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A Comparative Economic Assessment of Urban Transport Infrastructure Options in Low- and Middle-Income Countries

by

Minh Tam Vu

A thesis for the degree of Doctor of Philosophy

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Abstract

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The dominance of motorcycles in mixed transport systems in developing cities and countries might lead to several problems such as traffic congestion and accident. To solve these challenges and increase the modal share of public transport (PT), several new PT projects have been invested in these countries. However, there seems to be very little evidence on evaluation methods of all transport modes to analyse the feasibility of a new PT mode and identify the most cost-effective mixed transport system. Therefore, it is essential to have a comprehensive evaluation method for motorcycle, car, Demand Responsive Transit (DRT) and PT in mixed transport environments.

Hence, the main aim of this thesis is to develop a comparative economic assessment for evaluating the feasibility of a new PT mode and choosing the best mixed transport system based on the PT technologies' characteristics and the conditions of local transport networks. The comparative economic assessment is integrated from four models: Social Cost Model, Incremental Elasticity Analysis, Incremental Multinomial/Nested Logit Model and Microscopic Simulation Model. The Social Cost Model calculates the social costs of exclusive private transport (PRV), segregated PT, exclusive DRT and mixed transport at a strategic planning level. The Incremental Elasticity Analysis evaluates endogenous changes in total general demand of all transport modes by using the demand elasticity with respect to a composite cost (a logsum). The Incremental Multinomial/Nested Logit Model estimates the choices of passengers in favour of all transport modes with respect to generalised costs. The Microscopic Simulation Model simulates all existing transport modes' flows on the local network by using a microscopic simulation model in VISSIM, which is developed, calibrated and validated based on the data collected from one real urban corridor in Hanoi, the capital of Vietnam.

The comparative economic assessment was applied to compare the existing mixed transport situation and twelve transport infrastructure options with a new PT technology (Bus Rapid Transit, elevated Metro or Monorail) replacing the existing bus services; either wholly or partially, and with or without a congestion charge scheme for PRV on the chosen corridor in Hanoi, in terms of average social cost, total general demand and PT share. The results show that eight options with Bus Rapid Transit or Monorail or Metro are feasible. In addition, the BRT option that replaces all existing buses with a congestion charging scheme is the best alternative in terms of average social cost. Transport planners and decision makers in Hanoi can draw on the findings of this thesis. Moreover, the methodology of the comparative economic assessment might be applied and modified to various transport networks with an abundance of motorcycles to assess the costs and benefits of each new PT technology and mixed transport systems with or without the congestion charge. However, various limitations are identified and further work is suggested.

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Research Thesis: Declaration of Authorship

Print name: Minh Tam Vu

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I declare that this thesis and the work presented in it are my own and has been generated by me as the result of my own original research.

I confirm that:

1. This work was done wholly or mainly while in candidature for a research degree at this University;
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Vu, T. and Preston, J. (2020) Assessing the Social Costs of Urban Transport Infrastructure Options in Low and Middle Income Countries. *Transportation Planning and Technology,* 43 (4), 365-384. [in special issue: Universities' Transport Study Group UK Annual Conference 2019]

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Abbreviations

ASC	Average Social Cost
ATS	Acceleration Testing System
BRT	Bus Rapid Transit
CBA	Cost-benefit analysis
CEA	Comparative Economic Assessment
DRT	Demand Responsive Transit
FAC	Fully Allocated Costs
GoV	Government of Vietnam
GSOV	General Statistics Office of Vietnam
HLM	Hierarchical Logit Model
HPC	Hanoi People's Committee
HMC	Hanoi Metro Company
IDR	Indonesian Rupiah
IEA	Incremental Elasticity Analysis
IMLM	Incremental Multinomial Logit Model
IPTE	Institute of Planning & Transportation Engineering
IVT	In-vehicle time
JICA	Japan International Cooperation Agency
LMICs	Low- and Middle-Income Countries
LRT	Light Rail Transit
MCC	Marginal Congestion Charge
MCU	Dynamic Motorcycle Unit
MNL	Multinomial Logit Model
MSC	Mode Specific Constant
MSM	Microscopic Simulation Model
PCU	Passenger Car Unit
pdd	Passenger/direction/day
PPP	Purchasing Power Parity
PT	Public Transport
PRV	Private Vehicle/Private Transport
PVR	Peak Vehicle Requirement
QT-TP-NT corridor	Quang Trung-Tran Phu-Nguyen Trai corridor
RoW	Right of Way
SCM	Social Cost Model
TEDI	Transport Engineering Design Incorporated
TMP	Transportation Master Plan

TOC	Total Operator Cost
TRAMOC	Hanoi Transport Management and Operation Centre
TRANSERCO	Hanoi Transport & Services Corporation
TSC	Total Social Cost
TUC	Total User Cost
URT	Urban Rail Transit
VH	Vehicle-Hours
VoT	Value of Time
VKM	Vehicle-Kilometre
VND	Vietnamese Dong
WKT	Walking time
WTP	Willingness to Pay
WTT	Waiting time

Chapter 1 Introduction

1.1 Background and Research Questions

Due to the rapid development of technology and increase in travel demands in urban areas, innovative Public Transport (PT) technologies and Demand Responsive Transit (DRT), rather than conventional bus and heavy rail transit, have come into focus, in particular in low- and middle-income countries (LMICs).[1] The background trend is a significant increase in private vehicle (car and motorcycle) users in mixed traffic environments in developing countries, especially in urban areas of Asia (e.g. Taiwan, Indonesia, Malaysia, Thailand and Vietnam). The dominance of motorcycles in mixed transport causes transport problems such as traffic congestion, air pollution, noise pollution and traffic accidents (Chang and Yeh, 2006; Nguyen and Sano, 2012; Bray and Holyoak, 2015). To solve these issues and to raise the modal share of PT, several PT projects have been invested in these countries as Bus Rapid Transit (BRT), Metro and Monorail (Malaysia Economic Planning Unit, 2010; Taipei Department of Transportation, 2013; Government of Vietnam, 2016). However, an important question is whether improving PT can lead to improvements in system efficiency given motorcycle dominance. In other words, transport planners and decision makers need to analyse the feasibility of a new innovative PT technology for a local network. Furthermore, when several PT modes are feasible, it can be difficult for them to determine the most cost-effective mixed transport system where transport modes share infrastructure facilities with the dominance of motorcycle, in terms of given criteria such as average cost per passenger, modal share of public transport or increases in total general demand. However, there seems to be very little evidence on combined evaluation methods for motorcycles, cars, Demand Responsive Transit (DRT) and PT technologies, which cover the benefits and costs involving travellers, operators, traffic accident, transport-related air and noise pollution, climate change and congestion. As a result, a more comprehensive evaluation method for these transport modes needs to be formulated. This will be shown in more detail in Section 1.3.

1.2 Introduction of Transport Modes

To supply the high demand for travelling in the urban areas, there is a range of transport modes including private transport, PT and DRT, which are briefly reviewed below.

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[1] As of 1st July, 2019, LMICs are defined as those with a Gross National Income per capita, calculated using the Atlas method, of US$ 12,375 or less in 2018 (World Bank, 2019).

1.2.1 Private transport (PRV)

Motorcycles

According to Directive 2002/24/EC of the European Parliament and of the Council of 18 March 2002, motorcycles are defined into two types. Firstly, two-wheel vehicles with an internal combustion engine having a cylinder capacity of not more than 50 cm^3 if of the internal combustion type and/or having a maximum design speed of not more than 45 km/h. Secondly, two-wheel vehicles with an internal combustion engine having a cylinder capacity of more than 50 cm^3 if of the internal combustion type and/or having a maximum design speed of more than 45 km/h. Motorcycles with small engines ranging from 100 to 150 cm^3 are especially popular in developing Asian countries, such as Taiwan (Chang and Yeh, 2006), Malaysia (Hussain, Radin Umar and Ahmad Farhan, 2011) and Vietnam (Bray and Holyoak, 2015).

Passenger cars

Based on Directive 2007/46/EC of the European Parliament and of the Council of 5 September 2007, passenger cars are defined as four-wheel vehicles designed and constructed for the carriage of passengers, comprising no more than eight seats in addition to the driver’s seat.

1.2.2 Public transport

Public transport plays an important role in daily travelling in all countries around the world. Currently, more and more PT technologies have attracted the interest of operators and decision makers. In addition, several new innovative PT forms have been developed to meet various passenger requirements. This section shows the main transit modes below.

Conventional bus

The conventional bus as a PT mode which is operated by rubber-tyred vehicles that follow fixed routes and schedules along roadways where buses and private vehicles share infrastructure facilities (Transportation Research Board, 2010). The conventional bus is the most popular PT mode in the world and has the highest percentage of PT passenger share and/or passenger miles travelled. For example, in 2012, approximately 51% of all transit passengers in the United States used the buses (Federal Transit Administration, 2012).

Bus rapid transit (BRT)

‘BRT is a flexible, rubber-tired form of rapid transit that combines stations, vehicles, services, running ways, and Intelligent Transport System (ITS) elements into an integrated system with strong identity’ (Levinson *et al.*, 2003).

Danaher *et al.* (2007) stated the main features of BRT systems as follows: (i) Dedicated (bus-only) running ways (preferably, physically separated from other traffic); (ii) Accessible, safe, secure, and attractive stations; (iii) Easy-to-board, attractive, and environmentally friendly vehicles; (iv) Efficient (e.g., off-board) fare collection; (v) ITS applications can provide real-time passenger information, signal priority, and service control; (vi) Frequent, all-day service; and (vii) Distinctive system identity.

All BRT systems must have running ways, stations, and vehicles. Other major components consist of service design, the fare collection system, the application of ITS technology, and branding. Of these, service design is the *key* to system design. All components must be compatible and must support the service design (Danaher *et al.*, 2007).

Urban railway transit (URT)

The Office of Rail and Road (n.d.) determines the most popular urban railway transit to be light rail transit (LRT), tram system and underground system.

A tram system, tramway or tram is a railway on which streetcars or trolleys run. It is typically built at street level, sharing roads with traffic. This is defined as transit right-of-way (ROW) Category C (Vuchic, 2007).

Light rail transit is an urban rail transportation system that uses electric-powered rail cars along exclusive ROW at ground level, on aerial structures, in tunnels, or occasionally in streets. The operation is under full signal control and the current UK systems have full automatic train protection. As the name suggests, the term ‘light’ refers to operations carried out under a less rigorous set of regulations, using lighter equipment at lower speeds than those used by heavy rail, such as services provided by train operating companies. The ROW of light rail transit is also classified into Category B (Vuchic, 2007).

An underground system is defined as an electric railway public transport network (a metro or subway system) that runs both above and underground. The ROW of an underground system is classified into Category A, which is a fully controlled ROW where other vehicles and persons cannot access it (Vuchic, 2007).

Monorail

There are two types of monorail systems developed from the early stages of development below (Timan, 2015).

(i) The suspension railway systems on which the vehicle hangs under the fixed track-originally designed as freight transportation. The earliest urban application was the Wuppertal Monorail that was installed in 1901 and is still in use today (Wuppertal, n.d.).

Figure 1-1 The suspension Schwebebahn Wuppertal, Germany

Source: Wuppertal (n.d.)

(ii) The straddle-beam monorail system uses a vehicle that straddles a reinforced beam. In the 1950s, a German company by the name of ALWEG pioneered this technology, and installed its first system at Walt Disneyland in California. Most successful wheeled monorails today can trace their roots to the straddle beam ALWEG type monorail technology including the extensive Chongqing Monorail as well as Hitachi, Scomi and Bombardier Monorail (Timan, 2015).

1.2.3 Demand Responsive Transit (DRT)

DRT services provide transport ‘‘on demand’’ from passengers using fleets of vehicles scheduled in order to pick up and drop off people according to their needs. DRT is an intermediate form of transport, somewhere between bus and taxi which covers a wide range of transport services ranging from less formal community transport through to area-wide service networks (Mageean and Nelson, 2003). Currently, the most popular DRT are Taxi and ‘Ridesourcing’.

Taxi

Taxi can be categorised into the following types: taxi ranks; hailed taxis; dispatched taxi; Limousines; and shared Jitney and taxibus. Of these, the first three types seem to be common. Firstly, the primary objective of the taxi rank is to define a location at which prospective passengers may engage a taxi. Secondly, the concept of hailing a taxi has an equally long standing to taxis at ranks. Hailed taxis ply for hire and are engaged by an intending passenger flagging down an unoccupied taxi. Thirdly, for dispatched taxis, taxis available for pre-booking are a more recent innovation arising from the development and widespread use of telephone and radio technologies (Cooper and Mundy, 2010).

Ridesourcing (Uber and Lyft)

‘Ridesourcing’, also named as on-demand and app-based ride services, are rapidly expanding mobility options in many cities. Ridesourcing companies (e.g. Uber, Lyft and Sidecar) have made it possible for non-professional drivers of private vehicles to offer safe, reliable, affordable point-to-point rides, and allow the fare-paying public to efficiently summon a ride with a tap on a smartphone. These ridesourcing companies connect available private vehicle owners with travellers. Their smartphone apps also provide real-time location and navigation information, decreasing probabilities drivers will take circuitous routes or become lost, and informing travellers exactly when and where to expect their ride. In addition, riders choose the quality and size of the vehicle, and whether or not to share their ride with other travellers. The ridesourcing companies can pair travellers with overlapping routes into the same ride, and can suggest pick up points, dramatically cutting service cost, decreasing wait times and increasing vehicle occupancy. Flexible pricing ensures vehicles remain available late at night or in bad weather and automatic payment eliminates the need for passengers to carry cash or negotiate tips. The personal details of both passengers and drivers, as well as the history of their encounter, are recorded, reducing the likelihood of crime and facilitating the resolution of disputes. Passengers and drivers rate each other, and these ratings affect the ability of both to access future rides, creating an incentive system designed to reward civil interactions. This combination of features sets ridesourcing apart from traditional taxis and not-for-profit ridesharing (Flores and Rayle, 2017).

Ridesourcing services were first launched without legal authorization. Sidecar began testing its ridesourcing app in February 2012 and Zimride (later known as Lyft) began testing its app in May 2012. Sidecar launched publicly in June 2012, and Lyft in August 2012 whilst UberCab launched in San Francisco in June 2010 (Flores and Rayle, 2017).

1.3 Aims and Objectives

Given the above, the main aims of this thesis are:

- Analyse the feasibility of new public transport technologies in a mixed traffic environment with a dominance of motorcycles.
- Identify the most cost-effective mixed transport system in terms of given criteria where transport modes share infrastructure facilities.

To achieve these aims for the thesis, the research objectives can be specified as follows:

- Assess social costs including operator costs, user costs and external costs of the fixed line PT technologies, private transport (PRV), DRT and mixed transport for different user demand levels.

- Develop traffic simulation models of mixed transport with a dominance of motorcycles, to present their interactions and congestion effects in an existing mixed traffic environment. These models can evaluate the performance of each transport mode such as vehicle travel time.

- Develop transport demand models to evaluate changes in total demand of each transport mode and all transport modes after introduction of a new PT mode and/or a transport policy in an existing mixed traffic environment. These models can find out how the performance of the PT system and the transport policy might affect level of service of each transport modes, and therefore the total user demand levels.

- Integrate the social cost model, microscopic simulation model and demand models into the comparative economic assessment. Apply this assessment to a case study in Hanoi, Vietnam where a new PT mode and/or a transport policy are introduced. This application might demonstrate the usefulness of the comparative economic assessment in analysing the feasibility of a new PT technology and determining the most cost-effective mixed transport system.

1.4 Comparative Economic Assessment Structure

To obtain these objectives stated above, a Social Cost Model (SCM), an Incremental Elasticity Analysis (IEA), an Incremental Multinomial/Nested Logit Model (ILM) and a Microscopic Simulation Model (MSM) are developed for the first stage. These four models are then integrated into a comparative economic assessment (CEA). The integrated assessment compares mixed transport systems with the introduction of a new PT mode and/or transport policy in terms of average social cost (ASC), hence, the SCM is the core model. The SCM is developed for PT, PRV, DRT and mixed transport, which include operating costs, capital costs, user costs, accident costs, air pollution cost, noise pollution cost and climate change cost for different user demand levels. However, a stand-alone SCM has some disadvantages. First, as a strategic level model, the SCM considers an isolated corridor without any interactions of different modes and any junctions. This could be not true for mixed traffic environments where several transport modes share infrastructure facilities such as cars, motorcycles and buses. The MSM can overcome the first drawback because the MSM simulates all existing transport modes’ flows on the local network and therefore represent the vehicle interactions to obtain traffic data such as operating speed and travel time. Second, the demand for each transport mode would vary rather than be fixed. The IEA appears to solve this disadvantage because the IEA can evaluate endogenous changes in demand levels according to any change to existing transport conditions by using the demand elasticity with respect to a composite cost for general traffic. The changes in the total demand are caused by changes in parameters such as travel time, waiting time, fuel cost, alternative specific constant, etc. Third, the modal choice of users among all alternative modes is not taken into account in the SCM. The ILM overcomes this issue because it analyses preferences of users for all alternative transport modes with respect to generalised costs. As a result, the four models are needed to be integrated into a comprehensive assessment of urban mixed transport options. The structure of the CEA is shown in Figure 1-2.

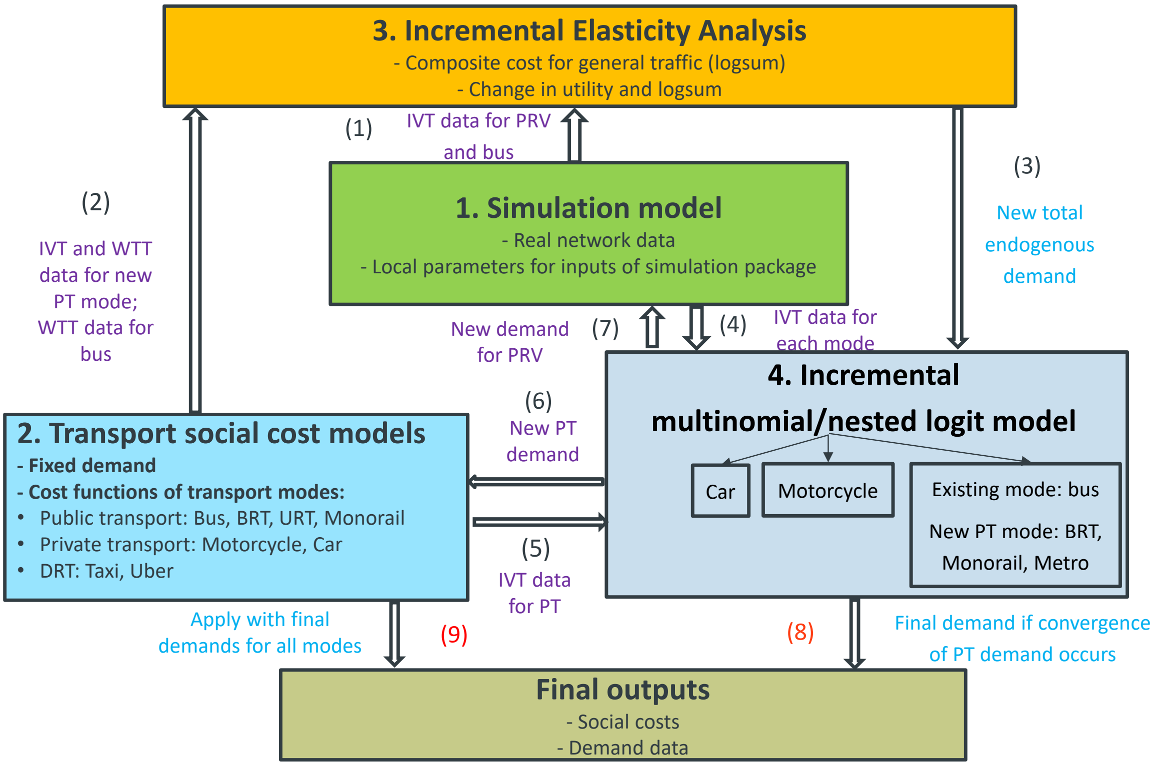


Figure 1-2 Operating procedure of completed assessment

The comparative economic assessment begins with providing existing passenger demand levels for all transport modes and required PT service frequency data, as well as an introduction of a new PT technology and/or a transport policy. The MSM simulating the existing mixed transport system and the SCM evaluating in-vehicle time and waiting time of new PT users provide required data (travel time, operating speed, etc.) for the IEA to estimate changes in total demand of all transport modes. The required data obtained from the MSM and SCM; and the new endogenous demand from the IEA are input to the ILM to estimate new modal share and demand level of each transport mode. These new demand levels are used as inputs for the MSM and the SCM for the next iteration of the CEA. Once the endogenous PT demand is converged, final outputs will be produced from the SCM to show the total social cost and average cost of each transport mode, as well as for the mixed transport system on the local transport network.

1.5 Thesis Structure

This study is divided into nine chapters. The contents of each chapter are summarised below to provide a brief introduction and guide through the research.

Chapter 1 Introduction

Chapter 1 is divided into five parts. The first part introduces a background trend and research problems. The second part introduces generally a range of existing urban transport modes including PRV (e.g. car and motorcycle), PT (e.g. conventional bus, BRT, URT and Monorail) and DRT (e.g. Taxi and Uber/Lyft). The third part lists Research Aims and Objectives. The fourth part illustrates the structure of the comparative economic assessment. The final part shows the structure of the thesis.

Chapter 2 Literature Review of Transport Supply

Chapter 2 summarises the key findings from a literature review of evaluation methods for infrastructure transport projects and transport cost models to find gaps. Firstly, it critically reviews economic and non-economic analysis techniques of transport infrastructure options and thereby identifies their drawbacks. These techniques include cost-benefit analysis, cost-effectiveness analysis and multi-criteria analysis. Of these, the cost-effectiveness analysis is selected for this study. Secondly, it critically reviews transport cost models to justify that social cost models for motorcycle, DRT (e.g. Uber and Taxi) and new PT technologies (e.g. Monorail) need to be studied deeply, as well as for a mixed transport system where many transport modes share infrastructure facilities.

Chapter 3 Literature Review of Transport Demand

Chapter 3 summarises the key findings from a literature review of transport demand models and traffic simulation models. Firstly, transport demand models are reviewed to determine which demand models are suitable for a situation where a new public transport technology is introduced in an existing mixed transport system. Secondly, different traffic simulation approaches are reviewed and a traffic simulation package is selected as the most appropriate modelling software for a mixed transport environment with the dominance of motorcycles.

