,1);
    end
    va_c(1,lk)= sum(temp_va_c(1,:));
end

va_sum = va_r+va_c;

end
```

```
%ta function

function [ta] = Ta(va_hand,pf_toll,t0,ca)
% Travel time on the link function


load digraph_G.mat;
pwr_function = [digraph_G.Edges.pwr]';
cap_time = [digraph_G.Edges.cap_time]';

[va_sum,~,~] = feval(va_hand,pf_toll);
ta = t0 .* (1+ (va_sum./ca).^pwr_function);

ta = min (ta ,cap_time);

end
```

```
%cp function

function [cp_r,cp_c,cp_min_r,cp_min_c,ca_r,ca_r_toll,ca_c] =
Paths_ct_linktoll(paths_links_incidence_r,paths_links_incidence_c,paths_O
D_r,paths_OD_c,ta_hand,Da,pf_toll,vot_c,vop_c,vot_r,vop_r)
%UNTITLED2 Summary of this function goes here
%   Detailed explanation goes here
cp_r = zeros (sum(paths_OD_r),1);
cp_c = zeros (sum(paths_OD_c),1);
cp_min_r = zeros (size(paths_OD_r,1),1);
cp_min_c = zeros (size(paths_OD_c,1),1);

[ta,ta_r] = feval (ta_hand,pf_toll);

%link cost (ca) for each UC
ca_r = vot_r .* ta +  vop_r .* (ta ./ Da);
ca_c = vot_c .* ta +  vop_c .* (ta ./ Da);

ca_r = round (ca_r,4,'significant');
ca_c = round (ca_c,4,'significant');

%link cost includes toll
link_toll_index_ew = [88 116]; % index toll for east west
%link_toll_index_ns = [115  127 126 102 100 87  85  66]; %index toll for
north south
%link_toll_index_om = [88 116 115   127 126 102 100 87  85  66 ]; % index
toll for combination
%park_toll_index = [137 84  88  135 44  39  42]; %index toll for park
%vcr_toll_index = [116  130 135 57  37  64  88  151 46  84]; %index toll
for most congested links by CV user class

toll = 0;
ca_r_toll = ca_r;
ca_r_toll(link_toll_index_ew) = ca_r_toll (link_toll_index_ew) + toll ;

%%
%path cost for each UC
%cost for va_r
for pt = 1: sum(paths_OD_r)
    cp_r (pt) = sum (ca_r_toll .* paths_links_incidence_r (pt,:));
end

%cost for va_c
for pt = 1: sum(paths_OD_c)
    cp_c (pt) = sum (ca_c .* paths_links_incidence_c (pt,:));
end

%min path cost for each OD for each UC
%min cost for UC retailers
path_counter = 0;
for od = 1 : size(paths_OD_r)
    cp_min_r (od) = min
(cp_r(path_counter+1:path_counter+paths_OD_r(od)));
    path_counter = path_counter + paths_OD_r(od);
end

%min cost for UC cars
path_counter = 0;
for od = 1 : size(paths_OD_c)
```

```
    cp_min_c (od) = min
(cp_c(path_counter+1:path_counter+paths_OD_c(od)));
    path_counter = path_counter + paths_OD_c(od);
end

end
```

```
%va_ext function

function [va_ext_r, va_ext_c] = Va_ext (pf_toll,paths_links_incidence_r,
paths_links_incidence_c, paths_OD_r,paths_OD_c, paths_ct_hand, od_r,
od_c)
%calculating va_extreme

% find the value of va_ext for each OD
va_ext_r_od = zeros(size(od_r,1),1);
va_ext_c_od = zeros(size(od_c,1),1);
total_paths_used_r = zeros(sum(paths_OD_r),1);
total_paths_used_c = zeros(sum(paths_OD_c),1);
binary_path_r = zeros(sum(paths_OD_r),1);
binary_path_c = zeros(sum(paths_OD_c),1);
extreme_link_r = zeros(size(paths_links_incidence_r));
extreme_link_c = zeros(size(paths_links_incidence_c));
num_path_used = 0;
[ct_r,ct_c] = feval(paths_ct_hand,pf_toll);

%% calcualte va_extreme for UC retailers
round_ct_r = round (ct_r,1);

%calculate the number of path used and the minimum travel time
path_counter = 0;
for d=1: size (od_r,1);
    min_tt_temp = inf;
    current_path_tt = round_ct_r(path_counter + 1 : path_counter +
paths_OD_r(d));
    for pt= 1 : paths_OD_r(d);
        if current_path_tt(pt) < min_tt_temp
            min_tt_temp = current_path_tt(pt);
            num_path_used = 1;
        elseif current_path_tt(pt)== min_tt_temp ;
            num_path_used = num_path_used + 1;
        end
    end
    total_paths_used_r (d,1) = num_path_used;
    path_counter = path_counter + paths_OD_r(d);
    va_ext_r_od (d,1) = od_r(d)/num_path_used;
end

%create binary value for each path, 1 if the path is used 0 otherwise
path_counter = 0;
for d=1: size (od_r,1);
    current_path_tt = round_ct_r(path_counter + 1 : path_counter +
paths_OD_r(d));
    for pt = 1 : paths_OD_r(d);
        if current_path_tt (pt) == min(round_ct_r(path_counter + 1 :
path_counter + paths_OD_r(d)));
            binary_path_r(path_counter+pt)= 1;
        else
            binary_path_r(path_counter+pt)= 0;
        end
    end
```

```
    path_counter = path_counter + paths_OD_r(d);
end

%assign the va_extreme for each OD to the link and sum the values
path_counter = 0;
for d=1: size (va_ext_r_od,1);
    for pt = path_counter + 1:path_counter+paths_OD_r (d,1)
        if binary_path_r (pt)== 1
        extreme_link_r(pt,:) = paths_links_incidence_r(pt,:).*va_ext_r_od
(d);
        else
        extreme_link_r(pt,:)= paths_links_incidence_r(pt,:).*0;
        end
    end
    path_counter = path_counter + paths_OD_r(d);
end

va_ext_r= sum (extreme_link_r);

%% caculate va_extreme for UC cars

round_ct_c = round (ct_c,1);

%calculate the number of path used and the minimum travel time
path_counter = 0;
for d=1: size (od_c,1)
    min_tt_temp = inf;
    current_path_tt = round_ct_c(path_counter + 1 : path_counter +
paths_OD_c(d));
    for pt= 1 : paths_OD_c(d)
        if current_path_tt(pt) < min_tt_temp
            min_tt_temp = current_path_tt(pt);
            num_path_used = 1;
        elseif current_path_tt(pt)== min_tt_temp
            num_path_used = num_path_used + 1;
        end
    end
    total_paths_used_c (d,1) = num_path_used;
    path_counter = path_counter + paths_OD_c(d);
    va_ext_c_od (d,1) = od_c(d)/num_path_used;
end

%create binary value for each path, 1 if the path is used 0 otherwise
path_counter = 0;
for d=1: size (od_c,1);
    current_path_tt = round_ct_c(path_counter + 1 : path_counter +
paths_OD_c(d));
    for pt = 1 : paths_OD_c(d);
        if current_path_tt (pt) == min(round_ct_c(path_counter + 1 :
path_counter + paths_OD_c(d)));
            binary_path_c(path_counter+pt)= 1;
        else
            binary_path_c(path_counter+pt)= 0;
        end
    end
    path_counter = path_counter + paths_OD_c(d);
end

%assign the va_extreme for each OD to the link and sum the values
path_counter = 0;
```