Chapter 4 Methodological Framework

This chapter shows how the methodological framework seeks to fill the gaps in the literature. Therefore, a comparative economic assessment of a four-model structure is described. The four-model structure includes the Social Cost Model, the Incremental Elasticity Analysis, the Incremental Multinomial/Nested Logit Model and the Microscopic Simulation Model.

In addition, this chapter justifies the choice of a case study approach based on Hanoi, the capital of Vietnam. Then, Chapter 4 also explains the reasons for determining types of data in a real case study to be collected for filling the gaps and the comparative economic assessment.

Chapter 5 Transport Social Cost Model

Chapter 5 demonstrates social cost models for PT, PRV, DRT and mixed transport. The total social costs of each transport mode are the sum of three main components covering total operator costs, total user costs and total external costs. The total social costs for mixed transport are the sum of total social costs for PT, PRV and DRT, except infrastructure costs, which are shared by all transport modes. The infrastructure costs are calculated separately. In addition, the operating speed of all transport modes sharing infrastructure facilities is discussed.

The Hanoi case study is also shown in this chapter. The basic parameters and unit costs for the Hanoi case study are estimated. Additionally, the four cost models above are calculated for different infrastructure options and the results of these models are then discussed.

Chapter 6 Traffic Microscopic Simulation Model

Chapter 6 contains three main sections. Firstly, the data collection process for the Hanoi case study is summarised and the data analysis for inputs simulation models is then discussed. Secondly, the simulation models are developed in the VISSIM package to simulate the detailed traffic networks. Finally, the calibration and validation of the simulation models are implemented.

Chapter 7 Incremental Demand Model

Chapter 7 explains the reasons for choosing appropriate demand models for existing mixed transport environments. The Incremental Elasticity Analysis is used to estimate endogenous changes in total general traffic after an introduction of a new PT mode and/or a transport policy. The Incremental Multinomial Logit model is selected for situations where the new PT technology replaces all existing bus services while the Incremental Nested Logit model is chosen when the partial current bus services are replaced by the new PT mode. The outlines of these models are described in this chapter.

Chapter 8 Comparative Economic Assessment Application

This chapter illustrates the application of the comparative economic assessment. One main corridor in Hanoi, Vietnam is chosen as a case study of this CEA, where the existing mixed transport situation is compared to twelve transport infrastructure options with an introduction of a new PT technology (Bus Rapid Transit, elevated Metro or Monorail) replacing the whole or partial existing bus services; and with or without a congestion charge scheme for PRV in terms of ASC, total general demand and PT share.

Chapter 9 Conclusion

The final chapter summarises the whole study and discusses the main findings and contributions. The limitations of the study are identified and the future work is suggested.

Chapter 2 Literature Review of Transport Supply

2.1 Introduction

Transport has played an important role in social and economic development. Building and upgrading transport infrastructure stimulates economic activity and development. Increasing and improving the quality of the supply of transport services would benefit such a change (Cowie, 2009). As a result, the evaluation of transport schemes is vital for decision makers to choose the best option on the basis of an agreed criterion or set of criteria. The best alternative can maximise utility to society, which can be defined as maximising revenue, environmental benefits, the number of employed people, road safety, modal share of public transport, or any combination of these and many other factors. The two types of evaluation method for transport infrastructure projects including economic and non-economic analysis techniques are reviewed in the next part of this chapter.

The form of evaluation method varies considerably between countries. Because this study focuses on infrastructure options of all transport modes in urban areas in LMICs where motorcycles are dominant, the cost-effectiveness analysis is chosen. The reason for that will be explained below. For this analysis, all relevant costs are measured in monetary terms and the project outputs are expressed per unit cost. Therefore, cost functions for PT, PRV and DRT are reviewed separately in the third part of this chapter.

2.2 Transport Assessment

There are two distinct types of assessment for transport infrastructure projects including economic analysis and non-economic analysis techniques. The economic analysis methods are involved in conventional microeconomics, where small segments of the economy (e.g. individual company or public organisations), are calculated. Cost-benefit analysis (CBA) and cost-effectiveness analysis are the most popular economic analysis methods. The most common non-economic analysis method is the multi-criteria technique that goes beyond economic terms (Rogers and Duffy, 2012).

2.2.1 Economic analysis methods

2.2.1.1 Cost-benefit analysis

Cost-benefit analysis attempts to measure the net social benefit of a development project. The analysis thus tends to choose those projects for which there is a high surplus of social benefit over cost. The analysis framework can cover relevant costs and benefits, which are then expressed in monetary terms (Cowie, 2009; Rogers and Duffy, 2012). CBA guides decision makers through two main types of decision as follows. Firstly, a 'yes/no' decision determines whether a development scheme should be undertaken or not. Secondly, an 'either/or' decision identifies a situation, either where one of several proposed options is chosen for implementation, or where there is a choice between two or more alternative paths to achieving some agreed objectives (Rogers and Duffy, 2012).

CBA considers all costs and benefits that can be monetised. Each country or international organisation defines its own components in CBA. In UK transport practice, the costs include capital and operating costs such as maintenance, drivers' wages and operating power supply whilst the main benefits cover time savings, accident reductions, decreases in operating costs, reductions in noise, air pollution and greenhouse gases (Cowie, 2009; Department for Transport, 2018a). However, in the CBA framework of the World Bank Bus Rapid Transit project in Ho Chi Minh City, Vietnam, the benefits include time savings, improved traffic safety and reductions in vehicle operating costs because transport-related air pollution, noise reduction and other wider benefits cannot be monetised with enough certainty (World Bank, 2015a).

CBA is one popular approach for assessing transport projects in developing countries funded by the Asian Development Bank's loans (Asian Development Bank, 2017). For example, CBA is required for feasibility studies of Bus Rapid Transit (Asian Development Bank, 2008). Transport demand forecast is an important and critical element in CBA. In practice, the demand forecast seems to be simple in most Asian Development Bank appraisals. In addition, using the 'rule of half' in CBA cannot be appropriate in projects involving a modal shift such as an investment in a new PT mode (BRT, LRT or Metro) (Asian Development Bank, 2013). Hence, Asian Development Bank (2013) suggested that sophisticated multi-modal transport models (e.g. variable demand models) would be required for large transport projects with significant effects on the mode choice, travel time and origin-destination flows (e.g. Metro systems).

Asian Development Bank (2007) proposed a road improvement project in Vietnam and Cambodia, which is an integral part of the large Southern Economic Corridor from Bangkok, Thailand across Cambodia to Nam Can in Vietnam. The improved road option was chosen because neither improved rail nor water corridor were feasible. The main reason is that great capital investment was required for improving rail networks while goods movement by water is very slow. Then, using a basic cost-effectiveness calculation, initial project screening for three improved road options was conducted to choose the most efficient alternative one for detailed appraisal. CBA was implemented for the selected option in the initial project screening. The project's costs included construction costs, maintenance costs and costs arising from land acquisition and resettlement compensation. The benefits include reductions in vehicle operating costs and travel time due to an improvement in the existing road network. The benefits were calculated from the differences between the costs in the with- and without-project scenarios. The results of CBA showed that the project should go ahead. However, there are the following drawbacks of the CBA in the project. Firstly, the shifts between transport modes were not considered. Secondly, traffic accidents costs and environmental costs were not included in CBA.

In a different study, Grimaldi, Laurino and Beria (2010) developed a stylised CBA model to evaluate the choice between conventional bus and upgrading towards a light rail transit (LRT) system in an urban corridor where different bus services superimpose their routes while having different paths in the outskirts (see Figure 2-1). An alternative would be upgrading to a light rail system on the corridor where existing bus lines overlap. By using the investment cost of a 30 years lifetime light rail system, fixed maintenance and operating costs and passengers' generalised time costs consisting of in-vehicle time, delay time, waiting time and modal interchange time, Grimaldi, Laurino and Beria (2010) evaluated the total costs and benefits of the two options (existing bus services and new light rail system) in terms of Net Present Value (NPV). The benefits of the introduction of LRT include decreases congestion external cost due to a shift from car users to PT and improved regularity of the systems. Some obvious findings of this study are shown below.

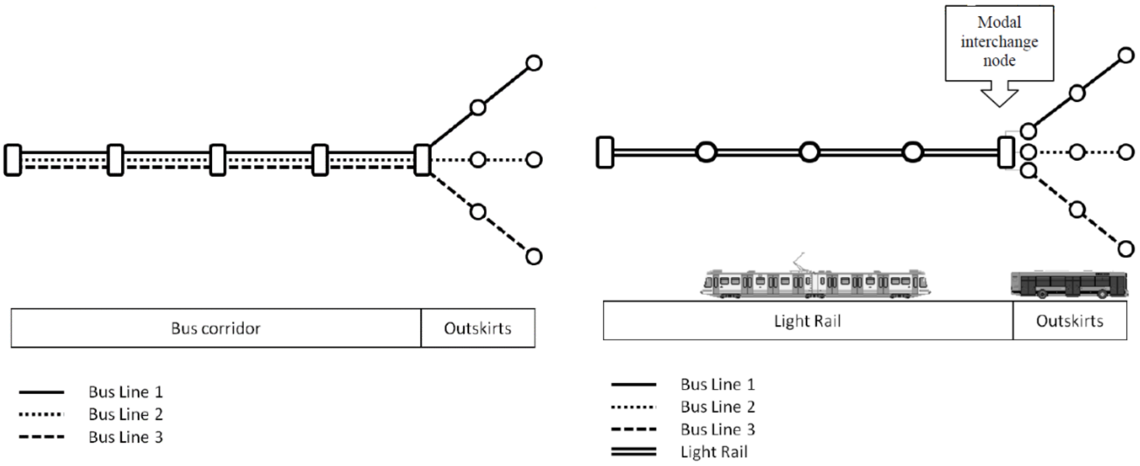


Figure 2-1 Stylised network with existing bus services (left) and alternative LRT (right)

Source: Grimaldi, Laurino and Beria (2010)

- The new (generated and diverted) demand due to an introduction of LRT is important only in case of extreme congestion.

- When demand is high, replacing from bus to LRT can lead to lower operating costs.

- LRT can be reasonable with the short average journey length if the investment cost of LRT is extremely cheap.

- If the demand is below 6 Million passengers/year, LRT is feasible only under very special conditions: cost less than €200 Million and (i) no interchange users, or (ii) generated demand represents over 50% of the total demand, or (iii) the average trip length is higher than 10 km, or (iv) more than 50% of streets are under congestion conditions, or (v) operating speed above 25 km/h, or (vi) extreme reduction in operating costs.

- If the investment cost is higher than €800 million, LRT is feasible only under very particular cases: demand of more than 20 Million pax/year and (i) no interchange users or (ii) a reduction of operating cost of more than 50%, or (iii) diverted demand from cars is above 50%, or (iv) average journey length is greater than 15 km, or (v) more than 80% of streets and hours of a day are under congestion condition, or (vi) average operating speed is above 30 km/h.

However, there are some issues with CBA. Firstly, a major drawback is that any costs and benefits that cannot practicably be quantified in monetary terms are excluded from the framework. When several relevant benefits of the comparative option cannot be monetised, the cost-effectiveness analysis can overcome this issue (Independent Evaluation Group, 2010; Asian Development Bank, 2017). Secondly, the potential lack of a clear direct relationship in CBA between the outputs and objectives of transport schemes is another disadvantage. This can be solved by multi-criteria analysis in such situations (Cowie, 2009). Moreover, CBA of a completed project can be troubled by the failure to collect relevant data, in particular, this might occur in LMICs (Independent Evaluation Group, 2010).

2.2.1.2 Cost-effectiveness analysis

The cost-effectiveness analysis is an important variant of CBA, which retains half the basic structure of CBA. This is especially useful in situations where the relevant benefits of the comparative options are not quantified in monetary terms and/or an objective of the project is not measurable in monetary terms (Mackie, Nellthorp and Laird, 2005). Indeed, all relevant costs are measured in monetary terms, whilst the expected benefits of a proposed project are quantified as some measure of effectiveness. The project outputs are described in physical terms and expressed per unit cost. These outputs are then compared with some base cases such as a ‘do nothing’ scenario (Rogers and Duffy, 2012).

The most important step in the cost-effectiveness analysis is to select which measure or measures of effectiveness to use in the process. The measures of effectiveness in this analysis for transport projects can be an average cost per passenger, transport passenger demand, reductions in accident levels, reductions in noise level, savings in travel time and improvement in air quality. Of these, the number of actual public transport users that will be attracted by each option is fundamental to the feasibility of any transit system, as well as the average cost per passenger (Rogers and Duffy, 2012).

As detailed in Preston (2021), several studies on comparative costs of transport modes have been conducted following the pioneering study of Meyer, Kain and Wohl (1965). This original study analysed comparative costs for different transit modes (rail, express bus, flier bus) and automobile for three scenarios (6-mile, 10-mile and 15-mile service) in both medium population densities and high population densities. The output measure in this study was the average passenger trip cost. The results showed that costs for all PT services decrease as a function of hourly passenger volume along the corridor. At the lowest passenger demand of around 5,000 passenger/direction-hour, automobile is the cheapest mode. The rail systems are the cost-effective modes in high population densities, whilst bus systems have the lowest cost in the low population density areas.

Brand and Preston (2003) studied the Tools for Evaluating Strategically Integrated Public Transport (TEST) project, which developed a strategic evaluation tool for integrated PT. The prototype software helps users to explore the most appropriate PT technology (or technologies) for urban and short distance inter-urban corridors. In the TEST project, the authors developed a stand-alone model to compare total social costs of 15 different PT modes including conventional bus, light rail and heavy rail system, and personal rapid transit at a strategic planning level. In conjunction with the stand-alone model, an integrated model was also developed to evaluate alternative options in a case study of a guided bus system on a busy urban/inter-urban corridor in Oxfordshire, UK (Abingdon - Kidlington).

In the stand-alone model, the total social costs of the 15 conventional and advanced PT technologies were calculated for a single 12 km route corridor rather than a complete network. The demand was assumed to be fixed demand ranging from 1,000 to 200,000 daily passenger. Final outputs of the stand-alone model included ASCs, marginal operating costs and marginal external costs of congestion (in pence per passenger-km). The results showed that the conventional bus has advantages for low daily demand of less than 40,000 passengers/day, while suburban heavy rail is the best mode when demand ranges from 40,000 to 88,000 passengers/day. Underground has advantages when demand is higher than around 100,000 passengers/day.

In the integrated model, three alternative networks for the case study were coded in the VIPS software, which is now part of the wider VISUM package (Brand and Preston, 2003):

- *Option 1, or default*: simulating existing public transport supply for the Abingdon – Kidlington corridor.

- *Option 2*: simulating alternative supply, which was based around the proposed guideway, with a city centre loop to connect to the same zones as in the default option. Three busy services re-routed via Guided Transit Express, which enter the road network located to the South of Oxford Railway Station. Simulated corridors for Options 1 and 2 are shown in Figure 2-2.

- *Option 3*: simulating alternative supply, which is based around the proposed guideway, with direct routing past the railway station. There is no city centre loop and the average additional walk time from/to city centre is assumed as 7.5 minutes.

The stand-alone model was linked with a public transport network model (VIPS) and with highway network models (CONTRAM, SATURN) to develop an appraisal spreadsheet broadly consistent with Transport User Benefit Assessment (TUBA). The default option was compared to Options 2 and 3 in terms of main performance (e.g. total trips, PT boardings and trips per vehicle-hour) and cost indicators (e.g. generalised costs, operating costs and capital costs). The findings for this evaluation are shown as follows (Brand and Preston, 2003):

- The guided bus system causes modest reductions in operating costs and, at least for Option 2, increases in revenue.

- PT passengers travelling from Kidlington and Abingdon to the City Centre and P&R users at Peartree and Redbridge have advantages whilst PT travellers that have origins or destinations in Oxford (not the City Centre) experience disadvantages due to reduced bus frequencies.

- The limited mode shift from cars to PT leads to modest non-user benefits.

- The corridor does not seem to be appropriate for a relatively capital intensive guided bus system due to the daily demand of less than 30,000 passengers per day.

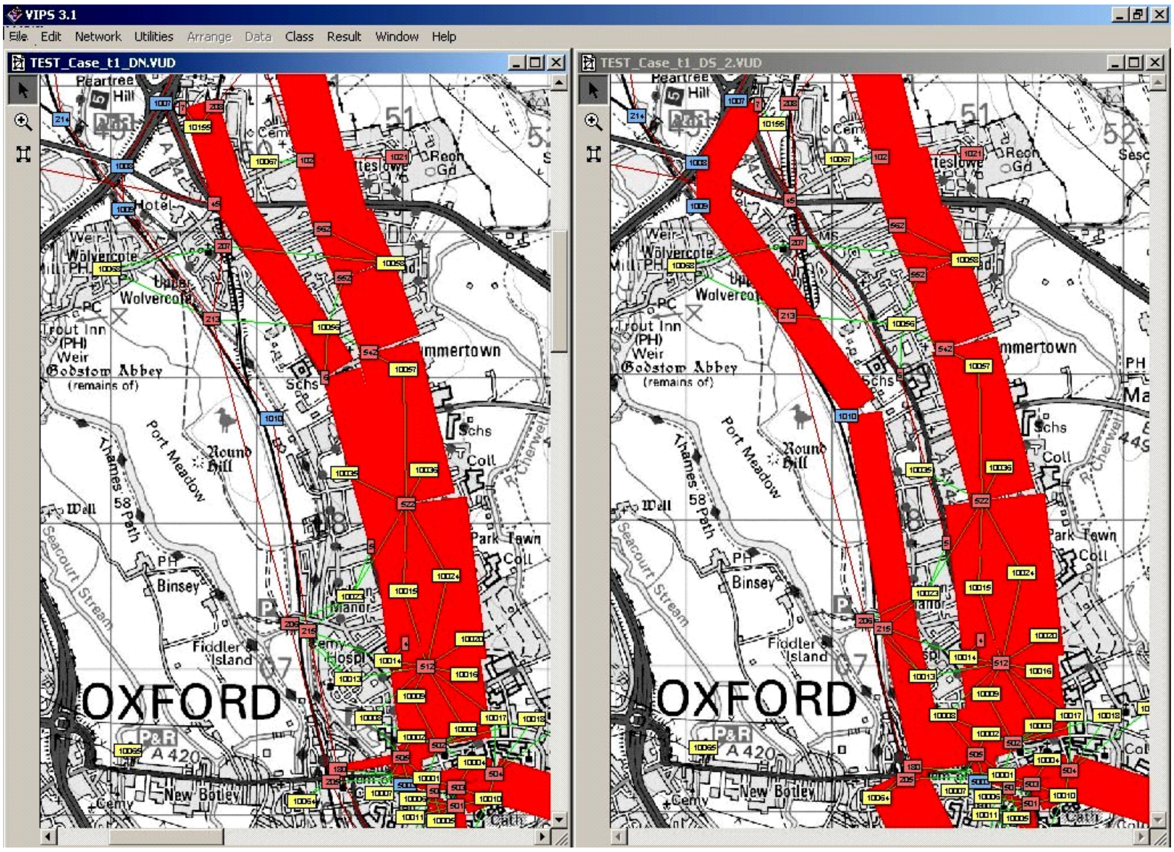


Figure 2-2 Simulated corridor in Oxfordshire, UK for Option 1 (left) vs. Option 2 (right)

Source: Brand and Preston (2003)

In addition, Jakob, Craig and Fisher (2006) assessed the total costs of private transport (passenger car) versus public transport (bus) in the Auckland region of New Zealand. The total costs included the external and internal costs. The former consists of accident costs, air pollution cost and climate change cost while the latter is directly spent by the government to run the transport system. That study did not consider vehicle capital cost and other costs such as congested-related delay costs. The results showed that the external costs of cars and buses account for around 53% of the total costs. In addition, the total costs of cars per passenger-kilometre are twice those numbers of buses in Auckland.

Moreover, Tirachini, Hensher and Jara-Díaz (2010) compared bus rapid transit, light rail and heavy rail transit over a radial trunk network with the objective of minimising the total costs (operator and user costs). The route length and the average trip distance were 30 km and 10 km correspondingly. The optimisation of the total costs was based on the frequency and number of PT lines, which impact on walking, waiting and in-vehicle time for PT users as well as on the total operator costs (a combination of land, infrastructure and operating costs). Based on data from Australian cities, the results suggested that BRT is the most cost-effective mode in most of the scenarios analysed due to lower operator costs, access time cost and waiting time cost. Light rail (heavy rail) transit is more cost effective than BRT only if the speed of these technologies is at least five (nine) km/h than the BRT speed of 31 km/h.

In a different study, Wang (2011) compares the full costs of seven passenger modes in large Chinese cities. The seven modes, which include heavy rail transit, light rail transit, arterial bus, bus rapid transit, expressway bus flier, automobiles and bicycles, are evaluated at varied traffic volumes in hypothetical radial and circumferential commuting corridors (see Figure 2-3). Using detailed estimates of private and social costs, the full costs of each mode covering capital, operation, user time, safety and environmental costs, are minimised by optimising infrastructure investment and operational plans. Firstly, public transport vehicle size and train length are optimised within given ranges in addition to service frequency, and a maximum service frequency is applied to single-route operation of each public transport mode. Secondly, road widths at different segments of the corridors are optimised in accordance with the traffic volume of the respective section. Finally, the operating speed of transit is estimated as a function of passenger volume.

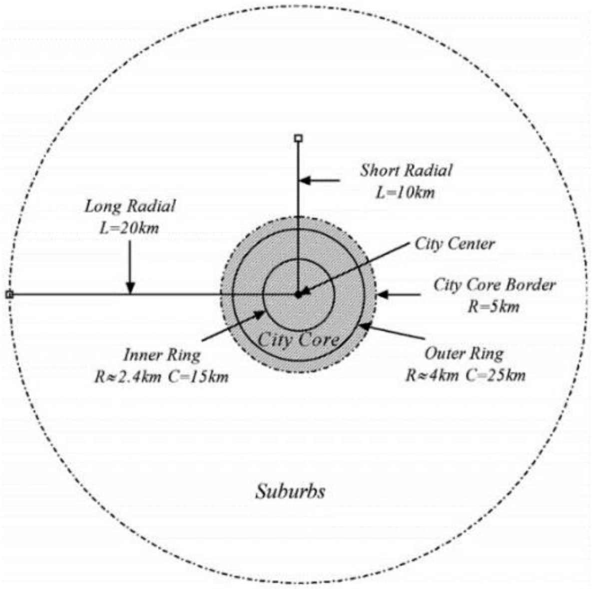


Figure 2-3 Representative large Chinese city and corridors

Source: Wang (2011)

Some of the key outcomes of the study were shown below. On all corridors and across different social discount rates scenarios, commuting by one or more forms of bus transit or bicycle is cheaper than automobile or rail in terms of average cost per passenger-km. However, in ring corridors, rail can be almost as cheap as bus under certain conditions, and bicycle can be less cost-effective than bus in some cases. Commuting by automobile is more expensive than bus transportation at low traffic volumes (Wang, 2011).