```
for d=1: size (va_ext_c_od,1);
    for pt = path_counter + 1:path_counter+paths_OD_c (d,1)
        if binary_path_c (pt)== 1
        extreme_link_c(pt,:) = paths_links_incidence_c(pt,:).*va_ext_c_od
(d);
        else
        extreme_link_c(pt,:)= paths_links_incidence_c(pt,:).*0;
        end
    end
    path_counter = path_counter + paths_OD_c(d);
end

va_ext_c= sum (extreme_link_c);
```

```
%UB_C function

function [ benefit_c ] =
Ben_function_c(pf_toll,dc,paths_OD,paths_ct_hand,cp_min_0)
%UNTITLED Summary of this function goes here
%   Detailed explanation goes here
dc_var = zeros (size (paths_OD,1),1);
benefit_c = zeros (size (paths_OD,1),1);
ct_min = zeros (size(paths_OD,1),1); % size tt min variable
[~,cp_c,~,~]= feval(paths_ct_hand,pf_toll);
round_cp_c = round (cp_c,4);

%calcualte tt min for each OD
path_counter = 0;
for od = 1 : size(paths_OD);
    ct_min (od) = min
(round_cp_c(path_counter+1:path_counter+paths_OD(od)));
    path_counter = path_counter + paths_OD(od);
end

for k = 1 : size(paths_OD);
    dc_var(k,1) = dc (k,1) .* (ct_min(k,1) ./ cp_min_0(k,1)).^-0.57;
end

for k = 1 : size(paths_OD);
    benefit_c(k,1) = -1.33 .* cp_min_0(k,1) .* dc(k,1).^1.75 .*
dc_var(k,1).^-0.75;
end

benefit_c(isnan(benefit_c)) = 0;

benefit_c = sum (benefit_c);
end
```

```
%D-1 function

function [inv_demand_c] =
Inv_demand_c(pf_toll,dc,paths_OD,paths_ct_hand,cp_min_0)
%var_demand: calculating variable demand using demand power func

dc_var = zeros (size (paths_OD,1),1);
inv_demand_c = zeros (size (paths_OD,1),1);
cp_min = zeros (size(paths_OD,1),1); % size cp_min variable
```

```
[~,cp_c,~,~] = feval (paths_ct_hand,pf_toll);
round_cp = round (cp_c,4);

%%
%calcualte cp_min for each OD
path_counter = 0;
for od = 1 : size(paths_OD);
    cp_min (od) = min
(round_cp(path_counter+1:path_counter+paths_OD(od)));
    path_counter = path_counter + paths_OD(od);
end

%%
%calculate dc_var for each OD
for k = 1 : size(paths_OD);
    dc_var(k,1) = dc (k,1) .* (cp_min(k,1) ./ cp_min_0(k,1)).^-0.57;
end

%%
%calculate inverse demand
for k = 1 : size(paths_OD);
    inv_demand_c(k,1) = cp_min_0 (k,1) .* (dc_var(k,1) ./ dc(k,1)).^-
1.75;
end

inv_demand_c(isnan(inv_demand_c))=0;
end
```

```
%objective function

function y =
param_obj_fun(pf_toll,va_hand,ta_hand,ben_function_c_hand,ben_function_r_
hand,vot_c,vot_r)
%UNTITLED3 Summary of this function goes here
%   Detailed explanation goes here

[ta,~]= feval(ta_hand,pf_toll);
[va_sum,va_r,va_c]= feval (va_hand,pf_toll);

tot_cost_r = vot_r .* ta .* va_r;
tot_cost_c = vot_c .* ta .* va_c;
%tot_cost = ta .* va_sum;

y = sum (tot_cost_r+tot_cost_c) - ben_function_c_hand(pf_toll)-
ben_function_r_hand(pf_toll);

end
```

# Appendix D. Inverse of multinomial logit (MNL) demand function

To be able to write the demand function as a variational inequality problem, the demand function needs to be invertible. For the multinomial logit function the invertibility does exist (see Fisk and Boyce, (1983)) as follow:

Let the multinomial logit model depict the case in which retailers have three supplier choices, the proportion of retailers to choose supplier location 1 can be written as

$$d_1 = D_r \frac{e^{-\beta\,(u_1)}}{e^{-\beta\,(u_1)} + e^{-\beta\,(u_2)} + e^{-\beta\,(u_3)}} \qquad \text{E.1.1}$$

$$d_1 = D_r \frac{e^{-\beta\,(u_1 - u_3)}}{e^{-\beta\,(u_1 - u_3)} + e^{-\beta\,(u_2 - u_3)} + 1} \qquad \text{E.1.1}$$

Let,

$$\omega_i = u_i - u_k \;;\; i \neq k \;;\; i, k \in w \qquad \text{E.2}$$

Then, by substituting equation E.2. into equation E.1. we get,

$$d_1 = D_r \frac{e^{-\beta\,\omega_1}}{e^{-\beta\,\omega_1} + e^{-\beta\,\omega_2} + 1} \qquad \text{E.3.1}$$

$$d_1 = D_r \frac{e^{-\beta\,\omega_1}}{\sum_{k \neq 3} e^{-\beta\,\omega_s} + 1} \qquad \text{E.3.2}$$

Using equation E.3. above, we then can write the demand for supplier location 3 as:

$$d_3 = D_r - \sum_{k \neq 3} d_k \qquad \text{E.4.1}$$

$$d_3 = D_r - D_r \frac{e^{-\beta\,\omega_1}}{\sum_{k \neq 3} e^{-\beta\,\omega_k} + 1} - D_r \frac{e^{-\beta\,\omega_2}}{\sum_{k \neq 3} e^{-\beta\,\omega_k} + 1} \qquad \text{E.4.2}$$

$$d_3 = \frac{D_r}{\sum_{k \neq 3} e^{-\beta\,\omega_k} + 1} \left[ \sum_{k \neq 3} e^{-\beta\,\omega_k} - e^{-\beta\,\omega_1} - e^{-\beta\,\omega_2} + 1 \right] \qquad \text{E.4.3}$$

$$d_3 = \frac{D_r}{\sum_{k \neq 3} e^{-\beta\,\omega_k} + 1} \left[ e^{-\beta\,\omega_1} + e^{-\beta\,\omega_2} - e^{-\beta\,\omega_1} - e^{-\beta\,\omega_2} + 1 \right] \qquad \text{E.4.4}$$

$$d_3 = \frac{D_r}{\sum_{k \neq 3} e^{-\beta\,\omega_k} + 1} \qquad \text{E.4.5}$$

Then inverting the multinomial logit function formulated by equation E.32. we get

$$e^{-\beta\,\omega_1} = \frac{d_1 \left[\sum_{k \neq 3} e^{-\beta\,\omega_s} + 1\right]}{D_r} = \frac{d_1}{D_r \big/ \left[\sum_{s \neq 3} e^{-\beta\,\omega_s} + 1\right]} \qquad \text{E.5}$$