2.2.2 Non-economic evaluation methods

Among non-economic evaluation methods, multi-criteria analysis is the most common methods for evaluating transport alternative options. The multi-criteria analysis (MCA) can be used in situations where there are several different kinds of impacts and objectives of projects that cannot readily be valued (Department for Transport, 2018a). This type of decision model is particularly relevant to the appraisal process for a public sector based engineering proposal where environmental and social criteria are as important as the economic considerations (Rogers and Duffy, 2012).

The overall strategy within multi-criteria decision models includes decomposition and aggregation. The decomposition process breaks a problem down into a number of smaller problems, which involves each of the individual criteria. This division of a problem into a number of smaller problems helps the decision maker to analyse the information that comes from varied origins. The aggregation process combines all the individual pieces of information together to make a final decision. In the multi-criteria technique, the aggregation process involves either the use of information or the making of certain assumptions, which considers the relative importance weightings of dissimilar criteria. The process is one that enables inclusion of all possible factors, rather than one that causes the exclusion or marginalisation of certain classes of attribute, and therefore makes it easier to gain public acceptance of the appraisal findings (Rogers and Duffy, 2012).

The application of multi-criteria analysis in the transport sector covers the evaluation of policy measures in passenger transport, strategic decisions, technologies, and infrastructure projects. Generally, the multi-criteria analysis includes the seven following steps: (i) Step 1: Define alternatives; (ii) Step 2: Stakeholder analysis; (iii) Step 3: Define criteria and weights; (iv) Step 4: Choose criteria, indicators and measurement methods; (v) Step 5: Overall analysis and ranking; (vi) Step 6: Show results; (vii) Step 7: Implementation (Macharis, De Witte and Ampe, 2009). For example, Tzeng, Lin and Opricovic (2005) use a multi-criteria analysis of alternative-fuel buses to improve environmental quality in Taiwan. In this study, the authors assessed 12 alternative fuels (e.g. electricity, hydrogen, and methanol). Then, 11 evaluation criteria including energy supply, energy efficiency, air pollution, noise pollution, industrial relationship, costs of implementation, costs of maintenance, vehicle capability, road facility, speed of traffic flow and sense of comfort are established and assessed by the relevant decision-marking experts, who are from the electric bus manufacturing, academic institutes, research organisation, and bus operations sectors. Two multiple-criteria analyses, called the Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) and the compromise ranking (VIKOR) methods, are then used for analysis and ranking. The results of this study showed that the hybrid electric bus is more suitable at present for public transport to improve environmental quality. However, it appears that many believe that the impacts of transport infrastructure project are mainly economic (i.e. quantifiable) in nature and therefore the multi-criteria analysis has rarely been used in the transport sector (Mackie, Nellthorp and Laird, 2005). Similarly, Broniewicz and Ogrodnik (2020) examined the possibility of using multi-criteria methods to select the best route variant in terms of the environment. After reviewing the literature of MCA in the transport sector, those authors selected four methods including Analytic Hierarchy Process, Fuzzy Analytic Hierarchy Process, TOPSIS and PROMETHEE (a method encompassed in the so-called European trend) for evaluating the variant of the expressway section in north-eastern Poland. The results of the analysis were compared results of the analysis with the choice made in the analysed environmental impact report produced by the Polish General Directorate for National Roads and Motorways. The results of the conducted multi-criteria analysis almost overlap with the results of the analysed report for the selected undertaking.

Moreover, Ward, Dimitriou and Dean (2016) developed a generic multi-criteria analysis framework and attendant processes, which emphasise policy leadership within multi-stakeholder decision-making. This is termed as Policy-led Multi-criteria Analysis (PLMCA). The framework is applied to mega transport projects by using appropriate appraisal criteria to achieve sustainable development goals. This analysis focuses on both quantitative and qualitative dimensions and concerns of multiple stakeholders including feedback between appraisal and policy. Policy-led Multi-criteria Analysis was then applied to the appraisal of a mega transport project in the form of the Northern Line Extension in London (Ward et al., 2016). This application might help to identify the distribution of costs and benefits of projects, as well as the possible ‘winners’ and ‘losers’ over space and time, and under given scenarios. However, the results of this application do not present outcomes from an appraisal of the Northern Line Extension Project (NLE Project). In the study, the ‘NLE Project’ constitutes the ‘Preferred Option’ together with its envisaged related developments. The three main stakeholders consist of the public sector, private sector and civil society that involve local, regional, national and international ones. Eight different project dimensions include overall vision, economic, financial, transport, environment, regeneration, social and implementation. A PLMCA implemented a series of three multi-sector stakeholder role-playing workshops at three phases: project analysis and problem structuring, model building and model use. Three considered scenarios were under the policy guidance of the Greater London Authority with the support of the Treasury of the UK Government as follows. Scenario 1 is a ‘business as usual’ scenario that is based on projected improved current economic conditions that reflect past trends. Scenario 2 is a ‘prolonged economic downturn’ scenario that is aggravated by an unexpected pull-out of a key major investor or by some other unexpected major economic/political event. Scenario 3 is an ‘unexpected economic boom’ scenario where localised real estate and passenger patronage revenues well exceed those predicted. To conclude, it is proved that PLMCA can help determine the most relevant policies, related plans and stakeholder agendas affecting the project. In addition, this information platform might identify (i) areas of shared with a view to capitalise on where advantageous and/or (ii) divergent stakeholder interests with a vision of mitigating their risks where possible.

In another study, Barbosa et al. (2017) developed a multi-criteria model to assess urban public transport by focusing on user perceptions. The model combining the Multiple Criteria Decision Making/Aiding (MCDM/A) can identify the objective and subjective factors which determine a user's opinion of the service. The proposed method combines the MCDM/A techniques focused on the assessment of the transport services. The method includes seven steps: (1) development of the user journey map, (2) identification of evaluation items, (3) grouping the items, (4) setting the weights for items, (5) obtaining descriptors, (6) creation of scales for descriptors, and (7) obtaining the final tree and the overall equation. The model was then applied for the Integrated Public Transport System in Florianópolis, Brasil. The data were collected from 260 users of the Florianópolis transport service through a survey and interviews, as well as an expert on public transport service through interviews. Ten groups of users' opinions include comfort, vehicles, customer service, information, reliability, security, payment, entertainment, accessibility, and terminal infrastructure. These ten groups include 30 items, that were produced in the structure of a tree with weights for each item. The results proved that the evaluation model might provide support to public transport operators for improvements of transport services by offering a comprehensive view. This evaluation model can be used as a reference to understand whether or not there have been service improvements over time.

2.2.3 Summary

When building or upgrading transport infrastructure is identified as a solution for meeting specific objectives of government, community or other involved parties, then choosing an evaluation method is very important for decision makers in order to select the best option. Multi-criteria analysis, cost-benefit analysis and cost-effectiveness analysis have been reviewed. Scope of application and issues of each method have been also discussed. CBA might be used in situations when all costs and benefits can be monetised. Multi-criteria analysis can be used in situations where several types of project impacts and objectives cannot readily be valued (Department for Transport, 2018a). In particular, public sector engineering projects have environmental and social criteria that are as important as the economic considerations (Rogers and Duffy, 2012). The cost-effectiveness analysis is especially useful for transport projects where some relevant benefits of the comparative options are not monetised and/or another objective of the project is not measured in monetary terms such as the number of public transport passengers (Mackie, Nellthorp and Laird, 2005).

Because the topic of this thesis is about urban transport infrastructure options in LMICs, the cost-effectiveness analysis is chosen because of the following reasons. Firstly, there are several alternatives of new PT technologies (e.g. BRT, Monorail and Metro) for existing mixed traffic environments with many modes such as motorcycles, cars, DRT and conventional bus. In conjunction with the introduction of the new PT mode, some transport policy can be introduced such as a congestion charge scheme or air pollution charge scheme for private transport. This leads to a huge range of options, which will be compared with the base case, in terms of criteria such as an average cost per passenger, increases in modal share of PT or general traffic. Therefore, the cost-effectiveness analysis might be most consistent with these kinds of projects because this analysis helps simplify analysis, especially across a range of transport modes. The drawback of the 'rule of half' in CBA is overcome by CEA. Secondly, in LMICs, there seems to be a lack of available data for monetising benefits for projects, which involve transport-related air and noise pollution and climate change impacts for certain urban transport modes. Moreover, the failure for collecting relevant data might cause trouble for CBA of a completed project in LMICs (Independent Evaluation Group, 2010). This means that the CEA approach might be better than the CBA approach. Thirdly, there are a few drawbacks of MCA for the study context. Since major policy decisions that have far-reaching consequences with regard to both space and time, the identification of all the potential stakeholders and their agendas seems to be a problem and is made even more difficult by time and budget constraints to undertake the analysis in many cases (Mouter, 2020). In addition, weights appear to be one of the most controversial aspects of any MCA exercise. In the course of time, difficulties in determining suitable weighting schemes have hampered the use of MCA in several countries (Annema, Mouter and Razaei, 2015). Moreover, the overall score obtained by combining scores and weights might not indicate the possible net social benefits generated by the study options (Dobes and Bennett, 2009). Hence, the 'best' option, which is the one with the highest overall performance score, might establish an economically inefficient allocation of resources and cause a reduction in overall welfare within society (Mouter, 2020). Finally, more informed, transparent and holistic decision-making is required in MCA for mega infrastructure projects (Dimitriou, Ward and Dean, 2016) but might not easily be achieved in low- and middle-income countries. As a result, cost functions of different types of transport modes, which are included in the cost-effectiveness analysis, are going to be discussed in the next section.

2.3 Transport Cost Models

Litman and Doherty (2011) stated that there are 23 cost categories in cost-benefit analysis in the transport sector. These include vehicle ownership, vehicle operation, operation subsidies, travel time, internal crash, external crash, internal activity benefits, external activity benefits, internal parking, external parking, congestion, road facilities, land value, traffic services, transport diversity, air pollution, greenhouse gas pollution, noise, resource externalities, barrier effect, land-use impacts, water pollution and waste. However, total costs for PT, PRV and DRT have different cost elements and dissimilar estimation of these cost elements. Furthermore, available data can dictate which cost elements can be considered for the evaluation of the transport project. Therefore, in order to understand cost functions for each transport mode group in more detail, the following subsections will review the cost functions of PT, PRV and DRT separately.

2.3.1 Cost functions of public transport

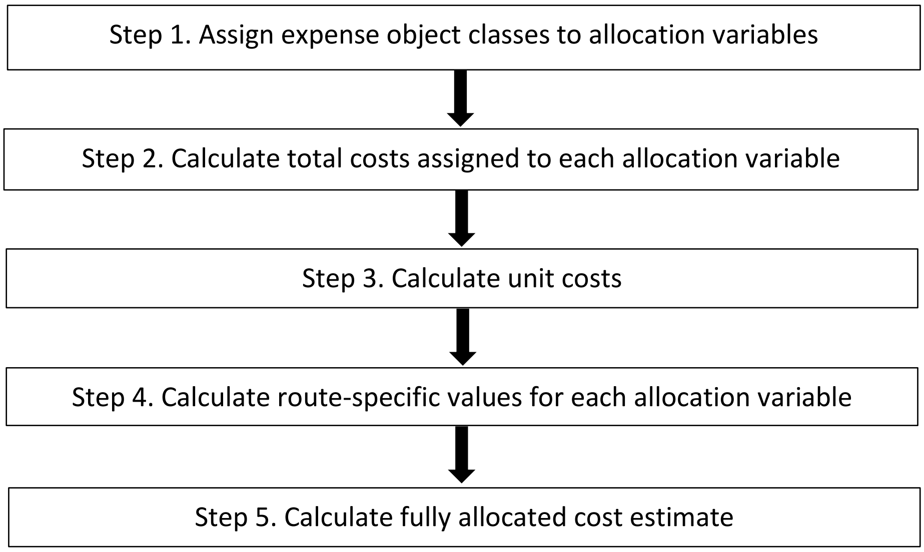
The social costs generated by PT modes and borne by society include operator costs, user costs and external costs (Brand and Preston, 2003). In addition, 'wider economic impact' of a new transport scheme is guided by the Department for Transport (2018b). Elements of each cost group are detailed below.

2.3.1.1 Operator cost

The evaluation of the total operator cost may be classified in three ways: engineering approach, accounting approach and statistical approach. Firstly, an engineering cost model utilises cost-estimating equations proportional to the main resources consumed in support of specific service (Bruun, 2007). Secondly, an accounting approach is a cost model where cost is assumed to be a linear function of intermediate outputs such as Route-Miles, Peak Vehicles, Vehicle-Hours and Vehicle-Miles. This method involves a Fully Allocated Costs model, in the sense that all cost objects are distributed to one and only one output: there are no fixed costs and no shared costs (Small and Verhoef, 2007). Finally, the statistical cost method collects data from numerous transit agencies and/or time periods and uses statistical inference to estimate the parameters of cost functions (Small and Verhoef, 2007). In practice, the boundaries between engineering, accounting and statistical approaches might be unclear. Furthermore, the available descriptive data has a strong influence on cost modelling decisions and the precise definitions of the resource variables.

Fully Allocated Costs (FAC) Model

Studies using the ‘FAC’ model usually assume that cost is a linear function of a few measures of intermediate outputs such as Route-Miles, Peak Vehicle, Vehicle-Hours and Vehicle-Miles (Small and Verhoef, 2007). The US Department of Transportation (1987) provided a step-by-step summary of the cost allocation process using a three-variable, fully allocated, unit cost model, which is shown in Figure 2-4. The three variables used for allocation are Vehicle-Hours (VH), Vehicle-Distance (VKM) and Peak Vehicle (PV).



Step 1. Assign expense object classes to allocation variables

Step 2. Calculate total costs assigned to each allocation variable

Step 3. Calculate unit costs

Step 4. Calculate route-specific values for each allocation variable

Step 5. Calculate fully allocated cost estimate

Figure 2-4 Summary of the cost allocation process using a unit cost model

Source: US Department of Transportation (1987)

Similarly, White (2002) gives an example of a systematic method for assigning the total short-term expenditures to three variables of bus service (VH, VKM and PV). In step 5 of Figure 2-4, the operator costs of transit systems (OC) are expressed as follows:

$$OC = c_1 VH + c_2\, VKM + c_3\, PV \tag{2-1}$$

Where,

c_1, c_2, c_3 are the unit costs, which are calculated in Step 3 of Figure 2-4;

VH, VKM, PV are the outputs, which are calculated in Step 4 of Figure 2-4;

Note that accounting practices vary from agency to agency and country to country, and occasionally inaccurately reflect the economic costs (Small and Verhoef, 2007).

Engineering approach

The study by Meyer, Kain and Wohl (1965) used the engineering approach, supplemented by the accounting approach and the statistical approach. The operator cost of several public transport forms is estimated as.

$$TC = \alpha nU + \beta M + \gamma L + S \tag{2-2}$$

Where,

TC is the total cost for some specified time period (usually, taken to be one year);

U is the number of basic vehicle groups needed;

M is the miles of vehicle travel during the period;

L is the lane-miles or track-miles of roadway or roadbed needed;

S is the structure and related costs (for example, highways, roadbed, right-of-way), which is the sum of the annual maintenance cost and capital cost obtained by using a capital recovery factor;

n is the number of vehicular units operating as a coordinated group or train;

α is the cost per period per vehicular unit employed;

β is direct costs assignable on the basis of miles of travel performed;

γ is cost assignable on the basis of miles of roadway or roadbed required.

Data for the engineering approach are from public transport operators' accounts, statistical analysis and from actual price quotes (Small and Verhoef, 2007).

Statistical approach

Different to the accounting approach, statistical studies use not only linear cost function but also other forms such as products, quadratic, logarithms and exponentials of the variables. For example, Wunsch (1996) compiled cost data from a cross-section of 178 different operating agencies in Western and Northern Europe. The author assumed that the cost per km travelled for each mode is equal to the sum of following variables: (i) A constant which does not depend on wages such as fuel; (ii) A constant which depends on wages such as administration cost; (iii) Costs that depend on the inverse of speed and wages such as drivers costs; and (iv) Costs that depend on vehicle capacity and wages such as maintenance costs. Then, the local wage rate and average wage rate over the sample are taken into account in the cost estimation.

2.3.1.2 User cost

Transit users spend time accessing the services, waiting for vehicles, riding in vehicles, probably transferring between vehicles, and walking to their final destinations (Small and Verhoef, 2007; Kittelson & Associates *et al.*, 2013). The total costs of PT users are converted from generalised time as per the following equation (Brand and Preston, 2003):

$$TUC = (W_{walk} * TT_{walk} + W_{wait} * TT_{wait} + TT_{IV}) * VoT \tag{2-3}$$

Where,

TUC is the total annual user cost (£/year);

W_{walk}, W_{wait} are the factors to represent the weighting perception of walking time and wait time relative to in-vehicle time.

TT_{walk}, TT_{wait}, TT_{IV} are the total annual walking time, wait time and in-vehicle time correspondingly (hours);

VoT is the value of IVT for the PT technology (£/hour);

Transit walking time

Transit walking time is defined as the total time taken to access from the origin to the nearest transit stop/station and to walk from the alighting stop/station to the destination. Service coverage is the area located within walking distance of the transit service. For a planning analysis, the service coverage of a bus stop can be defined as falling within a 400-m radius, while for rapid transit (rail or BRT) this radius is 800 m (Kittelson & Associates *et al.*, 2013). According to the results of a survey sample of 20,000 households, which were implemented for the Hanoi Transportation Master Plan by the Transport Engineering Design Incorporated in 2012, the service coverage of a bus stop in the main districts of Hanoi is 480 m (Transport Engineering Design Incorporated, 2013). For a more detailed analysis, the service coverage of a transit stop can be decreased in proportion to the additional time required to climb hills, cross streets, etc. (Kittelson & Associates *et al.*, 2013). Brand and Preston (2003) suggested an equation to evaluate the walking distance from/to a stop based on the average service coverage and the average distance between stops/stations. The walking time is then calculated by taking into account an average walking speed.

Transit waiting time

Simply, the average transit waiting time can be estimated as one-half the headway between successive public transport vehicles at stops/stations (Mohring, 1972; Small and Verhoef, 2007).

When the PT service frequency is high (around 10 min or less), passengers will arrive at stops/stations randomly. If public transport vehicles with perfect depart reliability and capacity are sufficient to avoid pass-ups, the average passenger wait time is half the average headway (Kittelson & Associates *et al.*, 2013). However, if actual transit departures are not perfectly reliable, the average waiting time is longer than half the average headway and needs to be taken into account in the spread of the headway distribution (Kittelson & Associates *et al.*, 2013). The service frequency and dwell time are considered to estimate the average passenger wait time by assuming all transit passengers are evenly distributed (Brand and Preston, 2003).

Transit in-vehicle time

The IVT of PT passengers is estimated by dividing the trip length by the average operating speed.

Average transit operating speed

Brand and Preston (2003) defined transit operating speed, which accounts for the stop density restraint without capacity restraints, is estimated as:

$$V_{NoCap} = \frac{V_{max}*A*D_{stop}*1000}{\left(\frac{V_{max}}{3.6}\right)^2+A*\left(D_{stop}*1000+T_{dwell}*\frac{V_{max}}{3.6}\right)} \quad \textbf{(2-4)}$$

Where,

V_{NoCap} is the transit operating speed (km/h);

A is the acceleration and deceleration of the vehicle (m/s^2);

D_{stop} is an average distance between stops/stations (km);

T_{dwell} is an average vehicle dwell time per stop/station, including time required to open and close the doors; and passenger boarding/alighting time (seconds);

V_{max} is the maximum possible running speed (km/h).

Then, Li (2015) revised the equation of operating speed by considering two cases: traffic volume is smaller than capacity and traffic volume is higher than capacity. Li (2015) improved the equation in the study of Small (1983), which is shown in Equation (2-11). Li's revised equation is shown as follows:

$$V_{all} = \begin{cases} V_{NoCap} & if\ F \leq\ C_{fac}\left(= f * C_{inf}\right) \\ \frac{V_{NoCap}}{1+(1/0.15)*(\frac{F_t}{C_{fac}}-1)} & if\ F >\ C_{fac}(= f * C_{inf}) \end{cases} \quad \textbf{(2-5)}$$

Where,

F is the required service frequency (vehicles/hour);

C_{inf} is the infrastructure capacity;

f is capacity percentages, as listed in the following Table.

Table 2-1 Facility capacity as % of a base condition in different operating environments

Transit type	Mixed traffic (urban street)	Semi-exclusive (transit lane)	Exclusive (street median)	Exclusive (private right-of-way)	Grade-separated (busway or subway)
Bus	38%	52%	61%	87%	100%
Rail	41%	67%	100%	92%	100%

Source: Li (2015), adapted from Kittelson & Associates *et al.* (2013)

Transfer time

If the origin and destination of a passenger are not located in one PT service route, this passenger needs to transfer to other PT service. Hence, transfers appear to be a necessary part of a transit trip and transfer time is a part of the passenger's total trip time. Transfers can increase the possibility that a missed connection occurs, which might cause longer the total trip time of PT users (Kittelson & Associates *et al.*, 2013). However, if the ratio of transit trips is minor, the transfer time can be ignored. Because this thesis focuses on only one transport infrastructure corridor rather than a complete network, the transfer time will be not considered.

The value of time

The value of time (VoT) is very important and sensitive to estimate user costs. ''The value of saving a given amount and type of travel time by a particular person is the amount that person could pay, after receiving the saving, and be just as well off as before. This amount, divided by the time saving, is that person's average the value of time saved for that particular change'' (Small and Verhoef, 2007). These authors reviewed the literature on empirical estimates of the value of time over the world. The Transport Canada (1994) and the US Department of Transportation (1997) recommended using a value for personal travel by car equal to 50% of the average wage rate. In the UK, Wardman (1998) found that an average VoT in late 1994 prices is equal to 52% of the wage rate. Additionally, Mackie et al (2003) estimated that the VoT for commuting and other trips is 51% of the relevant wage rate. To conclude from empirical evidence, it seems to be evident that the value of time for personal journeys varies widely by circumstances, usually between 20% and 90% of the gross wage rate and averaging around 50% (Small and Verhoef, 2007).