Observe that the denominator of the inverse function is equal to the equation E.4.5, and by applying the $\ln$ function for both sides of equation E.5. we get

$$\omega_1 = \frac{1}{-\beta} \ln \frac{d_1}{d_3} = \frac{1}{-\beta} \ln \frac{d_1}{D_r - \sum_{k \neq 3} d_k} \qquad \text{E.5}$$

Equation E.5. formulated the inverse demand function for the example of three supplier location choices, and for more general cases, the inverse demand function for MNL function can be written as:

$$\omega_i = -\frac{1}{\beta} \ln\left( \frac{d_w}{D_r - \sum_{s \neq w_s} d_w} \right), \forall w\, ; \ w \in W \qquad \text{E.6}$$

## Appendix E. Integral of MNL inverse demand function

To be able to calculate the benefit for multinomial demand function, we need to integrate the inverse demand function. The integration process is as follows:

$$UB = \sum_{w} \int_{0}^{D_w} -\frac{1}{\beta} \ \ln\left( \frac{d_w}{D_r - \sum_{s \neq w_s} d_w} \right) d(d_w)$$

$$= \sum_{w} -\frac{1}{\beta} \int_{0}^{D_w} \ln\left( \frac{d_w}{D_r - \sum_{s \neq w_s} d_w} \right) d(d_w)$$

$$= \sum_{w} -\frac{1}{\beta} \int_{0}^{D_w} \ln(d_w) - \ln\left( D_r - \sum_{s \neq w_s} d_w \right) d(d_w)$$

$$= \sum_{w} -\frac{1}{\beta} \left\{ (d_w \ln(d_w) - d_w) - \left( \ln\left( D_r - \sum_{s \neq w_s} d_w \right) d_w \right) \right\}_{0}^{D_w}$$

$$= \sum_{w} -\frac{1}{\beta} D_w \ln D_w$$

# Appendix F. Networks link cost

There are two networks in the thesis (i) small network for small numerical example (ii) Bandung city centre network.The link cost follows the BPR function.

$$t_a = t_0 * \left(1 + \pi * \frac{v_a}{k_a}\right)^{\alpha}$$

The link cost value for the small network is as follow

| Links | $t_0$ (hour) | $k_a$ (vehicle/hour) | $\pi$ | $\alpha$ |
|---|---|---|---|---|
| 1 | 11.6 | 700 | 0.15 | 4 |
| 2 | 5.2 | 1000 | 0.15 | 4 |
| 3 | 3.6 | 900 | 0.15 | 4 |
| 4 | 3.6 | 1000 | 0.15 | 4 |
| 5 | 6.6 | 900 | 0.15 | 4 |
| 6 | 4.8 | 1200 | 0.15 | 4 |
| 7 | 8.4 | 1200 | 0.15 | 4 |

As for, Bandung city centre network, the link cost value is as follow

| Links | $t_0$ (hour) | $k_a$ (vehicle/hour) | $\pi$ | $\alpha$ |
|---|---|---|---|---|
| 1 | 0.0136 | 4950 | 1 | 2.9 |
| 2 | 0.0286 | 1740 | 1 | 1.4 |
| 3 | 0.0136 | 4950 | 1 | 2.9 |