Value of working time and non-working time

Value of travel time savings is derived on a Willingness-To-Pay basis by using stated preference evidence. Value of travel time savings can be categorised by journey purpose, specifically between values for journeys made on employers business (or working time) and non-working time values including commuting and all other leisure purposes (Department for Transport, 2017b).

The value of working time (excluding professional and freight drivers) varies significantly over a number of characteristics, such as traveller income, trip time, trip cost and trip distance. However, based on the recommendation from the 2015 Value of Travel Time Savings study, the value of working time is recommended for appraisal varies with distance and mode only. In addition, in a very limited number of cases (e.g. link-based), a single average of the value of time may be proper (Department for Transport, 2017b).

In terms of non-working trips, passengers put a value on their own time in that they will trade a cheaper, slower journey against a faster and more expensive one. Value of non-working time can vary in two following ways (Department for Transport, 2017b):

- Time spent on the same activity by dissimilar passengers, who have different income and journey characteristics; and

- Time spent on the same people on different journeys or parts of journeys.

Sensitivity testing should be carried out separately for both working time value and non-working time value (Department for Transport, 2017b).

For LMICs, World Bank (2005b) and Asian Development Bank (2013) recommended using the cost savings or wage rate approach for estimating working time value. A stated or revealed preference analysis is required to evaluate non-working time value. If the analysis is not conducted, the non-working time value for adults can be equal to 30% of household income per head while the number for children is 15%. Additionally, a study, which estimated the value of time in developing countries, was conducted in Bangladesh from 2000 to 2002 by the IT Transport (UK) with financial support from the Department for International Development (UK). The results showed that the average values of working time and non-working time were about 75% and 63% of the estimated wage rate in Bangladesh respectively (IT Transport, 2002). A subsequent study by the IT Transport was undertaken in Ghana and Tanzania in 2004. The key findings illustrated that the average base values of in-vehicle time were 64% and 49% of the wage rates for Ghana and Tanzania correspondingly (IT Transport, 2005).

Value of walking time, waiting time and in-vehicle time

Value of walking and waiting time can be greater than value of in-vehicle time. The values of time in the TAG Data Book should be multiplied by 2.0 for time spent waiting for public transport, as well as the value of time spent accessing or interchanging between modes of transport by walking or cycling. This applies to all journey purposes (Department for Transport, 2017b). Similarly, the value of walking and waiting time are slightly less than twice the value of in-vehicle time (Abrantes and Wardman, 2011). The value of walking and waiting time for transit journeys is 1.6 to 2.0 times that of in-vehicle time (Small and Verhoef, 2007). A ratio of the value of walking/waiting time to the value of in-vehicle time is recommended as 1.5 for developing countries (World Bank, 2005b; Asian Development Bank, 2013). This ratio was equal to 1.77 for Ghana in the study of IT Transport (2005).

The value of time for different transport modes

Wardman, Chintakayala and de Jong (2016) used an estimated meta-model for the value of in-vehicle time (IVT) for European countries. The results showed that the value of IVT might vary by mode due to differences in comfort, privacy, the ability to use travel time in a worthwhile manner, externalities due to the environment and security. Moreover, the value of IVT by car commuters is higher than by bus commuters in urban areas for all objective European countries. For example, in the UK, the value of IVT by car commuters in urban areas with free flow situation and congestion situation are €7.12 and €10.13 per hour correspondingly, whilst that number by bus commuters is only €5.41 per hour.

The value of time transfer over time and location

Value of travel time can be converted over time and prices in line with the growth in income (with GDP/capita elasticity of 1) and changes in prices (using the GDP deflator) between time periods. Both the value of working time and non-working time are assumed to increase with income over time with an elasticity of 1.0 (Department for Transport, 2017b). In terms of traffic congestion measurement, transfer of the value of time from one country to another country in Europe generally reflect WTP values rather than unit costs derived from macro-economic indicators (Maibach *et al.*, 2007). For evaluation of transport projects in LMICs, Asian Development Bank (2013) suggested the value of working time should increase with rising productivity while the value of non-working time rises with increases in average income over time.

2.3.1.3 External cost

In several previous studies, external costs are included in total social costs. The main external cost components are accident cost, noise pollution, air pollution, climate change and congestion cost

(Sansom *et al.*, 2001; Brand and Preston, 2003; Maibach *et al.*, 2007; Litman and Doherty, 2011). As those cost components are associated with levels of traffic volume (vehicle-kilometre), the total external costs are calculated by using the sum of the external unit cost of each PT mode to multiply the total vehicle kilometre. In these studies, several public transport modes are studied, which include bus and rail transit. Table 2-2 shows external unit costs by impact category in the UK. There appears to be very little evidence on external costs in LMICs, therefore, the benefit transfer method can be used for LMICs based on available evidence in developed countries (Asian Development Bank, 2013).

Table 2-2 External unit costs by impact category in the UK

Technology	Air pollution: p/vkm			Noise pollution: p/vkm			Climate change: p/vkm			Accidents: p/vkm		
	Low	Central	High	Low	Central	High	Low	Central	High	Low	Central	High
Single bus	14.5	27.6	42.1	2.8	11.8	13.9	2.1	2.4	2.8	0.3	1.7	3.2
Single bus on busway	14.5	27.6	42.1	2.8	11.8	13.9	1.8	2.1	2.5	0.3	1.7	3.2
Modern light rail	7.1	13.3	23.6	10.0	21.8	33.6	3.7	7.5	14.9	-	0.0	-
Underground	-	24.8	-	-	26.3	-	-	8.3	-	-	0.0	-

Source: Adapted from Sansom *et al.* (2001) and cited from Li and Preston (2015).

Additionally, there seem to be very few studies relating external costs of Monorail because Monorail might be less popular than bus, BRT, light right and underground. Regarding air pollution and climate change by Monorail, Manoratna, Kawata and Yoshida (2017) estimated the environmental impact for commuters who travel to Colombo city in Sri Lanka when the proposed Monorail system is in place to solve traffic congestion situation. These authors established a mono-centric city model with symmetrically distributed radial highways where traffic congestion occurs frequently. Then, those authors estimated the environmental impacts of introducing a monorail along the highway by comparing the total CO_2 emission from traffic. The results showed that CO_2 emission unit for Monorail users is equal to 23.6 g/passenger-km. Therefore, based on this number and the value per tonne of CO_2, the climate change cost of Monorail can be estimated.

Vehicle occupancy rate

In order to take into account vehicle occupancy, external unit costs of each PT mode should be transferred from pence/vehicle-distance into pence/passenger-distance. Private vehicle occupancy is the sum of driver occupancy (always 1.0) and passenger occupancy in the vehicle. Dissimilarly, train and bus figures are based on the percentage of seats occupied (ratio of seats occupied to person capacity). The mean of train occupancy rates in 14 European countries is about 35% (European Environment Agency, 2015).

Transfer external costs from one country into another country

When required data for estimation of external cost are not available in a developing country, Willingness To Pay approach can be used in order to transfer from a transfer country where the required data available (Gwilliam, Kojima and Johnson, 2004; Nellthorp, Bristow and Day, 2007; Asian Development Bank, 2013). The WTP estimate from the transfer country is calculated by the following formula (Gwilliam, Kojima and Johnson, 2004; World Bank, 2005a).

$$WTP_T = WTP_S * [\frac{Income_T}{Income_S}]^{\varepsilon} \tag{2-6}$$

where,

WTP_T, WTP_S are the willingness to pay estimate from the transfer country and study country correspondingly (£);

$Income_T$, $Income_S$ are the Purchasing Power Parity income per capita in transfer country and study country correspondingly (£/year). A Purchasing Power Parity is a price index, which provides a measure of price level differences across countries and should be used to convert expenditures in national currencies to a common currency;

ε is the income elasticity of WTP – the percentage change in WTP corresponding to a one percent change in income. An approach to benefits transfer is to use an income elasticity of 1.0, including smaller and larger values for sensitivity analysis (Gwilliam, Kojima and Johnson, 2004; Bickel *et al.*, 2005; World Bank, 2005a; Maibach *et al.*, 2007).

2.3.1.4 Wider economic impact

‘Wider economic impact’ is defined as economic impacts, which are additional to transport user benefits. These occur due to market failures in secondary markets (non-transport market), such as the labour and land markets. This means that the full welfare impact of a transport investment cannot be reflected in the transport market (Department for Transport, 2018b).

There may be a huge of data sources for a wider economic impact appraisal, which involves transport network, private vehicles, public transport, employers and jobs (Department for Transport, 2018b). Therefore, the wider economic impacts are ignored in this thesis due to a lack of economic data required to be collected at a network scale.

2.3.1.5 Summary

The PT operator costs should cover capital investment costs for both vehicles and infrastructure and costs incurred through the operation stage. To estimate the PT operator costs, there are three approaches including engineering approach, accounting approach and statistical approach. However, the boundaries between these methods might be unclear in practice. Furthermore, choosing a suitable approach for one local situation is based on the available descriptive data and the precise definitions of the resource variables. The selection of a suitable approach for this thesis will be shown in more detail in Section 5.2 in Chapter 5.

The PT user costs should include walking time, waiting time and in-vehicle time while transfer time is not considered for one transport infrastructure corridor rather than a complete network. The value of time, which is very important to calculate the user costs, differs from transport modes to transport modes (Wardman, Chintakayala and de Jong, 2016). Additionally, the value of time is different among walking time, waiting time and in-vehicle time (Department for Transport, 2017b). Moreover, the value of time can be transferred from one country into another country by using the WTP values (Maibach *et al.*, 2007). Furthermore, the value of travel time can be converted over time and prices in line with income growth and changes in prices between time periods.

Many previous studies stated that the four main external cost components are accident cost, noise pollution, air pollution and climate change (Sansom *et al.*, 2001; Brand and Preston, 2003; Maibach *et al.*, 2007; Litman and Doherty, 2011). When the required data for calculating external costs are not available in a developing country, external costs can be transferred from another country with the available required data by using a WTP approach (Gwilliam, Kojima and Johnson, 2004; Nellthorp, Bristow and Day, 2007; Asian Development Bank, 2013). In addition, unit external costs of each mode are transferred from pence/vehicle-distance into pence/passenger-distance by taking into account the vehicle occupancy. These transfers can be applied to private transport and DRT.

2.3.2 Cost functions of private transport

Total social costs of private transport are the sum of operating costs for users, vehicle capital costs, user costs presenting travel time, schedule delay costs, government services, external costs, infrastructure costs and parking costs (Small and Verhoef, 2007).

2.3.2.1 Operating costs for users

Operating costs for private transport users include fuel and non-fuel costs. Fuel costs for cars are calculated by multiplying the price of fuel by fuel consumption, which depends on vehicle speed and vehicle types. Non-fuel operating costs for cars cover oil, tyres, maintenance and mileage-related depreciation, which is estimated as a function of speed (Department for Transport, 2017b).

However, there appear to be few studies on operating costs for motorcyclists. Karathodorou, Graham and Noland (2010) estimated the ratio of motorcycle fuel consumption per km to car fuel consumption per km for each of the regions of the world by using the 2000 reference values of the International Energy Agency and Sustainable Mobility Project. The results are shown in Table 2-3. Furthermore, Sugiyanto *et al.* (2011) estimated congestion cost of motorcycles in Malioboro, Yogyakarty, Indonesia, as well as calculated the vehicle operating costs for motorcycles as a function of motorcycle speed, which is as:

$$OC = 0.0921 * V^2 - 8.8647 * V + 555.51 \quad \textbf{(2-7)}$$

Where,

OC is the motorcycle operating cost (Indonesian Rupiah-IDR per kilometre);

V is the speed of motorcycle (km per hour).

Table 2-3 Ratio of motorcycle fuel consumption per km to car fuel consumption per km for each region over the world

Region	Ratio
OECD North America	0.44
OECD Europe	0.55
OECD Pacific	0.33
Former Soviet Union	0.24
Eastern Europe	0.27
China	0.12
Other Asia	0.12
India	0.12
Middle East	0.21
Latin America	0.21
Africa	0.1

Source: Karathodorou, Graham and Noland (2010)

2.3.2.2 Private vehicle capital cost

Private vehicle capital costs, which can be estimated by combining interest and depreciation costs, might be averaged over the life of the private vehicle by applying the Capital Recovery Factor to the price of a new vehicle (Small and Verhoef, 2007). Therefore, the vehicle capital costs can be estimated from actual price quotes in local conditions.

2.3.2.3 Travel time

Private vehicle users spend time accessing the vehicle at parking areas, riding in vehicle, walking from parking areas to final destinations. In-vehicle time, which accounts for the main part of travel time of private transport users, depends on the speed and speed-flow relationship. There are three basic established forms for the shape of the speed-density relationships including the linear, logarithmic and exponential curves. Firstly, Greenberg (1959) cited that Greenshields (1934) first proposed the simple linear speed-density model. However, most recent studies have indicated that speed-density data are not perfectly linear. Secondly, Greenberg (1959) suggested a logarithmic shape for the speed-density relationship. In this study, traffic was assumed to behave as a continuous fluid. This methods of fluid dynamics can be used except for the lowest densities of traffic because the speed can be extremely high at the lowest density. Thirdly, Underwood (1961) suggested an exponential model of speed-density. This model seems to be reasonable at low densities, but can be unreliable because the speed can asymptotically approach zero without ever reaching it (cited in the study of Hussain, Radin Umar and Ahmad Farhan (2011)).

In the Greenberg model, the flow *q* and the speed *v* relationship is shown as follows (Greenberg, 1959):

$$q = k_j * v * e^{(-\frac{v}{c})} \qquad \textbf{(2-8)}$$

Where,

v is the speed;

k_j is the density for a traffic jam (or jam density);

c is a constant that is determined from the state of the fluid. This parameter must be obtained for a particular roadway;

Small and Verhoef (2007) stated that travel time as a power function of the volume-capacity ratio:

$$T = T_f * \left[1 + a * (\frac{V}{V_k})^b\right] \qquad \textbf{(2-9)}$$

Where,

T denotes travel time per mile (the inverse of speed).

T_f is the average travel time at free flow (hour), which is:

$$T_f = L/S_f \qquad \textbf{(2-10)}$$

Where,

L is the length of the highway (miles).

T_f is the speed at free flow (miles/h).

a, b are parameters. Parameter *b* typically is assumed to be between 2.5 and 5.0. With parameter values *a* = 0.15 and *b* = 4, it is known as the Bureau of Public Roads (BPR) function, used widely in US transportation planning. With values *a* = 0.2 (freeways) or 0.05 (arterials), and *b* = 10, it is known as the 'updated BPR function'.

However, the equation above does not account for how long traffic exceeds capacity. This drawback is improved in a duration-dependent function derived by Small (1983) to express the average travel time over a peak of fixed duration *W*, when peak-period inflow *V* is at a uniform rate and delay results from queuing behind a single bottleneck with a constant capacity *C*. An average travel time (in minutes) along the fixed length (*L*) of highway can be estimated as follows (Small, 1983):

$$T = \begin{cases} 60 * L/S_0 & if\ V \le C \\ 60 * [L/S_0 + \frac{1}{2} * W * \left(\frac{V}{C} - 1\right)] & if\ V > C \end{cases} \tag{2-11}$$

Where,

V is a traffic volume (vehicle/hour);

S_0 is a fixed constant speed when volume *V* cannot exceed the capacity *C*;

However, the disadvantage of the equation above is that average speed is unchanged if flow does not exceed capacity. Then, the Department of Transport in the UK produced a general form of the speed-flow (*V*) relationship for a variety of link types in urban, suburban and inter-urban roads as follows (Ortuzar and Willumsen, 2011):

$$S = \begin{cases} S_0 & if\ V < F_1 \\ S_0 - \frac{S_0 - S_1}{F_2 - F_1}(V - F_1) & if\ F_1 \le V \le F_2 \\ S_1/[1 + (\frac{S_1}{8d}) * \left(\frac{V}{F_2} - 1\right)] & if\ V > F_2 \end{cases} \tag{2-12}$$

Where,

S_0, S_1 are the free flow speed and the speed at capacity flow F_2;

F_1 is the maximum flow at which free-flow conditions prevail;

d is the distance or length of the link.

The speed-flow relationship in the previous studies mainly focuses on passenger cars rather than motorcycles. A few research have studied on the speed-flow relationship of motorcycle for exclusive motorcycle road and mixed traffic. Hussain, Radin Umar and Ahmad Farhan (2011) established motorcycle speed-flow-density relationships and capacities of exclusive motorcycle lanes in Malaysia, where motorcycles account for 47% of the total vehicles. The authors reviewed three basic speed-density models, namely the Greenshields model, the Greenberg model and the Underwood model. The data for these models are examined using multiple linear regression analysis. For their study, Greenberg's model was selected for developing the motorcycle speed-flow-density relationships in the case study in Malaysia. For motorcycle space riding pattern with total lane width of more than 1.7 m, the motorcycle speed (*S*)-flow (*F*) relationship is shown as follows:

$$F = 0.45 * S * e^{-S/13,330} \tag{2-13}$$

For mixed traffic where motorcycle and other modes share facilities, the speed-flow-density relationships were investigated by using a motorcycle equivalent unit model (Chu, Sano and Matsumoto, 2005; Nguyen and Sano, 2012). To convert other transport modes into Dynamic Motorcycle Unit (MCU) by using a formula as follows:

$$MCU_i = \frac{V_{mc}/V_i}{S_{mc}/S_i} \tag{2-14}$$

Where,

MCU_i is the Motorcycle Equivalent Unit of vehicle type *i*;

V_{mc}, V_i are the mean speed of motorcycles and vehicle type *i,* respectively (km/h);

S_{mc}, S_i are effective space for one motorcycle and one vehicle type *i* respectively (m^2). The effective space for one vehicle is defined as the necessary space for this vehicle to maintain its desired speed. The effective space for vehicle type *k* can be calculated as the following equation (Nguyen, Sano and Chu, 2007):

$$S_k = S_{lok}\ x\ S_{lak} \tag{2-15}$$

Where,

S_k is the effective space for vehicle type *k* (m^2);

S_{lok}, S_{lak} are the effective longitudinal space and effective lateral space of running vehicle inclusive of vehicle length respectively (m);

Speed of different vehicle types are dissimilar, therefore, the weighted mean speed is defined as the stream speed and calculated by the following equation:

$$V_m = \frac{\sum_{i=1}^{k} n_i V_i}{\sum_{i=1}^{k} n_i} \qquad \textbf{(2-16)}$$

Where,

k is the total number of vehicle types in the stream;

V_m (V_i) is the mean stream speed (mean speed for vehicle type *i*) (km/h);

n_i is the number of vehicle type *i* in the stream.

Following this approach for establishing the flow-speed-density relationship, Nguyen and Sano (2012) revised the effective space for one vehicle in Equation 2-15 by including speed of surrounding vehicles in the real situation. The main purposes of that study are to establish the flow-speed-density relationship and to estimate road capacity for mixed traffic environments with a dominance of motorcycles. Two lanes, three lanes and four lanes per direction streets were considered in the study. The logarithmic equation from Greenberg (1959) was used to establish the shape of the mean stream speed-density relationship for these types of streets. The results of estimating capacity on the basis of MCU values of vehicles are shown in Table 2-4, as well as the speed-density relationship.

Table 2-4 Flow-speed relationship and capacity of corridors based on motorcycle equivalent unit

	Four lanes per each traffic direction	Three lanes per each traffic direction	Two lanes per each traffic direction
Traffic flow (F) and mean stream speed (S) relationship	F =5,852*S*exp(-S/11.3)	F = 5,271*S*exp(-S/11.2)	F = 2,951*S*exp(-S/12.3)
c parameter in Equation (2-8)	11.3	11.2	12.3
Capacity (MCU/direction/hour)	24,335	21,725	13,358

Source: Nguyen and Sano (2012)

For one mixed traffic lane per direction road, with a land width of 3.25 m, the mean speed is calculated as (Chu, Sano and Matsumoto, 2005):

$$S = -0.0018 * F + 28.29 \qquad \textbf{(2-17)}$$

Where,

S is the mean stream speed (km/h);

F is the flow (MCU/h).

In addition, for exclusive motorcycle flow in a two-lane per direction divided road with a lane width of 3.75 m, the mean stream speed is estimated as follows (Chu, Sano and Matsumoto, 2005):

$$S = -0.0018 * F + 37.90 \qquad \textbf{(2-18)}$$

Where,

S is the mean stream speed (km/h);

F is the flow (MCU/h).

2.3.2.4 Congested-related delay cost

The trade-off between non-ideal travel schedules and money defines the cost of tolerating those schedules, which is called as schedule-delay costs (Small and Verhoef, 2007). An example of schedule delay calculation is based on the full frequency distribution, which is shown below. Of the 527 commuters, 318 people arrive an average of 17.0 minutes early and 22 travellers arrive an average of 7.27 minutes late. Schedule-delay cost for the 187 punctual people is assumed as zero. Each minute of early or late schedule delay is estimated equal to 0.61 minutes or 2.40 minutes of travel time, correspondingly. As a result, the average commuter's schedule delay is equal to 7.0 minutes of travel time (Small and Verhoef, 2007).

Many research studies were implemented in urban areas in the UK to develop the travel time variability relationships for a wide sample of urban routes. The recommended form of model forecasts the Coefficient of Variation (CV) from Distance (d) and Congestion Index (ci) terms for each origin to destination flow in the urban area. The CV is the ratio of the standard deviation of travel time to the mean travel time, which is shown in the following equation (Department for Transport, 2017b):

$$CV = 0.16\, ci^{1.02}\, d^{-0.39} \qquad \textbf{(2-19)}$$

The Congestion Index (*ci*) is determined as the ratio of mean travel time to free flow travel time. Hence, it can be rearranged to predict the Standard Deviation of Travel Time (Journey Time) from Travel Time (*t*) and Distance (*d*).

2.3.2.5 Government services

Government services include three components: (i) maintenance and traffic service; (ii) administration and research; and (iii) highway law enforcement and safety. For example, the average government services cost of \$0.019/vehicle-mile is calculated by dividing total costs of \$55.7 billion by the total vehicle-miles of 2990 billion (in 2005 values), of which the majority is for highway maintenance (Small and Verhoef, 2007). As a result, only maintenance cost is considered in this thesis. However, the average highway maintenance cost, which can be estimated by dividing annual highway maintenance costs by annual all vehicles kilometre travelled, varies from country to country. This cost should be estimated by using available data from local firms and government.

2.3.2.6 Infrastructure cost

Capital infrastructure costs vary greatly with terrain (e.g. flat, rolling, or mountainous) and with the degree of urbanization. The reasons for this is that terrain and degree of urbanization affect the following factors such as the number and types of structures required (e.g. bridges, overpasses, intersections, drainage facilities, retaining walls, sound walls), ease of access to construction sites, difficulties of grading, extents of demolition, and land prices (Small and Verhoef, 2007).

Meyer, Kain and Wohl (1965) estimated a cost function based on engineering standards, assuming scale economies due to fixed costs of administration and fixed land requirements. The estimates of highway construction used in the study of Meyer Kain and Wohl (1965) were based on a predictive equation obtained for the Chicago area by Joseph (1960). The author fitted least squares regressions to data on construction costs of Congress Street, Edens, and Calument-Kingery Expressways as a function of net residential density (thousands of persons per square mile of residential land). Construction costs for facilities with various numbers of lanes can be estimated by assuming that all but base and paving costs are proportional to width, and that base and paving costs are proportional to the number of lanes. Based on data of many cities rather than those of Chicago alone, the costs of constructing a mixed-traffic expressway facility with varying numbers of lanes thus can be derived as follows (Meyer, Kain and Wohl, 1965):

$$Y_k = W_c\,(\$311{,}000 + \$70{,}800 * X) + \$86{,}000 * k \qquad \textbf{(2-20)}$$

Where,

Y_k is the construction cost in dollars per mile for k lanes,

X is net residential density in thousands of persons per square mile,

W_c is 0.65, 0.77, 0.88 and 1.0 for 2-lane highway, 4-lane highway, 6-lane highway and 8-lane highway respectively.

However, an issue of their assumption is that the right of way needed for median and shoulders is independent of the number of traffic lanes because the physical separation of traffic and provision for stopped vehicles are often used to maintain safety in the face of high total traffic levels. In order to estimate the capital infrastructure costs in local conditions, a good way is to adapt data from local terms and actual price quotes. For example, based on data provided by the People's Committee of Hanoi and T&D Vietnam Highway Consultancy Company, the unit infrastructure costs for 2-lane and 4-lane divided arterials are calculated as 9 and 15 million £/km in 2015 prices respectively.

Percentage of total infrastructure costs allocated to each vehicle type

The question is how to identify allocations of infrastructure costs for each transport mode in mixed traffic environments. Percentage of total infrastructure costs to each vehicle type reflects their cost responsibility. The cost responsibility of different vehicles for pavement, bridge, and certain other types of agency costs vary to the relative amount of travel on dissimilar highway functional classes. Average cost responsibilities for different vehicle types can be estimated based on their travel and operating weight distributions on different highway functional classes in each State and characteristics of pavements and bridges on each highway class in each State (U.S. Department of Transportation, 1997). For example, Small and Verhoef (2007) stated an illustration of the United States where 71% of the total entire United States highway cost are allocated to passenger vehicles.

Sansom *et al.* (2001) suggested the following three steps for calculating the infrastructure capital costs by using a fully allocated cost analysis as follows: (i) Estimate the net value of road infrastructure assets; (ii) Apply the public sector discount rate of 6%; and (iii) Allocate to vehicle types on the basis of Passenger Car Unit-km (85% of the total allocation) and gross maximum vehicle weight-km (15% of the total allocation).

2.3.2.7 External cost

External cost by passenger cars

Using FAC analysis, Sansom *et al.* (2001) estimated external costs for cars including air pollution, noise pollution, climate change and accidents in low and high cost sensitivities, which are shown in Table 2-5.

Table 2-5 External unit cost by passenger car in the UK (p/vehicle-km in 1998 prices)

Mode	Air pollution		Noise pollution	Climate change		Accidents	
	Low	High	Low	Low	High	Low	High
Car	0.18	0.88	0.16	0.12	0.47	0.07	0.82

Source: Sansom *et al.* (2001)

Air pollution cost and climate change cost by motorcycles

Several empirical studies have estimated pollutant emission by motorcycles. Tsai *et al.* (2005) developed a localised driving cycle in Kaohsiung, Taiwan to estimate fuel consumption and pollutant emission from motorcycles; and compared with Economic Commissions of Europe Driving Cycle using a case study of Kaohsiung. In this study, two routes with exclusive motorcycle lane and two mixed traffic routes were selected for collecting data, as well as ten 2-stroke 50 cm^3 (three new and seven in-use) and nine 4-stroke 125 cm^3 (three new and six in-use).

Similarly, Chen *et al.* (2003) tested a sampling of motorcycle on-road driving cycles in urban and rural environments and developed representative driving cycles estimate fuel consumption and pollutant emission using the principle of the least total variance in five regions in Taiwan. Motorcycle emission factors for carbon monoxide (CO), hydrocarbons (HC), nitrogen oxides (NOx) and carbon dioxide (CO_2) were estimated by using a chassis dynamometer on the four-stroke motorcycle with engine capacity of 150cc.

Vu *et al.* (2013) studied on the air quality and pollution caused by road traffic in five main districts in Hanoi, Vietnam, as well as the related health outcomes due to particulate matters (PM_{10} and $PM_{2.5}$). Air quality monitoring data including information of air pollutants (CO, SO_2, NO_2 and total suspended particles) were obtained from the Environmental Monitoring Centre of the National Environmental Agency and measured quarterly during the period 2005-2009 at five monitoring locations in these districts.

However, air pollution costs and climate change cost by motorcycle are still not calculated in these studies above. Therefore, in order to estimate air pollution in monetary terms in a study country, the values per tonne of pollutant emission and a PPP factor need to be used. Maibach *et al.* (2007) stated the values per tonne of PM_{10} and volatile organic compounds while the values per tonne of NO_x and CO_2 are shown on the Web Transport Analysis Guidance (WebTAG) Unit A3.

Noise cost by motorcycle

Based on the dense traffic situations in urban road networks, unit values for marginal noise costs for motorcycles during day time and night time in Europe are €ct 1.53/vehicle-km and €ct 2.78/vehicle-km respectively (in 2002 prices) (Maibach *et al.*, 2007).

Accident cost by motorcycle

Accident unit costs for passenger cars and motorcycles in urban road networks in the UK are €ct 2.61/vehicle-km and €ct 19.19/vehicle-km correspondingly (in 2000 prices) (Maibach *et al.*, 2007).

To conclude, most of studies on external costs by private transport have been implemented in developed countries. Therefore, to estimate these costs for LMICs, the Willingness To Pay approach can be used by transferring from a developed country where the required data available.

2.3.2.8 Congestion charge

Congestion charge for private transport is going to be reviewed separately in this subsection. The charging-relevant measure of congestion costs is the marginal external congestion cost, which is the difference between social marginal cost and private marginal cost. The marginal time cost accounts for the major portion of congestion costs, compared to additional fuel cost and environmental costs. The marginal external time cost can be estimated as the difference in journey time caused by one extra vehicle on the road multiplied by the value of time for this vehicle type. One major methodological issue is to estimate the marginal congestion costs after the introduction of a congestion charge by taking into account responses of travellers. An optimal congestion charge can be identified at the optimal traffic level. A second methodological issue is to measure how congestion costs rise with an increase in traffic. Several approaches for estimating the change in journey time are suggested such as speed-flow relationships and aggregate approximations (Link *et al.*, 2016). Walters (1961) suggested an estimation of a toll or tax for a single route. The toll or tax, which is the difference between social marginal cost and private marginal cost, should be equal to the marginal private cost multiplied by the elasticity of marginal private cost. The Marginal Congestion Cost (*MCC*) can be estimated as (Walters, 1961; Santos and Shaffer, 2004; Link *et al.*, 2016):

$$MCC = -E_S \cdot \frac{V}{S} \tag{2-21}$$

Where,

MCC is the marginal congestion cost (£/vehicle-km);

E_S is the elasticity of speed with respect to traffic;

V is the value of time and additional operating costs (£/vehicle-hour);

S is the speed (km/hour).

Issues concerning the costs and benefits of congestion pricing in practice are now discussed. Firstly, private transport users benefit from improved travel times and travel time reliability, however, they pay the congestion charge and adapt their travel patterns to the charges. Secondly, public transport passengers might suffer from increased transit crowding when some private transport users shift to use PT. In most cities, the congestion charge has been introduced with an expansion of public transport. This can not only attract more private transport users to use PT but also amend the potential problem of increased transit crowding. Thirdly, environmental benefits of congestion charges can be important although they seem to be comparatively small. The main reason can be caused by decreases in private transport volumes, which might lead to huge congestion reductions (Cowie and Ison, 2017).

The London Congestion Charging Scheme, which started on 17 February 2003, is an area licensing system. All vehicles entering, leaving, driving or parking on a public road within the charging zone between 7:00 am and 6:30 pm, Monday to Friday, excluding public holidays, were charged. As of

2021, the charging period is from 7:00 to 22:00, everyday, except Christmas Day (Transport for London, 2021). This charging scheme has had positive impacts. First, the average speed after the introduction of the scheme increased between 14% and 21%, compared to the average speed pre-charging. Second, bus passengers increased both in 2003 and 2004. While there was no evidence of any effect from the congestion charge scheme on the economy (Santos and Fraser, 2006). Moreover, the success of the London congestion charge scheme proves that urban road charging technology can become possible over the next decades. In addition to technology, political willpower is the other important factor to implement the congestion charge scheme in other urban areas (Kaparias and Bell, 2012).

2.3.2.9 Summary

The total social costs of private transport should include operating costs for users, vehicle capital costs, user costs presenting travel time, schedule delay costs, infrastructure maintenance costs, external costs, infrastructure costs and parking costs (Small and Verhoef, 2007). Because the average operating speed is used to calculate most cost elements, it is very important to choose an appropriate equation of the average speed, particularly in mixed transport environments where several transport modes share the infrastructure facilities such as bus, car and motorcycle or where motorcycles are dominant. Additionally, the infrastructure costs need to be allocated to transport modes in the mixed transport environments. Similar to the estimation of PT external costs, these costs of private transport can be calculated by using the WTP approach. A congestion charge is a transfer between the road user and operator. This charge affects demand in demand models but it is not included in the total social cost calculation.

2.3.3 Cost functions of Demand Responsive Transit

All costs of a Taxi/Uber service are generally defined as those costs which are incurred through the addition of the Taxi/Uber service to the public transport offer and which would not be included if the service was not operated. These costs divide into administrative costs, capital costs and operating costs. In any one scheme, some of these costs can be relevant, in other schemes additional items might be considered or items can be removed from the following list. But for all schemes, it seems to allocate costs at least to (Brake, Mulley and Nelson, 2006):

- Administrative costs: advertising, publicity, telephone, office supplies, light, power and postage.

- Capital costs: vehicle provision (buy/lease), office equipment, computer hardware and software.

- Operating costs: dispatchers' wages, drivers' wages, fuel, maintenance, insurance, tyres and vehicle cleaning.

2.3.3.1 Taxi cost models

Cooper (2007) stated that elements included in the taxi cost model vary between authority areas, but most have common parts including: (i) Vehicle costs cover vehicle purchase cost and vehicle operation cost; (ii) Infrastructure costs include licenses/permits, insurance and radio hire; (iii) Personnel cost or drivers' wages. Firstly, the cost of a vehicle is commonly based on the list price for a new vehicle, which can be either for a single vehicle type (the most common vehicle in a fleet) or a combined cost representing two or more major vehicle types. Most of the authorities use the survey of regulation determined the actual cost price of a taxi. The most popular estimate of maintenance costs of taxis is based on a typical basket of parts that varies between cities. Secondly, the infrastructure costs are defined as fixed costs, which do not increase in line with increased mileage. Thirdly, drivers' wages vary significantly between authorities and account for a major element of the total costs of taxis.

The Glasgow Taxi Cost model has been applied in the city since its development in 2008 (Cooper, 2007). Transport Research Partners (2016) calculated the following cost elements in the Glasgow Taxi Cost Model: vehicle costs, vehicle maintenance, fuel cost, infrastructure costs, radio dues costs and driver earnings. The model developed a structure, where changes in these costs measured between a base year and a target year are calculated, and then applied to the tariff by using an Industrial Price Index. Reviewing the model allows for the baseline values to be updated, regardless whether an increase is applied to tariff or not. This ensures that the growth is measured based on changes from year to year, rather than over a period of years.

However, there seems to be very little evidence on taxi cost models in LMICs, the cost elements in the Glasgow Taxi Cost Model can be used but parameters for estimating each cost element should be obtained from the local conditions in LMICs.

2.3.3.2 Cost functions of Uber

As a new transport mode in the last few years, there appear to be very little studies on cost functions of Uber. Hall and Krueger (2018) provided the first detailed analysis of a representative and national sample of Uber driver-partners in the US. Driver-partners of Uber provide transport services to customers who request rides using Uber's application on their smartphones or other devices. Driver-partners who made at least four trips for passengers in a given month are considered in the research. Anonymised administrative data from Uber on the driving histories, schedules, and earnings of drivers who used the Uber platform from 2012 to 2015 were used. From a base of near zero in mid-2012, the number of driver-partners of Uber in the United States reached more than 460,000 by the end of 2015. Furthermore, the authors draw on two surveys implemented by the Benenson Strategy Group (BSG) including a survey of 601 driver-partners conducted in December 2014 (BSG 2104) and a survey of 632 driver-partners conducted in November 2015 (BSG 2015). In addition, a comparison of driver's earnings between Uber and taxi was analysed by using data on the characteristics of a representative sample of taxi drivers and chauffeurs, and of all workers, on the basis of some Government surveys.

Hall and Krueger (2018) compared net hourly earnings (before vehicle expenses) of Uber driver-partners and hourly wages of taxi drivers and chauffeurs by using data in 20 survey markets in 2014. The average net hourly earnings of Uber driver-partners is 19.35$, compares with 12.56$ for taxi drivers. Then, the authors estimated Uber driving expenses by vehicle type and part-time and full-time driver-partners. These expenses include gasoline, maintenance, depreciation, or insurance. The results showed that the average hourly expense of $4 for part-time driver-partners and $5 for full-time driver-partners. To conclude, the authors stated that the average Uber driver-partner is likely to earn at least as much per hour, and probably more, than the average taxi driver and chauffeur.

Uber drivers using the driver application are charged the Uber Fee as a percentage of each trip fare. If surge pricing applies to a trip, the Uber Fee percentage is also deducted from the surge amount. The Uber Fee is defined as the administrative costs of Uber. The Uber Fee helps cover costs including technology, development of application features, marketing, and payment processing for driver-partners (Uber, 2018). The Uber Fee varies by countries and types of Uber. Indeed, Uber receives from 5% to 20% of the trip price, with the rest for the driver (Schneider, 2017). Mostly, that number is 20%, for example, as in the UK and for Uber Black in Netherland. The Uber Fee increased from 20% to 25% in Vietnam because the Uber company directly paid Value Added Tax and income tax of Uber drivers to the tax administration (Zeldin, 2016). However, Uber sold South East Asia operations (including the Vietnam market) to Grab in 2018 (Grab, 2018).

2.3.3.3 Summary

These previous studies mainly focused on the operator costs of Taxi/Uber, which should include at least administrative costs, capital costs and operating costs. Hence, Taxi/Uber user costs, external costs and unreliability costs should be included in the total social costs of Taxi/Uber. Compared to the cost functions of passenger cars, there are two main different cost components of Taxi/Uber, which are administrative costs and driver earnings. In addition, the waiting time of Taxi/Uber users, which is different from the waiting time of PT passengers, should be included in the user costs.

2.4 Conclusion

Transport evaluation methods including multi-criteria analysis, cost-benefit analysis and cost-effectiveness technique have been reviewed in this chapter. This thesis focuses on evaluations of urban transport infrastructure options in LMICs where motorcycles are dominant in mixed traffic environments and several potential new PT modes and transport policy are introduced. Hence, the cost-effectiveness analysis is chosen to develop in such situations. The cost-effectiveness analysis can be used for transport projects where all relevant costs are monetised while the expected benefits of the proposed projects are quantified as some measure of effectiveness. The measures of effectiveness including an ASC per passenger-km, a modal share of public transport and an increase in total general traffic are considered in this thesis.

The cost functions of different types of transport modes including PT, PRV and Taxi/Uber are also reviewed. Firstly, the total social costs cover operator costs, user costs, external costs and wider economic impacts. However, the last type of cost is ignored in this research due to a lack of a huge of data sources for a wider economic impact appraisal at a network scale. Brand and Preston (2003) developed a comprehensive cost model of PT by using the intermediate outputs of the PT performance, therefore this method is used for developing the PT social cost model in this study. Secondly, the total social costs of private transport consist of operating costs for users, vehicle capital costs, user costs presenting travel time, congested-related delay costs, infrastructure maintenance costs, external costs, infrastructure costs and parking costs (Small and Verhoef, 2007). Thirdly, based on cost functions of taxis by Transport Research Partners (2016), the total social cost model of Taxi/Uber cover administrative costs, capital costs and operating costs, unreliability costs, user costs and external costs. In general, these previous studies focused on automobile, conventional bus and PT technologies. However, there appears to be very little evidence on cost models for motorcycle, Uber and innovative PT technology (e.g. Monorail). Moreover, the following main things in these social cost models need to be considered carefully. The first problem involves the operating speed of each transport mode in mixed transport environments, as well as a segregated PT technology. Because the quality of service highly depends on the operating speed of vehicles and many cost components in these cost models are estimated as functions of the speed. The second issue relates to infrastructure costs allocated to each vehicle type in the mixed traffic. The third concern is a case where there is a lack of required data for estimating external costs in LMICs. By using the WTP approach, external costs can be transferred from another country with the available required data (Gwilliam, Kojima and Johnson, 2004; Nellthorp, Bristow and Day, 2007).

An average social cost per passenger-km is chosen as one of the measures of effectiveness for evaluating urban transport infrastructure options when several potential new PT modes and transport policy are introduced in mixed transport environments. After total social cost models of all transport modes are developed, transport demand needs to be considered to calculate this output. Furthermore, if a comparative cost model does not incorporate a suitable demand model (e.g. logit model), preferences of users for alternative transport modes cannot be taken into account. Hence, the transport demand models will be reviewed in the next chapter to choose suitable models for the situations above.

The strategic level modelling and traffic simulation modelling were integrated to evaluate alternative options in a case study of a guided bus system on a busy urban/inter-urban corridor in Oxfordshire, the UK (Brand and Preston, 2003). The key indicators of the real network are obtained from the traffic simulation in order to assess the costs and benefits of operating a PT service. To reflect the real mixed transport system, traffic simulation modelling needs to be used properly. As a result, Chapter 3 will review traffic simulation models and choose the most suitable package for the mixed transport system with the dominance of motorcycles.

Chapter 3 Literature Review of Transport Demand

3.1 Introduction

This thesis aims to develop a comparative economic assessment of urban transport infrastructure options in LMICs where a new PT mode and transport policy can be introduced in existing mixed traffic environments that are dominated by motorcycles. The comparative economic assessment then analyses whether any changes should be made to the existing network, and which option should be implemented. Decisions for ‘do something’ scenarios and choosing the best option should be informed by evidence of existing problems or potential future problems, as well as the consequences of each option (Department for Transport, 2017c). The improvements in the supply of transport services need to meet a basic demand because without a basic demand for an area’s goods and services these cannot stimulate that demand (Cowie, 2009). Hence, both transport supply and demand need to be reviewed.

After reviewing transport evaluation methods, the cost-effectiveness analysis is considered in this research. Measures of effectiveness chosen for comparing different transport infrastructure options include average social cost per passenger-km, modal share of public transport and increase in total general traffic. Hence, to compare different proposed transport infrastructure options, not only does cost per unit (supply) need to be calculated but also the number of units (demand) (Department for Transport, 2017c). Chapter 2 reviewed cost models of different transport modes including PT, PRV and DRT. Chapter 3 is going to review suitable demand models for such comparisons, which are considered for one urban corridor rather than a complete network. For general traffic, an elasticity model can be used to estimate changes in total demand according to changes in composite costs. The variable demand modelling can predict and quantify a change in demand when existing transport conditions change (Department for Transport, 2017c). For modal split, variable demand models with logit formulation calculate how many passengers are likely to choose specific transport modes. Those types of variable demand models are reviewed in the next part of this chapter.

Vehicle speed and vehicle travel time are important parameters in the transport cost models and variable demand models. Traffic simulation might obtain these parameters for existing transport networks. Therefore, traffic simulation is reviewed in the third part of this chapter. This study focuses on an existing mixed transport environment that is characterised by a dominance of motorcycles, hence the suitability of available traffic simulation packages will be considered in these terms.

3.2 Demand Model

In general, there are three broad approaches to representing travellers' response to cost. Firstly, a fixed demand approach might be used in a situation where demand is independent of cost and no behavioural model is required. Secondly, an own cost elasticity approach assumes that the demand for travelling between two locations is purely a function of the change in costs on a mode between the two points. Thirdly, in a variable demand approach, the demand of each transport mode may vary according to the demand of other modes and cost components. The full variable demand model is usually implemented using discrete choice models (Department for Transport, 2017c). The utility functions of transport models are discussed in the first place, the elasticity demand model is then reviewed, followed by the variable demand models of logit formulation.

3.2.1 Utility functions of transport modes

The concept of utility is used to represent the attractiveness of the alternatives in transport demand models. The utility is usually defined as a linear combination of variables that represent attributes of the option or of the traveller that represent the traveller's willingness to pay for the option. For example, variables can be time, cost, income, number of vehicle ownership. etc. The relative impact of each attribute is given by its coefficient. The alternative specific constant (or modal penalty) normally represents the effect of all unobserved (or not explicitly included) characteristics of the option and the traveller in its utility function. For example, this can include factors such as comfort, service reliability, convenience or safety that are difficult to measure or observe (Ortuzar and Willumsen, 2011).

Alternative/Mode specific constant (MSC)

Ben-Akiva and Morikawa (2002) presented an analysis of commuters' choice of travel mode using revealed preference survey data in Metropolitan Washington. The unique aspect of this analysis is the separate treatment of four different transit modes, namely: rapid transit (Metro), commuter rail, express bus and local bus. The estimated utilities of the mode choice model are used to obtain the preference order for these transit modes under eight corridor types. These utilities are functions of the alternative specific constants, travel times and costs. Multinomial logit models were estimated for each of the three segments (0, 1 and 2+ car households). The full choice set includes three primary travel modes: transit, drive alone and shared ride.