| 4 | 0.0073 | 4950 | 1 | 2.9 |
| 5 | 0.0218 | 1740 | 1 | 1.4 |
| 6 | 0.0073 | 4950 | 1 | 2.9 |
| 7 | 0.0072 | 1740 | 1 | 1.4 |
| 8 | 0.0179 | 4950 | 1 | 2.9 |
| 9 | 0.0218 | 1740 | 1 | 1.4 |
| 10 | 0.0078 | 1250 | 1 | 1.1 |
| 11 | 0.0134 | 4703 | 1 | 1.8 |
| 12 | 0.0150 | 1250 | 1 | 1.1 |
| 13 | 0.0058 | 4703 | 1 | 1.8 |
| 14 | 0.0171 | 1740 | 1 | 1.4 |
| 15 | 0.0286 | 1740 | 1 | 1.4 |
| 16 | 0.0110 | 1740 | 1 | 1.4 |
| 17 | 0.0158 | 1740 | 1 | 1.4 |
| 18 | 0.0068 | 1250 | 1 | 1.1 |
| 19 | 0.0056 | 1740 | 1 | 1.4 |
| 20 | 0.0129 | 1740 | 1 | 1.4 |
| 21 | 0.0286 | 1740 | 1 | 1.4 |
| 22 | 0.0118 | 1740 | 1 | 1.4 |
| 23 | 0.0078 | 1250 | 1 | 1.1 |
| 24 | 0.0200 | 1250 | 1 | 1.1 |
| 25 | 0.0198 | 1250 | 1 | 1.1 |
| 26 | 0.0042 | 1740 | 1 | 1.4 |
| 27 | 0.0059 | 1740 | 1 | 1.4 |
| 28 | 0.0110 | 1740 | 1 | 1.4 |
| 29 | 0.0200 | 1250 | 1 | 1.1 |

| Links | $t_0$ (hour) | $k_a$ (vehicle/hour) | $\pi$ | $\alpha$ |
|---|---|---|---|---|
| 30 | 0.0198 | 1740 | 1 | 1.4 |
| 31 | 0.0140 | 1740 | 1 | 1.4 |
| 32 | 0.0198 | 1740 | 1 | 1.4 |
| 33 | 0.0150 | 1250 | 1 | 1.1 |
| 34 | 0.0121 | 4703 | 1 | 1.8 |
| 35 | 0.0068 | 1250 | 1 | 1.1 |
| 36 | 0.0042 | 1740 | 1 | 1.4 |
| 37 | 0.0084 | 1740 | 1 | 1.4 |
| 38 | 0.0074 | 1250 | 1 | 1.1 |
| 39 | 0.0129 | 1740 | 1 | 1.4 |
| 40 | 0.0131 | 1740 | 1 | 1.4 |
| 41 | 0.0179 | 4950 | 1 | 2.9 |
| 42 | 0.0286 | 1740 | 1 | 1.4 |
| 43 | 0.0312 | 4950 | 1 | 2.9 |
| 44 | 0.0118 | 1740 | 1 | 1.4 |
| 45 | 0.0064 | 1740 | 1 | 1.4 |
| 46 | 0.0340 | 1740 | 1 | 1.4 |
| 47 | 0.0155 | 1740 | 1 | 1.4 |
| 48 | 0.0140 | 1740 | 1 | 1.4 |
| 49 | 0.0198 | 1250 | 1 | 1.1 |
| 50 | 0.0059 | 1740 | 1 | 1.4 |
| 51 | 0.0198 | 1740 | 1 | 1.4 |
| 52 | 0.0070 | 1250 | 1 | 1.1 |
| 53 | 0.0028 | 1250 | 1 | 1.1 |
| 54 | 0.0044 | 1250 | 1 | 1.1 |
| 55 | 0.0129 | 4703 | 1 | 1.8 |
| 56 | 0.0084 | 1740 | 1 | 1.4 |
| 57 | 0.0143 | 1740 | 1 | 1.4 |
| 58 | 0.0074 | 1250 | 1 | 1.1 |
| 59 | 0.0028 | 1250 | 1 | 1.1 |
| 60 | 0.0102 | 1250 | 1 | 1.1 |
| 61 | 0.0145 | 1250 | 1 | 1.1 |
| 62 | 0.0051 | 4703 | 1 | 1.8 |
| 63 | 0.0102 | 1250 | 1 | 1.1 |
| 64 | 0.0064 | 1740 | 1 | 1.4 |
| 65 | 0.0143 | 1740 | 1 | 1.4 |
| 66 | 0.0147 | 1740 | 1 | 1.4 |
| 67 | 0.0055 | 4703 | 1 | 1.8 |