Ben-Akiva and Morikawa (2002) estimated the relative attraction of bus and rail with the following assumptions: (i) the transit level of service coefficients are the same for all transit modes. Thus, if the transit travel times and costs are held constant, the relative attraction of each transit mode relative to the car modes is measured by the coefficients of the dummy variables, which represents the alternative specific constants. (ii) Only one transit mode is available and the constant represents the transit share in competition with drive alone and shared ride. This means that other modes (e.g. motorcycle) are not taken into account in competition in this analysis. Corridor type 5, which is ‘At least either origin or destination is in the central business district; not Metro low frequency line corridor; not HOV lane corridor’ can represent for urban corridors in this thesis. The results for the corridor type 5 are shown in Table 3-1.

Table 3-1 Preference order of transit modes for Corridor type 5

	0 car households	1 car households	2 + car households
Metro	4.78	2.74	2.37
Local bus	2.94	1.39	1.07
Express bus	2.88	1.34	0.62
Commuter rail	2.14	1.10	0.42

Source: Ben-Akiva and Morikawa (2002)

Notes: The values are the estimated transit mode specific constants in minutes of equivalent in-vehicle travel time.

Table 3-1 shows that Metro travel is most preferred under Corridor type 5. In other words, the Metro service in the central business area attracts more ridership than a bus service with comparable travel times and costs because of its quantified advantages as well as other attributes that were not quantified (Ben-Akiva and Morikawa, 2002).

In other study, Currie (2005) stated that the Mode Specific Factor (MSF) is the user-perceived attractiveness of one transit mode compared to another, excluding the influence of factors such as fare, walk time, wait time, in-vehicle travel time, and the need to transfer. The MSF is usually measured as a constant and expressed in minutes of equivalent in-vehicle travel time.

Currie (2005) summarised the evidence of the MSF measured in a range of previous studies. The values of the MSF for heavy rail, light rail and BRT are indicated. In each case, the MSF is expressed as the value of the difference of the transit mode relative to on-street bus. A positive value represents a preference to the transit mode whilst a negative value represents a preference to on-street bus. The results are shown as follows:

- Heavy rail is preferred over on-street bus with the value of preferences ranging between 2 minutes and 33 minutes. The overall average is around 4 minutes.

- All MSF values for light rail showed a preference of light rail over on-street bus ranging from 2 to 20 minutes. The average of the values shown is around 10 minutes.

- All MSF values for BRT systems also display a preference for BRT compared to on-street bus. Values range from 9 to 20 minutes with an average of around 12 minutes. The average results implied that BRT might be better than both light and heavy rail. However, the results are limited and scattered because the results for BRT are based on only four data points while there are some small number of negative values for heavy rail.

However, motorcycle is not taken into account in the studies mentioned above. Hence, the utility of motorcycle is reviewed below.

Utility of motorcycle

To investigate travel behaviour and individual mode choice preferences in some Asia cities, Dissanayake *et al.* (2012) developed multinomial logit models for inter-regional analysis by using databases from Bangkok (13,964 trip samples), Kuala Lumpur (12,667 trip samples) and Manila (15,000 trip samples). The MSC is equal to zero in the rail options for all models except Kuala Lumpur where there were no data on rail trips. Hence, The MSC is set to zero in the motorcycle option. Variables of utility functions for rail, bus, car, motorcycle, taxi and tricycle in these three cities were estimated, as shown in Table 3-2.

Table 3-2 Parameter estimates of the multinomial logit models in inter-regional analysis

Variables	Bangkok	Kuala Lumpur	Manila
MSC (Rail)	0	-	0
MSC (Bus)	0.31	1.83	1.40
MSC (Car)	-2.35	-0.20	-2.83
MSC (Taxi)	-2.71	-3.69	-1.02
MSC (Motorcycle)	-1.48	0	-3.57
Tricycle	-	-	0.17
Travel time (hours)	-0.15	-0.24	-0.34

Source: Dissanayake *et al.* (2012)

In addition, Bray and Holyoak (2015) studied travel behaviour in Hanoi, Vietnam by establishing a discrete choice modelling framework with the ability to represent mode choice. Two travel behaviour surveys were conducted via face-to-face interviews and paper-based forms. Respondents to the surveys were distributed across locations in all of Hanoi’s 21 districts. One of the two surveys was the mode choice survey, which establishes statistically valid explanations of the quantitative factors that impact the discrete choice decision to use a motorcycle, car, motorcycle taxi, existing bus or proposed rapid transit modes (e.g. Urban Railway Transit or Bus Rapid Transit). This survey design included:

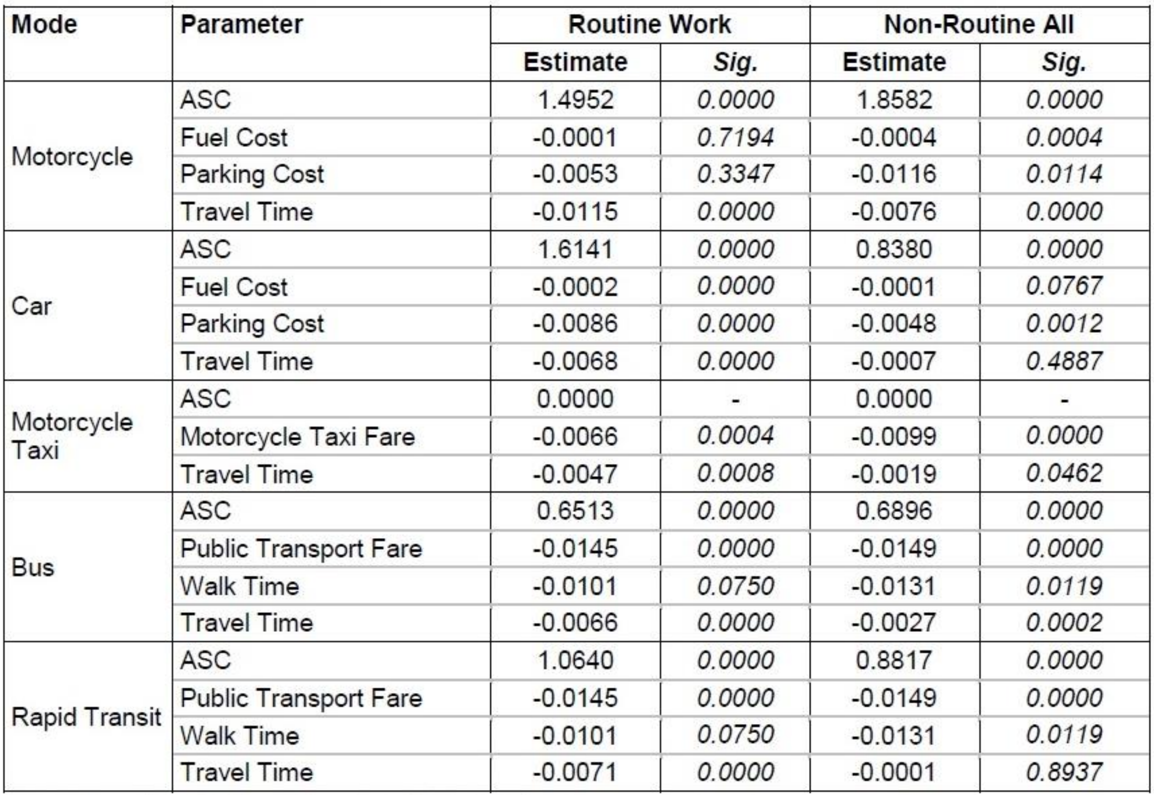
- Demographic and socioeconomic questions, including gender, household size, income, housing type and vehicle ownership.

- Questions related to either a routine trip or a non-routine trip.

- A stated preference survey included cost of fuel, cost of parking, travel time, existing bus walking time and proposed PT access time.

The survey was carried out between April and June 2014, and attracted a total of 6,047 responses. Then 5,993 complete records were distributed for both routine trips (such as trips related to work or education) and non-routine trips. The results of the mode choice survey were utilised to estimate discrete choice models representing the mode choice model in Hanoi. Utility function parameters were estimated for routine work (i.e. journeys related to work or education) and non-routine trips (i.e. shopping or recreation), which are shown in Table 3-3.

Table 3-3 Utility function parameter estimates for routine work and non-routine trips



Mode	Parameter	Routine Work		Non-Routine All	
		Estimate	*Sig.*	Estimate	*Sig.*
Motorcycle	ASC	1.4952	*0.0000*	1.8582	*0.0000*
	Fuel Cost	-0.0001	*0.7194*	-0.0004	*0.0004*
	Parking Cost	-0.0053	*0.3347*	-0.0116	*0.0114*
	Travel Time	-0.0115	*0.0000*	-0.0076	*0.0000*
Car	ASC	1.6141	*0.0000*	0.8380	*0.0000*
	Fuel Cost	-0.0002	*0.0000*	-0.0001	*0.0767*
	Parking Cost	-0.0086	*0.0000*	-0.0048	*0.0012*
	Travel Time	-0.0068	*0.0000*	-0.0007	*0.4887*
Motorcycle Taxi	ASC	0.0000	-	0.0000	-
	Motorcycle Taxi Fare	-0.0066	*0.0004*	-0.0099	*0.0000*
	Travel Time	-0.0047	*0.0008*	-0.0019	*0.0462*
Bus	ASC	0.6513	*0.0000*	0.6896	*0.0000*
	Public Transport Fare	-0.0145	*0.0000*	-0.0149	*0.0000*
	Walk Time	-0.0101	*0.0750*	-0.0131	*0.0119*
	Travel Time	-0.0066	*0.0000*	-0.0027	*0.0002*
Rapid Transit	ASC	1.0640	*0.0000*	0.8817	*0.0000*
	Public Transport Fare	-0.0145	*0.0000*	-0.0149	*0.0000*
	Walk Time	-0.0101	*0.0750*	-0.0131	*0.0119*
	Travel Time	-0.0071	*0.0000*	-0.0001	*0.8937*

Source: Bray and Holyoak (2015)

Notes:
Fuel Cost: VND/km
Parking Cost VND/1000 (e.g. 25,000 VND is represented in the model as 25)
Travel Time: minutes
MC Taxi Fare: VND/1000
Public Transport Fare: VND/1000
Walk Time: minutes

3.2.2 Incremental elasticity analysis

Demand elasticity involves the responsiveness of transport users to change in any of the determinants of demand, which can be price, income, travel time etc. (Cowie, 2009). A demand elasticity model can be applied to general traffic and to each transport mode. Firstly, the incremental elasticity analysis evaluates endogenous changes in total general demand by using the demand elasticity with respect to a composite cost of all transport modes. Secondly, for one transport mode, the level of initial demand for a mode is T_0 and its initial level of service S_0. A change in one (seldom more) level of service attributes, which can include travel time, fare, waiting time, etc., causes changes in demand. The elasticity of demand with respect to LOS is given by (Ortuzar and Willumsen, 2011):

$$E_S = \frac{S_0}{T_0}\frac{\partial T}{\partial S} \approx \frac{S_0}{T_0}\frac{T - T_0}{S - S_0} \qquad (3\text{-}1)$$

If T is a multiplicative function of S, the equation above can be rearranged as:

$$\frac{T}{T_0} = \left(\frac{S}{S_0}\right)^{E_S} \qquad (3\text{-}2)$$

If the change in S (and hence T) is non-marginal, the arc elasticity of demand is considered as (Allen and Lerner, 1934):

$$\frac{\Delta T}{T_0} = E_S * \frac{\Delta S}{S_0} \qquad (3\text{-}3)$$

However, the elasticity demand model cannot estimate the transfer trips from one transport mode to another when the generalised cost changes. An isolated elasticity demand model should not be recommended over full variable demand models in multimodal settings (Department for Transport, 2017d).

3.2.3 Incremental multinomial logit model

Ortuzar and Willumsen (2011) stated that the multinomial logit model is the simplest and most popular practical discrete choice model, which assumes the probability of an alternative *i* is chosen by the individual *q* as:

$$P_{iq} = \frac{\exp(\beta V_{iq})}{\sum_{A_j \in A(q)} \exp(\beta V_{jq})} \qquad (3\text{-}4)$$

Where,

P_{iq} is the probability that an alternative *i* is chosen by the individual *q*;

$V_{iq}(V_{jq})$ the utility of alternative *i (j)* is chosen by the individual *q*;

$A_j \in A_{(q)}$ is alternative *j* in all alternatives, which are chosen by the individual *q*;

β is the parameter, which is taken as 1.0 in practice.

The Department for Transport (2017d) stated the standard incremental multinomial logit model as:

$$P_p = \frac{P_p^0 \exp(\lambda \Delta U_p)}{\sum_q P_q^0 \exp(\lambda \Delta U_q)} \qquad \textbf{(3-5)}$$

Where,

P_p is the forecast probability of choosing alternative *p* out of *q* possibilities*;*

P_p^0 is the reference case probability of choosing alternative *p*;

λ is the positive parameter, which can be taken as 1.0 in practice.

ΔU_p is the change in the utility of alternative *p.*

Because the multinomial logit model is based on Independence from Irrelevant Alternatives (IIA), the main drawback of the multinomial logit model manifests when alternatives are not independent. For example, there are some alternatives that are more similar than others, such as public transport modes versus private transport modes (Ortuzar and Willumsen, 2011). In other words, the incremental multinomial logit model is suitable for mixed transport environments, where only one public transport mode is operated, but is no longer suitable if a new PT technology is introduced while the existing PT mode is still operated. A nested logit model, which might overcome this disadvantage, might be used for such situation.

3.2.4 Incremental hierarchical/nested logit model

A hierarchical/nested logit model can be expressed as follows (Ortuzar and Willumsen, 2011):

Step 1: All subsets of correlated (or more similar) alternatives are grouped in hierarchies or nests. Each nest is represented by a composite alternative which competes with the other options available to the individual.

Step 2: For the lower nest, the mean of the utilities of the composite alternatives has two components. The first component consists of the expected maximum utility (EMU) of the lower nest options. The second component considers the vector *z* of attributes which are common to all members of the nest. The EMU portion is determined as follows:

$$EMU = \log \sum_j \exp(W_j) \tag{3-6}$$

Where,

W_j is the utility of an alternative A_j in the nest, except variables *z* which are common to choice set. For example, if the cost of travel by bus and BRT (e.g. the fares) are the same, this cost would not enter the *W* function. Moreover, walking time can enter to *z* for PT modes. The composite utility of the nest *i* is:

$$V_i = \emptyset\, EMU + \alpha z \tag{3-7}$$

Where,

$\emptyset$ and α are parameters to be estimated from observed data. Note that $0 < \emptyset \leq 1$.

Step 3: A multinomial logit model for the higher nest is estimated, which contains all composite alternatives representing lower nests plus the alternatives which are non-nested at that level.

Step 4: Finally, the probability of each alternative in the lower nest is computed based on the probability of composite alternatives.

The first incremental form of the nested logit model is given by Bates, Ashley and Hyman (1987). Then, considering a situation where a new public transport mode is introduced, Preston (1991) suggested the Extended Incremental Logit Model (EIL). EIL was based on a multinomial logit model for non-car-owning households and a nested logit model for car-owning households. The structures of the models are given in Table 3-4, as well as the results adapted from data for five new stations and predicted for further potential sites.

Public transport's share in the upper nest is given by

$$P'_{PT} = \frac{P_{PT}\left[\exp(U'_{NT} - U_{XT}) + \exp(U'_{XT} - U_{XT})\right]^{\emptyset}}{P_{PT}\left[\exp(U'_{NT} - U_{XT}) + \exp(U'_{XT} - U_{XT})\right]^{\emptyset} + [1 - P_{PT}]} \tag{3-8}$$

Where,

P'_{PT} (P_{PT}) is the proportion of choosing public transport in the after (before) situation;

$U'(U)$ is the utility measure in the after (before) situation;

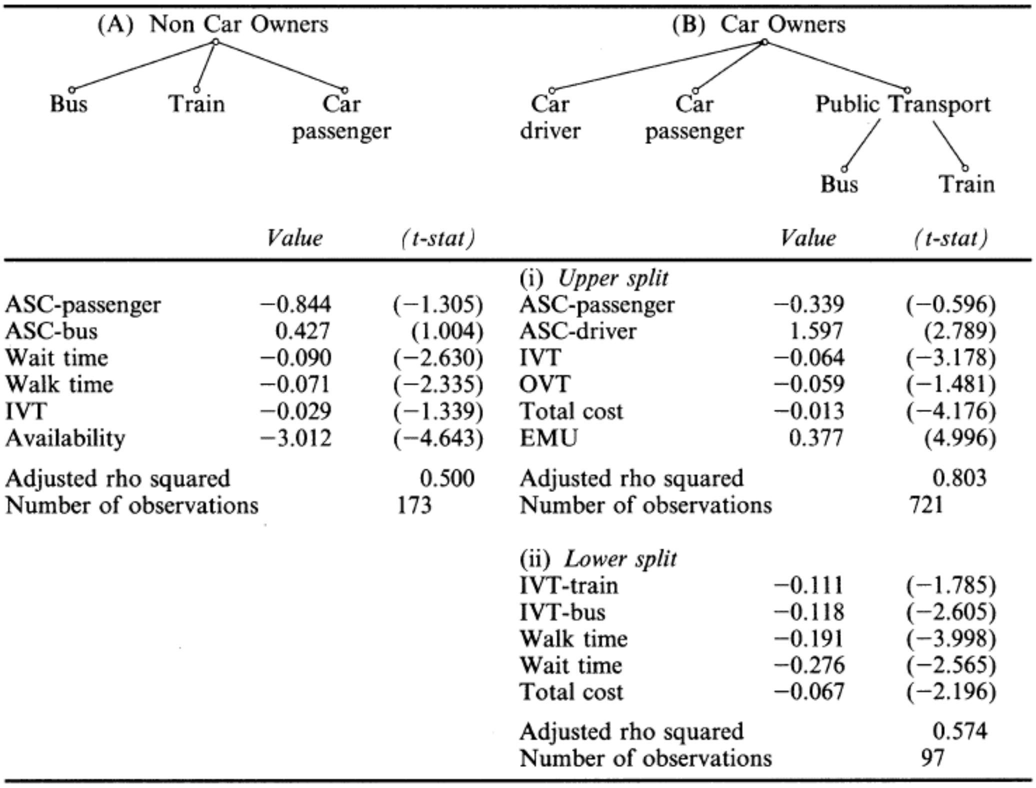
XT is the existing public transport mode (bus);

NT is a new public transport mode (rail); and

$\emptyset$ is the EMU parameter. The EMU portion is determined from all utility of each mode U_j as follows:

$$EMU = \ln \sum_j \exp(U_j) \qquad (3\text{-}9)$$

Table 3-4 Market Segmented hierarchical logit and multinomial logit models



(A) Non Car Owners: Bus, Train, Car passenger

(B) Car Owners: Car driver, Car passenger, Public Transport (Bus, Train)

	Value	*(t-stat)*		*Value*	*(t-stat)*
			(i) *Upper split*		
ASC-passenger	−0.844	(−1.305)	ASC-passenger	−0.339	(−0.596)
ASC-bus	0.427	(1.004)	ASC-driver	1.597	(2.789)
Wait time	−0.090	(−2.630)	IVT	−0.064	(−3.178)
Walk time	−0.071	(−2.335)	OVT	−0.059	(−1.481)
IVT	−0.029	(−1.339)	Total cost	−0.013	(−4.176)
Availability	−3.012	(−4.643)	EMU	0.377	(4.996)
Adjusted rho squared		0.500	Adjusted rho squared		0.803
Number of observations		173	Number of observations		721
			(ii) *Lower split*		
			IVT-train	−0.111	(−1.785)
			IVT-bus	−0.118	(−2.605)
			Walk time	−0.191	(−3.998)
			Wait time	−0.276	(−2.565)
			Total cost	−0.067	(−2.196)
			Adjusted rho squared		0.574
			Number of observations		97

Source: Preston (1991)

The lower nests are therefore:

$$P'_{NT} = \frac{\exp(U'_{NT} - U_{XT})}{\exp(U'_{NT} - U_{XT}) + \exp(U'_{XT} - U_{XT})} . P'_{PT} \qquad (3\text{-}10)$$

and

$$P'_{XT} = \frac{\exp(U'_{XT} - U_{XT})}{\exp(U'_{NT} - U_{XT}) + \exp(U'_{XT} - U_{XT})} . P'_{PT} \qquad (3\text{-}11)$$

If the utility of the existing public transport mode is assumed to be unchanged, $\exp(U'_{XT} - U_{XT})$ is equal to 1.

The probability for all other modes P_M in the upper nest is estimated as:

$$P'_M = P_M \frac{1 - P'_{PT}}{1 - P_{PT}} \qquad (3\text{-}12)$$

The main advantage of the EIL is that it reduces data requirements. Required data include the modal shares P_M and P_{XT} and the change in utility $(U'_{NT} - U_{XT})$.

In the nested logit model, alternatives within each nest are correlated while there is no correlations across nests. The main drawback of the nested logit occurs if alternatives might not be divided into well separated nests to reflect their correlation, for example, one alternative can be allocated in two different nests (Ben-Akiva and Bierlaire, 1999; Ortuzar and Willumsen, 2011). To overcome this issue, a cross-nested logit model, which allows alternatives to appear in multiple nests, allows for more flexible correlation patterns (Ben-Akiva and Bierlaire, 1999). For example, Vovsha (1997) developed a cross-nested logit model for mode choice, where the 'park & ride' alternative can belong to the 'composite automobile' and the 'composite transit' nests. Although the social cost models reviewed in Chapter 2 include PT, PRV and Taxi/Uber, Taxi/Uber can be only considered in the total social cost models and compared to PT and PRV at a strategic planning level. Due to time limits and unavailable data, the comparative economic assessment cannot include Taxi and Uber. As a result, the cross-nested logit model is not considered in this thesis.

3.2.5 Summary

Utility is defined as a linear function of the alternative specific constant, time and cost (Ortuzar and Willumsen, 2011). Several approaches have focused on demand analysis of the impact of changes to transport conditions. The best known of these methods are demand elasticity analysis and variable demand models with logit formulation (Ortuzar and Willumsen, 2011). The elasticity approach can be used when demand is purely a function of the change in generalised costs. The demand elasticity model can estimate the endogenous growth of total demand due to a change in composite costs of all transport modes; however, the demand elasticity approach might not forecast the shift from one mode to another. This drawback can be overcome by incremental multinomial/nested logit models. The incremental multinomial logit model can calculate the probability of an alternative chosen by transport users when their travel costs change. The incremental nested logit model seems to be suitable when alternatives are not independent, for example, when two public transport modes are operated at the same time.

3.3 Traffic Simulation

Due to the rapid development of computer technology, traffic simulation is widely used in the transport sector. Traffic simulation models represent the operation of a real traffic network and are used to forecast potential/future traffic conditions, which can be demand, modal share, vehicle speed, vehicle time, environment effects, etc. This section reviews traffic simulation approaches, existing simulation packages and highlights the most suitable simulation package for the current research, which considers an existing mixed transport environment in which motorcycles are dominant.

3.3.1 Simulation requirements

This study will model mixed transport environments where motorcycles, cars and PT modes share infrastructure facilities such as conventional buses, Monorail, Metro and BRT. The following key simulation requirements are listed:

- The traffic simulation model must simulate the operation of a fixed-line PT system, including the location of stops/stations, dwell time and passenger boarding and alighting.

- The traffic simulation model must simulate the operation of motorcycles, including driving behaviour and lane changing.

- The traffic simulation model needs to present detailed interactions and impacts between vehicles in order to reflect the changes in costs and benefits to users.

- The traffic simulation model must be flexible and adaptable to simulate the characteristics of the PT modes such as right-of-way and bus priority, as well as the impacts on other road users.

3.3.2 Simulation approaches

Macroscopic traffic simulation is developed based on traffic flow theory in order to consider the whole traffic network. The equations used in the model are based on a hydrodynamic theory of fluids and include variables such as volume, speed and density. Advantages of macroscopic simulation models include: (i) their ability to model the overall traffic picture; (ii) less detailed behaviour knowledge required; and (iii) quicker run-times.

Microscopic traffic simulation is able to simulate precisely each individual vehicle in the traffic flow and the interactions between vehicles by using their acceleration, deceleration, speed and driver behaviour, among other factors (Ortuzar and Willumsen, 2011).

Mesoscopic approach combines the individual vehicle analysis in microscopic simulation and the dynamics of traffic flow in macroscopic simulation (Barceló, 2010). This simulation approach is mainly used for large networks where a detailed microscopic approach is infeasible or where there is a lack of available resources for the network (Burghout, 2004).

3.3.3 Reasons for choosing microscopic simulation

Microscopic traffic simulation is preferable over the macroscopic and mesoscopic approaches for the comparative economic assessment for a number of reasons.

Firstly, the comparative economic assessment includes PT technologies and private transport (cars and motorcycles) in mixed traffic environments. There are significant interactions among several transport modes such as motorcycle, car, bus and BRT. Therefore, the interaction between each vehicle on the road should be simulated in detail.

Secondly, lane change behaviour must be able to be modified in the simulation model, because the lane changing behaviour of motorcyclists needs to be taken into account.

Thirdly, the traffic simulation needs to model junctions on the links, where PT technologies (such as BRT or exclusive bus) share the infrastructure facilities with car and motorcycle traffic. These PT modes can require some priority schemes when they enter the junctions.

As a result, microscopic simulation is used in this research.

3.3.4 Microscopic traffic simulation selection

Microscopic traffic simulation can simulate the behaviour of an individual’s choices, which are based on the probability of each choice being made and determined using random numbers. Using random seeds in microsimulation models, the outputs of each run will differ and hence microsimulations do not have a unique solution. Therefore, the equilibrium might not be based on a single run of the model. To overcome this issue, the average results from many model runs should be obtained as a convergence to a stable solution (Department for Transport, 2017c).

There are several existing microscopic traffic simulation packages including VISSIM, PARAMICS, AIMSUN and FLOWSIM.

VISSIM is a microscopic simulation tool, which is suitable for a wide range of traffic applications (PTV AG, 2011). Three key aspects, infrastructure, traffic and control, are built into the structure of a completed VISSIM model. The infrastructure covers the detail of the road, railway and all other fixed elements in the network. The traffic specifies vehicles in traffic flows either by automatically generated traffic or O-D matrices using a dynamic assignment module (PTV AG, 2011).

VISSIM is able to comprehensively simulate PT modes through its flexibility of setting transit routes, stops/stations and bus timetables (Feng, Perrin and Martin, 2003). PT vehicles in VISSIM are treated similar to private vehicles by adding more characteristics and operating PT stops/stations on the selected route. The operation of PT modes such as buses, trams and LRT might be simulated and presented in a 3D animation. Of the various simulation packages, VISSIM has been argued to the most suitable for simulation of PT networks (Papageorgiou *et al.*, 2009).

In addition, VISSIM users can define points in the networks at which to collect travel time data from simulated vehicles. The model can then produce time-space and speed-distance diagrams along the route (Dowling, 2005).

PARAMICS (PARAllel MICroscopic Simulation) is a micro-simulation developed by Quadstone Ltd. and SIAS Ltd. in Edinburgh, the UK, which is able to simulate large networks with ITS (Cheu, Tan and Lee, 2003). These two companies developed their own version of PARAMICS called Q-PARAMICS and S-PARAMICS and provided the simulation package for outside the UK and Ireland and within the UK and Ireland, respectively. The model building procedure in PARAMICS mainly requires two inputs: network construction and vehicle demand. The limitations of PARAMICS include its limited options in modelling traveller information/guidance (e.g. the model updates the routing instructions at each intersection); and its inability to explicitly model several control options such as bus signal pre-emption from mixed lanes (Dowling, 2005).

AIMSUN is a traffic simulation software developed by Transport Simulation Systems Ltd. (TSS). AIMSUN is able to simulate not just microscopic but also macroscopic and mesoscopic traffic networks (Transport Simulation Systems, 2014). One drawback of AIMSUN is that it is unable to present motorcycle parameters (Government of South Australia, 2013). However, external and extra functions can be coded by users with the C++ or Python programming languages and then inserted into the original traffic network model (Transport Simulation Systems, 2014). In practice, for the simulation of mixed traffic with motorcycle, motorcycle parameters need to be coded using adapted bicycle parameters. Motorcycle physical parameters and bicycle physical parameters are similar; however, there are several differences between the two modes, including lane changing, behaviour and speed.

FLOWSIM (Fuzzy Logic based Motorway Simulation) is a micro-simulation modelling tool featuring fuzzy inference systems, and was developed by Jianping Wu at the Transportation Research Group, University of Southampton. Compared to other modelling packages, FLOWSIM is more focused on the drivers' behaviour on speed and gap acceptance (Cacciabue, 2007). FLOWSIM also includes its unique model for bicycles and pedestrians for networks with large numbers of those user types. However, there seems to be no literature reporting on FLOWSIM's ability to model bus signal priority and motorcycles.

To conclude, VISSIM is considered as the most appropriate microscopic simulation package and is therefore selected for use in this study.

3.3.5 Calibration and validation of a simulation model

The development of a complete traffic simulation model requires a calibration and validation process to prove the model can successfully represent actual traffic conditions and provide reliable results. This has been argued to be the most important part of the procedure (Hellinga, 1998).

Model validation is defined to be the process of determining if the model logic is correctly represented by the computer code. This means the outputs from the computer code are consistent with the model logic. Model validation does not make any assessment of the validity of the proposed model logic or of the theory on which the logic is based. Model validation is primarily the responsibility of the model developers (Hellinga, 1998).

Model calibration is the process by which the model user establishes input parameter values in order to reflect the local traffic conditions being modelled. Model calibration is the responsibility of the model user (Hellinga, 1998). For model calibration, Hellinga (1998) proposed a process that consists of three main phases and eight component steps as presented in Figure 3-1.

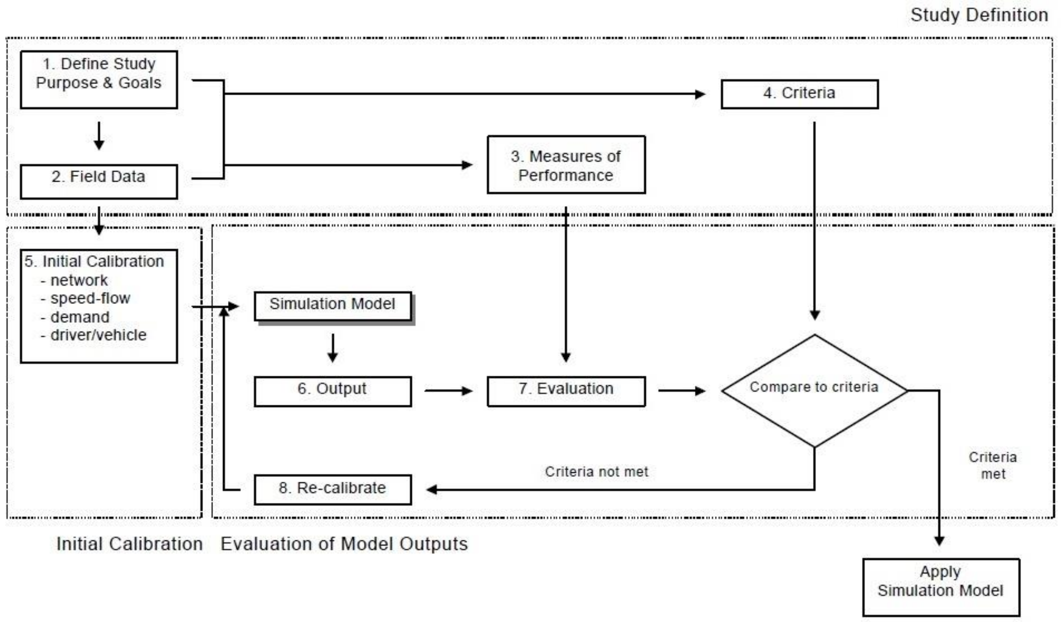


Figure 3-1 Structure of the calibration process

Source: Hellinga (1998)

In practice, the calibration activity is typically limited by constraints on data collection. Therefore, data requirements should be clearly and realistically defined, and these requirements should be prioritised on the basis of their relative importance to the calibration process (Hellinga, 1998). Similarly, for the calibration and the validation, it is essential to use different field data under untried condition, and the validation data should be collected in different time periods or conditions compared with the calibration data (Park and Schneeberger, 2003).

Based on the works of Hellinga (1998) and Sacks *et al.* (2002), Park and Schneeberger (2003) proposed a nine-step procedure for the calibration and validation of a microscopic simulation model and presented a case study which is widely used among transport researchers. The nine-step procedure is shown below.

Step 1. Measures of effectiveness selection. The first step is to decide the controllable and uncontrollable input parameters in the model and one performance measure to identify if the model is suitable for the selected real traffic network. The reason for that is the research does not require the simulation model to reflect the real traffic network exactly in every aspect but at one or some important points in order to give the outputs about the concerning problems. Therefore, the calibration and validation procedure should identify all measures of effectiveness in the first place before any data is collected.

Step 2. Data Collection. The second step is to collect data from the real traffic system. This data collection must include one performance measurement (e.g. travel time) and all identified uncontrollable parameters. Controllable parameters are optional, as they can be changed in the simulation model.

Step 3. Calibration parameter identification. The third step is to identify all parameters needed in the calibration stage, as those parameters are going to be adjusted. This step is also going to decide the acceptable ranges for all of the controllable parameters for the calibration.

Step 4. Experimental design. The experimental design step is used to determine the process of the simulation because the number of combinations of those controllable parameters could be very large and the required simulation run would be very difficult to proceed. Therefore an effective simulation plan must be designed beforehand.

Step 5. Run simulation. The fifth step is to run the simulation according to the experiment plan and then record the average value and the standard deviation for the performance measure determined in step 1.

Step 6. Surface function development. After collecting the performance measure results from the simulation, a surface function can be developed to present the relationship between the performance measurements and the controllable parameters.

Step 7. Candidate parameter set generation & *Step 8. Evaluation*. The seventh and eighth steps are to find the best related set of controllable parameters for the calibration and then to test if they can give significant results that link to the measure of performance. Once the sets of controllable parameters are verified according to these two steps, the final data collection activity can be performed for the model validation.

Step 9. Validation through new data collection. A new data set for all of the verified parameter sets must be used and compared again with the output from the model in order to prove that the model is validated and able to provide accurate results to reflect the actual traffic conditions.

This procedure, proposed by Park and Schneeberger (2003), strictly includes every step not just for the calibration but also the validation of a microscopic simulation model and has been acknowledged by many other transport researchers (Toledo *et al.*, 2004). As this pattern is well developed for microscopic simulation model calibration and validation, the simulation model of the comparative economic assessment will follow this nine-step procedure.

3.3.6 Summary

To develop a comparative economic assessment for a mixed transport environment with the dominance of motorcycles, the traffic simulation package must be able to simulate the operation of mixed traffic including motorcycles, cars and public transport modes. Travel time and vehicle speed need to be obtained from the traffic simulation in order to link social cost models and demand models. Hence, microscopic simulation, rather than macroscopic or mesoscopic simulation, has been chosen to evaluate detailed interactions between all transport modes. Among several microscopic simulation packages, VISSIM has been selected for this comparative economic assessment because this software can effectively simulate not only public transport modes but also private transport vehicles, particularly in mixed traffic with an abundance of motorcycles. As an important role in developing the microscopic traffic simulation, the nine steps procedure proposed by Park and Schneeberger (2003) is selected for this research.

3.4 Conclusion

To create a comparative economic assessment of urban transport infrastructure options in LMICs, where there are mixed traffic environments with the dominance of motorcycles, transport demand has been reviewed. The demand elasticity model can be used to calculate endogenous changes in total demand with respect to changes in composite costs of all transport modes. The incremental multinomial logit model might be used in a situation where there are no correlated transport modes. The incremental nested logit model is suitable for a case where two public transport modes are operated at the same time.

Because travel time and vehicle speed are treated as important inputs of social cost models and incremental demand models, a traffic simulation that includes these parameters for an existing traffic network needs to be adopted. After reviewing traffic simulation approaches and software options, VISSIM, a microscopic traffic simulation, has been chosen for the comparative economic assessment in this study. Of the various options, this software is the most suitable for the context of the current study, for example, mixed traffic with a dominance of motorcycles.

The VISSIM simulation can simulate one existing urban corridor to obtain key parameters such as travel time and speed of each vehicle. The incremental elasticity demand model might forecast the endogenous changes in general traffic with respect to any change in transport conditions. The incremental multinomial/nested logit models can predict modal share of each transport mode when generalised costs change. These models and the social cost models are integrated into a comparative economic assessment. The next chapter will discuss the methodology of the whole assessment and then describe how the assessment will be applied to a case study.

Chapter 4 Methodological Framework

4.1 Introduction

Cowie (2009) stated an example about investing in a new toll motorway which is located parallel to an overcrowded existing motorway. The first task is to estimate the total traffic on the route by developing a gravity type model incorporating tolls and reduced journey times in the generalised cost function. This is treated as the first estimate at the total traffic on the route. The next task is to forecast the share of traffic between the toll and the free motorway in the choice model. Then, the new prediction of traffic and journey time/average price is put into the models to generate a new share, recalculate total demands, re-estimate shares, recalculate costs, and so on. This is known as *iteration*. Similarly, this thesis focuses on the investment of a new PT technology on one existing mixed traffic corridor in urban areas. Multiple models must be integrated and run iteration to get outcomes in terms of given criteria. This chapter is going to discuss the methodology of the comparative economic assessment to evaluate options when one PT mode (e.g. BRT, Metro and Monorail) is invested in one urban corridor. Chapter 2 reviewed the social cost models of different transport modes. Chapter 3 reviewed demand models and traffic simulation models for such situations. The next part of this chapter describes the methodology of the completed assessment, which shows the connection between these models and displays how each model works. The third part of this chapter explains how this methodology can be applied to a case study.

4.2 Methodology

After reviewing literature in Chapter 2 and Chapter 3, there seems to be very little evidence on evaluation methods of motorcycles, cars, Taxi, Uber and PT technologies. Hence, the methodology of a comprehensive comparative economic assessment is suggested to fill this gap of literature. The comparative economic assessment will be made of four models: the social cost model, the incremental elasticity analysis, the incremental multinomial/nested logit model and the microscopic simulation model, which is shown in Figure 1-2. These four models would be closely interacting with each other to analyse the performance of different PT technologies, DRT and PRV modes at a strategic planning level. In addition, the integrated assessment might compare mixed transport systems with the introduction of a new PT mode and/or transport policy in terms of ASC. Hence, the SCM is the core model in this thesis. As a theoretical model, the stand-alone SCM has some drawbacks compared to the realistic traffic network. Firstly, as a strategic level model, it only considers an isolated corridor without any interaction of different modes and any junctions, as well as only one transport mode is operated in the corridor. This assumption could be not true for mixed traffic environments where several transport modes share infrastructure facilities such as bus, motorcycle and car. Therefore, the actual social cost calculations should take the interactions between different modes into account. The second disadvantage is that the actual number of passengers using each transport mode would vary rather than be fixed. It can depend on choices of travellers based on the generalised cost. The third drawback is that modal choice of users among all alternative modes is not taken into account.

Firstly, the mixed transport social cost model should consider the social costs of several transport modes sharing infrastructure facilities by allocating infrastructure costs to each transport mode and calculating vehicle speeds in mixed traffic. Additionally, the MSM can overcome the first drawback because the MSM seems to represent the vehicle interactions and the actual average speed of the vehicles, as well as the travel time of public transport passengers. These outputs are the main differences between the SCM model and the real world traffic network. Secondly, the IEA appears to solve the second drawback because the IEA can evaluate endogenous changes in demand levels according to any change to existing transport conditions. Therefore, the demand level will also become a dependent variable in the comparative economic assessment. Thirdly, the incremental multinomial/nested logit models might overcome the third disadvantage because these models analyse preferences of users for all alternative transport modes.

The comparative economic assessment begins with providing existing transport conditions and an introduction of a new PT technology and/or a transport policy such as a congestion charge scheme for private transport. A proposed PT demand needs to be set for introducing a new PT mode. This demand level should be assumed based on the infrastructure capacity of the new PT technology. Then, the main following steps of the completed assessment, which are shown in Figure 1-2, are described below.

Step 1: The microscopic simulation model simulates an existing mixed transport network to obtain traffic data for private transport and bus. The traffic data include travel time and vehicle speed.

Step 2: The social cost model evaluates operating speed, in-vehicle time and waiting time of new PT users.

Step 3: Traffic data obtained in Steps 1 and 2 are used as inputs for the incremental elasticity analysis to estimate the new endogenous general traffic with respect to composite costs of all transport modes. The utility of each transport mode is estimated by using data on time and cost in Steps 1 and 2, the composite cost is then calculated.

Steps 4 & 5: Input data for the incremental multinomial/nested logit models include: (i) In-vehicle time data and vehicle speed for each existing mode obtained from the microscopic simulation model in Step 1, (ii) Data on in-vehicle time, waiting time and operating speed for the new PT mode achieved from the social cost model in Step 2, and (iii) New endogenous total demand from the incremental elasticity analysis in Step 3. The outputs of the incremental logit models cover modal share and new demand for each transport mode. The incremental multinomial logit model is used in a situation where a new exclusive public transport is introduced to replace all bus services running on the partial and whole corridor. In other words, after the introduction of the new PT mode, conventional bus is not operated on the corridor. While the incremental nested logit model is used in a case where bus services running on the whole corridor are replaced by a new PT technology and bus services running on the partial corridor are still operated. This means that the existing bus and the new PT mode are grouped in a lower nest while the upper nest includes PT, car and motorcycle.

Step 6: The new demand for each transport mode in mixed traffic is input into the microscopic simulation to get new values of travel time and vehicle speed.

Step 7: The new demand for a segregated PT mode is input into the social cost model to obtain new values of operating speed, in-vehicle time and waiting time of new PT users.

After step 7, the first iteration of the assessment is finished. Implement the next iterations (Steps 1-7) until convergence - the difference between the previous PT passenger demand and current PT passenger demand is less than 1%. The Department for Transport (2017d) states that demonstrating the whole model system converges to a satisfactory degree proves that the model results are as free from error and ‘noise’ as possible.

After the convergence is achieved, the final demand levels of all transport modes are calculated and the ASC of each transport mode is estimated from the social cost models. Final outputs of each mixed transport option, where a new PT mode and/or transport policy is introduced, are identified and compared to choose the best option. The final results include the ASC, the modal share of public transport and the total general demand.

4.3 Case Study Approach

This section expresses a justification of choosing a case study approach based on Hanoi, Vietnam, as well as explains the reasons of determining types of data in a real case study to be collected for filling the gaps and the comparative economic assessment.

4.3.1 Hanoi case study

Hanoi, the capital of Vietnam, can be a good case study for this thesis because of following reasons.

Firstly, Vietnam is determined as a lower middle-income country with a gross national income per capita of US$ 2,400 in 2018 (World Bank, 2019).

Secondly, the characteristics of the transport system in Hanoi are representative of many cities in developing countries, particularly in South East Asia where motorcycles are dominant and most of them are small and medium-sized one (less than 150 cm^3 engine). Indeed, registered motorcycles accounted for about two-thirds of all motor vehicles at the end of 2003 in Taiwan. Motorcycles with small engines less than 150 cm^3 are especially popular, because of their high accessibility and low fuel consumption (Chang and Yeh, 2006). Furthermore, due to the low socioeconomic status of its people and relatively poor public transport services, especially in busy urban areas, motorcycle riding is an alternative and cheaper mode of transport which provides the freedom of door-to-door travel in countries such as Malaysia and other developing Asian countries. The small- and medium-sized motorcycles (less than 150 cm^3 engine) represented 99% of all motorcycles in Malaysia (Hussain, Radin Umar and Ahmad Farhan, 2011). Moreover, the transport characteristic in Yogyakarty, Indonesia is mixed traffic and overloaded on some road links. For example, in the Central Business District of Malioboro, motorcycle accounts for 82.15% of the total traffic volume in 2007 (Sugiyanto et al., 2011). In addition, in Khon Kaen, Thailand, the motorcycle share is 49% of all travel trips (Satiennam et al., 2011). Similarly, the motorcycle share in Hanoi in 2012 is high, at around 67.41% (Transport Engineering Design Incorporated, 2013). The rate of motor vehicle ownership in developing East Asian countries roughly tripled between 2003 and 2009 in line with nominal gross domestic product per capita increases. However, the huge volume of motorcycle in mixed traffic results in many challenges, including congestion, noise, emissions, and negative impacts on non-motorized transport and pedestrian spaces (Bray and Holyoak, 2015).