| 68 | 0.0200 | 1740 | 1 | 1.4 |
| 69 | 0.0051 | 1740 | 1 | 1.4 |
| 70 | 0.0053 | 1740 | 1 | 1.4 |
| 71 | 0.0218 | 1740 | 1 | 1.4 |
| 72 | 0.0070 | 1250 | 1 | 1.1 |
| 73 | 0.0044 | 1250 | 1 | 1.1 |
| 74 | 0.0170 | 1250 | 1 | 1.1 |
| 75 | 0.0155 | 1250 | 1 | 1.1 |
| 76 | 0.0155 | 1250 | 1 | 1.1 |
| 77 | 0.0132 | 1740 | 1 | 1.4 |
| 78 | 0.0029 | 1740 | 1 | 1.4 |
| 79 | 0.0058 | 1250 | 1 | 1.1 |
| 80 | 0.0173 | 4703 | 1 | 1.8 |

| Links | $t_0$ (hour) | $k_a$ (vehicle/hour) | $\pi$ | $\alpha$ |
|---|---|---|---|---|
| 81 | 0.0044 | 1740 | 1 | 1.4 |
| 82 | 0.0312 | 4950 | 1 | 2.9 |
| 83 | 0.0340 | 1740 | 1 | 1.4 |
| 84 | 0.0108 | 4950 | 1 | 2.9 |
| 85 | 0.0147 | 1740 | 1 | 1.4 |
| 86 | 0.0200 | 1740 | 1 | 1.4 |
| 87 | 0.0025 | 1740 | 1 | 1.4 |
| 88 | 0.0302 | 1740 | 1 | 1.4 |
| 89 | 0.0022 | 4703 | 1 | 1.8 |
| 90 | 0.0145 | 1250 | 1 | 1.1 |
| 91 | 0.0047 | 1740 | 1 | 1.4 |
| 92 | 0.0129 | 1740 | 1 | 1.4 |
| 93 | 0.0218 | 1740 | 1 | 1.4 |
| 94 | 0.0048 | 1740 | 1 | 1.4 |
| 95 | 0.0048 | 1740 | 1 | 1.4 |
| 96 | 0.0068 | 4703 | 1 | 1.8 |
| 97 | 0.0067 | 1740 | 1 | 1.4 |
| 98 | 0.0070 | 4703 | 1 | 1.8 |
| 99 | 0.0066 | 1740 | 1 | 1.4 |
| 100 | 0.0025 | 1740 | 1 | 1.4 |
| 101 | 0.0238 | 1250 | 1 | 1.1 |
| 102 | 0.0043 | 1740 | 1 | 1.4 |
| 103 | 0.0014 | 4703 | 1 | 1.8 |
| 104 | 0.0065 | 1740 | 1 | 1.4 |
| 105 | 0.0102 | 4703 | 1 | 1.8 |
| 106 | 0.0058 | 1740 | 1 | 1.4 |
| 107 | 0.0032 | 4703 | 1 | 1.8 |
| 108 | 0.0091 | 1740 | 1 | 1.4 |
| 109 | 0.0254 | 1250 | 1 | 1.1 |
| 110 | 0.0011 | 1740 | 1 | 1.4 |
| 111 | 0.0243 | 1740 | 1 | 1.4 |
| 112 | 0.0053 | 1740 | 1 | 1.4 |
| 113 | 0.0217 | 1740 | 1 | 1.4 |
| 114 | 0.0029 | 1740 | 1 | 1.4 |
| 115 | 0.0047 | 1740 | 1 | 1.4 |
| 116 | 0.0167 | 4703 | 1 | 1.8 |
| 117 | 0.0148 | 1740 | 1 | 1.4 |
| 118 | 0.0067 | 1740 | 1 | 1.4 |
| 119 | 0.0217 | 1740 | 1 | 1.4 |
| 120 | 0.0088 | 1740 | 1 | 1.4 |
| 121 | 0.0090 | 1740 | 1 | 1.4 |
| 122 | 0.0061 | 1740 | 1 | 1.4 |
| 123 | 0.0066 | 1740 | 1 | 1.4 |
| 124 | 0.0088 | 1740 | 1 | 1.4 |
| 125 | 0.0133 | 1740 | 1 | 1.4 |
| 126 | 0.0043 | 1740 | 1 | 1.4 |
| 127 | 0.0047 | 1740 | 1 | 1.4 |
| 128 | 0.0265 | 1740 | 1 | 1.4 |
| 129 | 0.0265 | 1740 | 1 | 1.4 |
| 130 | 0.0200 | 4703 | 1 | 1.8 |
| 131 | 0.0112 | 1740 | 1 | 1.4 |

| Links | $t_0$ (hour) | $k_a$ (vehicle/hour) | $\pi$ | $\alpha$ |
|---|---|---|---|---|
| 132 | 0.0108 | 4950 | 1 | 2.9 |
| 133 | 0.0302 | 1740 | 1 | 1.4 |
| 134 | 0.0123 | 1740 | 1 | 1.4 |
| 135 | 0.0123 | 1740 | 1 | 1.4 |
| 136 | 0.0046 | 4703 | 1 | 1.8 |
| 137 | 0.0106 | 1740 | 1 | 1.4 |
| 138 | 0.0243 | 1740 | 1 | 1.4 |
| 139 | 0.0287 | 1740 | 1 | 1.4 |
| 140 | 0.0058 | 4703 | 1 | 1.8 |
| 141 | 0.0175 | 1740 | 1 | 1.4 |
| 142 | 0.0090 | 1740 | 1 | 1.4 |
| 143 | 0.0175 | 4703 | 1 | 1.8 |
| 144 | 0.0127 | 1740 | 1 | 1.4 |
| 145 | 0.0148 | 1740 | 1 | 1.4 |
| 146 | 0.0235 | 1740 | 1 | 1.4 |
| 147 | 0.0061 | 1740 | 1 | 1.4 |
| 148 | 0.0002 | 1740 | 1 | 1.4 |
| 149 | 0.0039 | 1740 | 1 | 1.4 |
| 150 | 0.0036 | 4703 | 1 | 1.8 |
| 151 | 0.0176 | 4703 | 1 | 1.8 |
| 152 | 0.0106 | 1740 | 1 | 1.4 |
| 153 | 0.0312 | 1740 | 1 | 1.4 |
| 154 | 0.0112 | 1740 | 1 | 1.4 |
| 155 | 0.0183 | 1740 | 1 | 1.4 |
| 156 | 0.0028 | 1740 | 1 | 1.4 |
| 157 | 0.0114 | 1740 | 1 | 1.4 |
| 158 | 0.0043 | 1740 | 1 | 1.4 |
| 159 | 0.0287 | 1740 | 1 | 1.4 |
| 160 | 0.0179 | 1740 | 1 | 1.4 |
| 161 | 0.0152 | 4703 | 1 | 1.8 |
| 162 | 0.0034 | 4703 | 1 | 1.8 |
| 163 | 0.0061 | 1740 | 1 | 1.4 |
| 164 | 0.0241 | 1740 | 1 | 1.4 |
| 165 | 0.0091 | 1740 | 1 | 1.4 |
| 166 | 0.0034 | 4703 | 1 | 1.8 |
| 167 | 0.0241 | 1740 | 1 | 1.4 |
| 168 | 0.0076 | 1740 | 1 | 1.4 |
| 169 | 0.0062 | 1740 | 1 | 1.4 |
| 170 | 0.0120 | 1740 | 1 | 1.4 |
| 171 | 0.0127 | 1740 | 1 | 1.4 |
| 172 | 0.0179 | 1740 | 1 | 1.4 |
| 173 | 0.0135 | 1740 | 1 | 1.4 |
| 174 | 0.0043 | 1740 | 1 | 1.4 |
| 175 | 0.0118 | 1740 | 1 | 1.4 |
| 176 | 0.0018 | 1740 | 1 | 1.4 |
| 177 | 0.0111 | 1740 | 1 | 1.4 |
| 178 | 0.0135 | 1740 | 1 | 1.4 |
| 179 | 0.0088 | 1740 | 1 | 1.4 |
| 180 | 0.0118 | 1740 | 1 | 1.4 |
| 181 | 0.0046 | 1740 | 1 | 1.4 |
| 182 | 0.0027 | 1740 | 1 | 1.4 |

| Links | $t_0$ (hour) | $k_a$ (vehicle/hour) | $\pi$ | $\alpha$ |
|---|---|---|---|---|
| 183 | 0.0046 | 1740 | 1 | 1.4 |
| 184 | 0.0076 | 1740 | 1 | 1.4 |
| 185 | 0.0018 | 1740 | 1 | 1.4 |
| 186 | 0.0091 | 1740 | 1 | 1.4 |
| 187 | 0.0252 | 1740 | 1 | 1.4 |
| 188 | 0.0062 | 1740 | 1 | 1.4 |
| 189 | 0.0252 | 1740 | 1 | 1.4 |