The third reason for choosing the Hanoi case study is that in conjunction with existing conventional bus systems, several new PT projects have been invested in Hanoi such as BRT and urban rail transit. These investments have been implemented in other countries. Taipei, in Taiwan, is an obvious example, where the mode share of public transport (buses, mass rapid transit, shuttle buses, trains, long-distance buses and taxis) is 38.8%. Of these, the share of mass rapid transit is around 19.7%. This can prove the success of investments in new PT technologies. (Taipei Department of Transportation, 2013).

In addition, the following subsections will state a review of Hanoi in more details.

4.3.1.1 City site

Hanoi, the capital of Vietnam, is located in northern Vietnam, and also is the second largest city by population. Hanoi capital, which is hatched in the grey area in Figure 4-1, has an area of 3,324 km^2. In addition, Hanoi is the country's political, cultural, scientific and technological centre, and also plays an important role in the economy and international trade. The population of Hanoi was around 8.1 million in 2018 with an average annual growth rate at about 3% (General Statistic Office of Vietnam, 2020). Urban areas with high density including 12 districts cover approximately 6.86% of the whole city area and the density is high at 10,576 persons/ km^2 in 2012 (Transport Engineering Design Incorporated, 2013) whilst the average Hanoi density is 2,410 persons/ km^2 in 2018 (General Statistic Office of Vietnam, 2020).

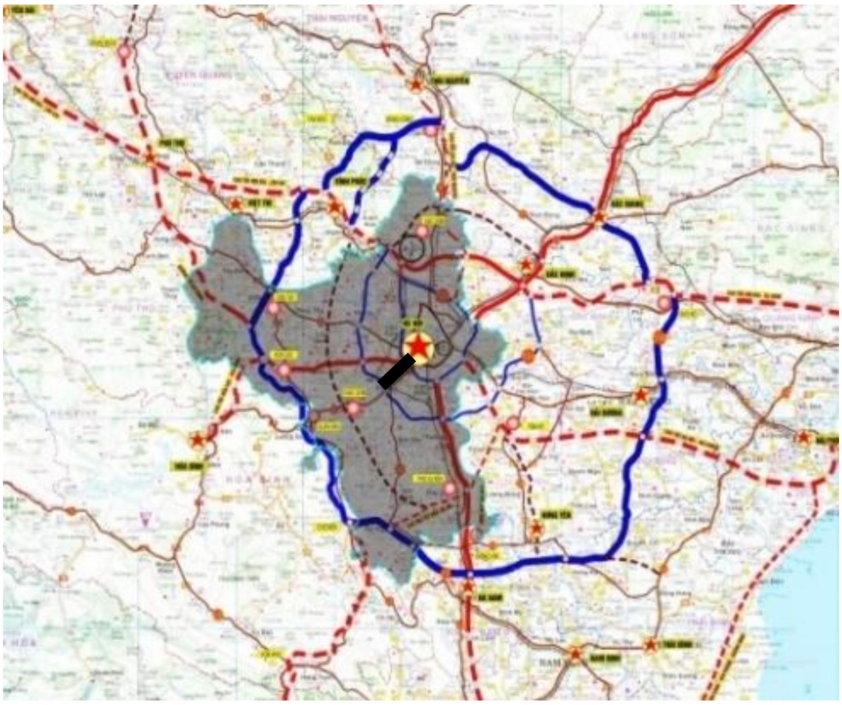


Figure 4-1 Location of Hanoi and transport networks

Source: Transport Engineering Design Incorporated (2013)

4.3.1.2 Traffic level

The road network in Hanoi can generally be summarized by being incomplete and consisting of major radial arterials converging into the city centre and ring roads linking the radial roads. The main road networks are shown in Figure 4-1. However, ring road system has not been completed in Hanoi, hence, several vehicles still have to go through the central area of Hanoi to access their destination. As a result, the probability of traffic congestion in the city centre can increase (Japan International Cooperation Agency, 2016).

4.3.1.3 Public Transportation

Currently, buses are the most popular means of PT in Hanoi, as well as the first BRT has been operated since January 2017. Up to 2017, Hanoi has 103 bus routes, including 79 urban bus routes and 24 sub-urban bus routes, operating from 5:00 am to 10:35 pm (Hanoi Transport & Services Corporation, 2017). Bus frequencies range from five to twenty minutes, depending on the type of route. The urban bus network, which has 1,272 vehicles, runs the total route mileage of about 2,300 km and transports over 1.1 million passengers per day (Hanoi Transport & Services Corporation, 2017).

4.3.1.4 PT network in the Hanoi Transportation Master Plan (TMP)

According to the TMP of Hanoi, one main objective is that the modal share of PT will continue to increase, and it is expected to reach between 50 per cent and 55 per cent by 2030 (Government of Vietnam, 2016). Table 4-1 shows not only the modal share of PT in the TMP but also historical numbers in 2005 and 2012. In order to obtain this aim, new PT technology networks will be built as radial and ring routes, which consists of light railway transit, mass railway transit, monorail and bus rapid transit. Four Metro lines and three BRT lines were expected to operate by 2020 (but see below) while eight LRT and/or Metro lines, three monorail routes and eleven BRT lines are expected to operate by 2030. In addition, the existing bus networks have been improved and expanded. The expected increase in the modal share of PT in the TMP of Hanoi is substantial. However, the aims were not achieved by 2020 in terms of development of new PT lines and PT share because of the following reasons. Firstly, only BRT line 1 has been operated since January 2017 while the first urban rail transit, named as line 2A, is under pilot operation from December 2020. Secondly, the PT share was around 10.5% in 2019 before the Covid-19 pandemic (Transport Department of Hanoi, 2020). In the TMP of Hanoi, there has not been any evidence on forecasting PT demand by 2020 or by 2030. As a result, the methodology of the comprehensive comparative economic assessment in this thesis is important for the Hanoi case study.

Table 4-1 Modal share of PT in Hanoi, Vietnam

Year	2005*	2012*	2020	2030	After 2030
Modal share of PT (%)	5.6	9.43	30-35	50-55	65-70

Source: Government of Vietnam (2016), * from Transport Engineering Design Incorporated (2013)

4.3.1.5 Chosen corridor in Hanoi case study

Nguyen Trai - Tran Phu - Quang Trung (NT-TP-QT) corridor with the length of 7.0 km, which is a major arterial in the Hanoi road networks shown as a black line in Figure 4-1, is selected for the Hanoi case study because of the following reasons.

Firstly, this corridor, which plays an important role in the Hanoi transport system, has four lanes per direction. This corridor links between the central Dong Da district and one coach station in the western area in the recently developed new district, Ha Dong district. On this corridor, the first urban rail transit line has been operated in the pilot scheme since December 2020.

Secondly, the corridor has extremely high levels of traffic volume at links and junctions. Adapt data on traffic survey at the Le Trong Tan-Quang Trung junction on 10/5/2016 from the TTS group, the total traffic volume in both directions on this corridor at this junction is around 7,000 PCU/hour.

Thirdly, a large number of PT services are operated on this corridor. Indeed, thirteen existing bus routes are operating on the whole or segments of the NT-TP-QT corridor. These bus services carried around 102,311,953 passengers in 2015 (Hanoi Transport Management and Operation Centre, 2017).

Finally, the potential availability of traffic data includes primary data and secondary data.

4.3.2 Main required data

Main data required for the social cost model, the microscopic simulation model and the incremental demand model include:

a) ***Costs of existing transport modes and proposed PT technology***

b) ***Existing traffic volume data*** for the simulation model and the incremental demand model cover car, motorcycle and bus at junctions and/or links.

b) ***Bus data***

(i) Total bus passenger demand of the chosen corridor for the simulation model and social cost model. The data involve bus passenger demand on the chosen corridor in the last few years, as well as bus infrastructure (bus stops) and bus fleet. These secondary data should be collected from the Hanoi Urban Transport Management and Operation Centre, who is in charge of all bus systems in Hanoi.

(ii) Primary data required at all bus stops on the corridor consist of numbers of boarding/alighting, bus occupancy, arrival/departure time and stopping time of each bus vehicle. These data are for the simulation model and the mixed transport social cost model

c) ***Signal data*** at all junctions on the corridor for the simulation model.

d) ***Infrastructure data***: Geometric data at junctions and links for the simulation model.

e) ***Data for the calibration and validation of the simulation model***:

- For Measures of Effectiveness: Travel time of conventional buses, motorcycles and cars between two given points on the chosen corridor.

f) ***Local acceleration parameters*** for inputs of the VISSIM software. These parameters of motorcycle are required to be collected by using a Stalker ATS II radar gun (see Figure 4-2). The reason for collecting these data is that VISSIM provides default acceleration/deceleration functions for vehicle types typically used in Western Europe. VISSIM uses functions instead of individual acceleration or deceleration data. In other words, acceleration and deceleration are functions of the speed. There are four types of functions: two acceleration functions and two deceleration functions that are illustrated as curves including maximum acceleration, desired acceleration, maximum deceleration and desired deceleration. VISSIM users can insert, select and edit acceleration/deceleration functions for local conditions (PTV AG, 2011). Among four functions, the difference between desired acceleration functions of dissimilar modes is the most significant.

Figure 4-2 The Stalker ATS II radar gun

Source: https://www.stalkerradar.com/sportsradar/ATS-II.html

A limitation of an available VISSIM package with student version 6.0 is to simulate a maximum corridor of 1.5 km. Hence, it is essential to select a segment with two or three intersections in the chosen corridor, of which length is less than 1.5 km. Moreover, this segment should represent the average traffic volume and the average bus passenger demand level of the entire corridor. Collected data for developing the simulation and the calibration and validation process is focussed for the selected segment.

4.4 Conclusion

The comparative economic assessment compares mixed transport systems with the introduction of a new PT mode and/or transport policy in terms of ASC. Therefore, the SCM is the key model in this completed assessment. However, the SCM has some drawbacks needed to be solved. The microscopic simulation model can overcome the first drawback of the SCM, which only considers an isolated corridor without any interaction between dissimilar modes and any junctions. The IEA might solve the second drawback of the SCM that demand is assumed to be fixed. The incremental multinomial/nested logit models can overcome the third disadvantage of the SCM, where preferences of users for all alternative transport modes are not taken into account. As a result, these four models are integrated into one comprehensive assessment, in which one iteration has seven steps showing the connection between these models and displaying how each model works. The iterations are implemented until the convergence is reached when the difference between the previous PT passenger demand and current PT passenger demand is less than 1%. The final outputs of the assessment are then obtained as well as the infrastructure options are compared to choose the best one.

Hanoi, the capital of Vietnam, is selected as a case study for this thesis because of the following main reasons. First, Vietnam is determined as a lower middle-income nation (World Bank, 2019). Second, the characteristics of the transport system in Hanoi can found in many cities in developing countries, where motorcycle is dominant in mixed traffic environments. Third, in conjunction with existing bus systems, several new PT modes have been introduced in Hanoi such as BRT and urban rail transit. The Nguyen Trai - Tran Phu - Quang Trung corridor, one main arterial, is chosen for collecting primary data. The main required data for four models in the comparative economic assessment have been determined and therefore collected for the next tasks of this study.

After developing the methodology of the completed assessment and choosing a case study for this research, as the core models of the assessment, the social cost models are developed in the next chapter in more details. The social cost models are built for PT, PRV, Taxi/Uber and mixed transport to evaluate total operator cost (or infrastructure operator costs for PRV), total user cost (vehicle user cost for PRV) and total external costs. These models might compare the performance of different PT technologies, PRV modes, Taxi/Uber and mixed transport at a strategic planning level.

Chapter 5 Transport Social Cost Model

5.1 Introduction

Chapter 4 illustrated the procedure of the comparative economic assessment, which is integrated from four models. The main aim of this assessment is to compare urban transport infrastructure options in terms of average social cost. Therefore, the social cost model is the core model in this completed assessment, which needs to be developed in more details. Based on the existing literature reviewed in Chapter 2, this chapter is going to describe the development of the social cost models for PT, PRV, and Taxi/Uber in the first place.

The PT, PRV and Taxi/Uber social cost models are developed for one single urban corridor rather than a complete network for fixed daily passenger demand. The main assumption is that only one transport mode is operated on the whole corridor. Moreover, the daily passenger demand level (Q) is assumed to be exogenous, with a starting total daily passenger demand level of 1,000 and increases with an increment of 1,000 total daily passengers until 700,000 passengers per direction per day (pdd). In general, the total social costs (TSC) of each transport mode include three main components: total operator costs - TOC (or infrastructure operator costs for PRV), total user costs - TUC (or vehicle user cost for PRV) and total external costs (TEC). However, elements of these three components and their calculations are different for dissimilar modes. The general equation of the total social costs is shown as:

$$TSC = TOC + TUC + TEC \tag{5-1}$$

The fifth section of the chapter illustrates total social costs for mixed transport, which is the sum of total social costs for PT, PRV and Taxi/Uber, except infrastructure costs. Because the infrastructure costs need to be allocated to transport modes sharing the facilities. The last section of the chapter discusses the application of the four social cost models to the Hanoi case study. These social cost models are calculated based on Microsoft Excel and MATLAB to compare the performance of different transport models at a strategic planning level. As a performance indicator, the average social cost (ASC), which indicates the relationships between costs and demand levels, is calculated as follows:

$$ASC = TSC / PKM \tag{5-2}$$

where,

PKM is the total annual passenger-kilometres, which is calculated by the product of total passenger demand and average passenger journey length as:

$$PKM = 2 * a * Q * JL \tag{5-3}$$

where,

Q is the daily passenger demand on the corridor (passengers/direction/day). Depending on local conditions, the daily passenger demands will be split into the different time periods including the peak and off-peak periods;

a is the annualisation factor, the default value is 261 (weekdays/year);

JL is the average passenger journey length (km).

5.2 Public Transport Social Cost Model

The PT social cost model is built based on the study by Brand and Preston (2003). The total social costs for PT cover total operator costs, total user costs and total external costs, which are described below.

5.2.1 Operator cost

As mentioned in Subsection 2.3.1.1, there are three approaches to estimate operator costs of public transport modes. In practice, available descriptive data has strong influence on cost modelling decisions and the precise definitions of the resource variables. Due to the available data for the case study, the Fully Allocated Costs model is used in this research.

Fully Allocated Costs (FAC) model

The procedure of the FAC model is implemented in five steps in Figure 2-4.

Step 1: Assign expense object classes to allocation variables.

The operator costs of the PT service include both operating cost and capital investment cost. The operating cost can be assigned to allocation variables such as Vehicle-Hours, Vehicle-Distance and Peak Vehicle. If vehicle depreciation is allocated to vehicle-related operating cost, hence, the capital investment cost should be infrastructure cost. The infrastructure cost might be allocated to Track/Lane Distance, number of Stops/Stations and number of Depots. For the available capital investment cost, these costs must be converted to an annual basis by using the Capital Recovery Factor (CRF), which is a function of economic life expectancy and discount rate (Rogers and Duffy, 2012). As a result, the operator cost allocation matrix for the PT services can be suggested as shown in Table 5-1 with six allocation variables.

Table 5-1 The operator cost allocation matrix for the PT services

Expense object / Allocation variables	**Vehicle-Hours**	**Vehicle-Distance**	**Peak Vehicle**	**Route Distance (Track /Lane)**	**Number of Stations / Stops**	**Number of Depots**
Crew, Admin	x					
Fuel, tyres, third party insurance		x				
Vehicle maintenance	x					
Vehicle depreciation and leasing			x			
Operating power supply		x				
Infrastructure cost for guide-ways/lane				x		
Infrastructure cost for power supply (only for electrical railway system)				x		
Infrastructure cost for signalling and communications (for railway system)				x		
Civil work cost for stops/stations					x	
Station equipment, escalators and lifts					x	
Infrastructure cost for depots						x

Step 2: Calculate total costs assigned to each allocation variable by using available local data. If any data is not available, a transfer approach with a PPP factor from one city into a study city can be used. However, this approach should be avoided to maximise the accuracy of the model.

Step 3: Calculate unit costs for each allocation variable by dividing the total costs allocated to each allocation variable by values of the allocation variable. The values of the allocation variable are estimated from available local data. Any expense objects cost related to infrastructure investment is converted to annual capital investment charge by using the Capital Recovery Factor below (Rogers and Duffy, 2012).

$$Capital\ Recovery\ Factor_{inf} = \frac{r\,(1+r)^{m}}{(1+r)^{m}-1} \tag{5-4}$$

Where,

m is the economic life expectancy of the PT infrastructure (years);

r is the discount rate for capital infrastructure investment (%).

In addition, because bus and BRT are road-based modes, the estimate of the infrastructure costs for these modes is also discussed in more details in subsection 5.3.6.

Step 4: Calculate route-specific values for each allocation variables. These values are estimated for the chosen corridor in this thesis and according to the daily passenger demands (*Q*), which start at 1000 pdd and go up with the increment of 1,000 pdd until 700,000 pdd.

Route distance/length: is the length of the study corridor in km.

Annual Vehicle-hours

Annual vehicle-hours *(VH)* for the PT technology are required to calculate the time-related operating costs of the operator, which is the total hours of the vehicles operating on the corridor:

$$VH = a * \sum_t F_t * T_t \frac{L_{track}}{V_{all}} \tag{5-5}$$

where,

V_{all} is the average operating speed, including all stop density and capacity restraints, which is shown in Equation (5-11) (km/hour);

T_t is the time period *t*, which presents for peak and off peak periods (hours);

L_{track} is twice of the length of the chosen corridor (km);

a is an annualisation factor, the default value is 261 (weekdays/year).

F_t is the service frequency at time period *t* (vehicles/hour);

Vehicle-kilometres

Total vehicle-kilometres (*VKM*) on the chosen corridor are calculated by the total distance travelled by the total number of vehicles in all time periods as:

$$VKM = a * L_{track} * \sum_t F_t * T_t \tag{5-6}$$

where,

F_t, T_t, L_{track} and *a* are shown in Equation (5-5).

Peak vehicle requirement

Peak vehicle requirement (*PVR*) is the number of public transport vehicles required to provide the service frequency on the corridor. This peak vehicle requirement is essential to calculate the maximum number of vehicles required by the operator and hence the capital investment required for the vehicle fleet.

$$PVR = CEILING\left[MAX\left(F_t \frac{L_{track}}{V_{all}}\right) * (1+\delta)\right] \quad \textbf{(5-7)}$$

Where,

δ is a factor allowing for spare vehicles, the default value is 10%.

CEILING() is a function to round up to integer values;

MAX() is a function to return maximum value over the different periods.

Number of stations/stops

The number of stations/stops is calculated by dividing the length of the corridor by the average distance between stations/stops, which is shown in the following equation:

$$N_{station/stop} = CEILING\left(\frac{L_{track}}{D_{station/stop}}\right) \quad \textbf{(5-8)}$$

Where,

$D_{station/stop}$ is an average distance between stations/stops (km);

L_{track} is twice of the length of the chosen corridor (km);

CEILING() is a function to round up to integer values.

Number of depots

The number of depots for the public transport service depends on vehicle fleets in local conditions. According to the secondary data provided by Hanoi Transport Management and Operation Centre (TRAMOC), Hanoi Metro Company (HMC), the numbers of depots for the first BRT line and the first Metro line are equal to one. The default value is therefore equal to 1.0 in this thesis.

Service frequency

The service frequency of public transport technology can be calculated based on the passenger demand level of the time periods and the maximum capacity of the vehicle as:

$$F_t = \alpha \cdot Q_t \,/\, \gamma \cdot Cveh \quad \textbf{(5-9)}$$

where,

F_t is the service frequency requirement for the passenger demand level in the time period *t* (vehicle/hour);

α is a supply/demand factor to allow for seasonal variation in demand (default value is assumed to be 1.1);

γ is a maximum load factor of the vehicle at which level a new vehicle is required;

C_{veh} is the total passenger capacity of the vehicle, including seating and standing (passenger/vehicle).

Qt is the passenger demand of the time period *t* (passenger/direction/hour), which is calculated as:

$$Q_t = \beta \cdot Q / T_t \qquad \textbf{(5-10)}$$

where,

β is passenger demand share of the time period *t* (%);

Q is the total daily passenger demand (passengers/direction/day);

T_t is the duration of the time period *t* (hours).

Operating speed

Based on speed equations of Small (1983), Brand and Preston (2003) and Li (2015), the operating speed of a PT mode is calculated as follows:

$$V_{all} = \begin{cases} V_{NoCap} & if\ F_t \leq\ C_{fac}\ (= f * C_{inf}) \\ \dfrac{L}{\frac{L}{V_{NoCap}} + \frac{1}{2} * W * \left(\frac{F_t}{C_{fac}} - 1\right)} & if\ F_t >\ C_{fac} (= f * C_{inf}) \end{cases} \qquad \textbf{(5-11)}$$

V_{NoCap} , C_{fac} are mentioned in Equations (2-4) and (2-5).

W is the peak period duration in hours. The default value can be 1 hour (Small, 1983).

L is the length of the study corridor in km.

f is capacity percentages, as listed in Table 2-1.

C_{inf} is the infrastructure capacity, which is the maximum possible number of vehicles per lane (for road-based systems) or per track (for rail-based systems), is calculated as the following equation:

$$C_{inf} = \frac{3600}{H} \qquad \textbf{(5-12)}$$

where,

H is the safety headway (second), which is calculated as the minimum possible service interval without any passenger boarding and alighting as follows:

$$H = T_{stop} + (\frac{2* L_{veh}}{A})^{1/2} + \frac{3.6*L_{veh}}{V_{max}} + \frac{V_{max}}{3.6*2*A_{max}} \tag{5-13}$$

where,

T_{stop} is the average fixed vehicle stopping time per stop/station (second), which includes opening/closing doors and changing shifts for drivers;

L_{veh} is the total length of the vehicle (metres);

A is acceleration/deceleration of the public transport vehicle (metres/second^2);

A_{max} is the maximum deceleration of the public transport vehicle in emergency braking situation as stopping distance (metres/second^2);

The average dwell time is assumed as a uniform distribution of the passengers in each stop/station. Therefore, the average dwell time per stop/station is estimated as (Brand and Preston, 2003):

$$T_{dwell} = T_{stop} + T_{pas} \frac{Q_t}{\left(\frac{L_{track}}{D_{stop}}\right)*F_t} \tag{5-14}$$

Where,

T_{dwell} is the average dwell time per stop/station (second);

L_{track} is the total track/lane length of the corridor (Km). In order to account for both direction of the transit route, the value of L_{track} is twice of the route length.

T_{pas} is the average boarding time per passenger (second);

D_{stop} is the distance between stops/stations (Km);

Q_t is the passenger demand in the time period t, which is calculated based on the total daily passenger demand Q (passenger/direction/hour);

F_t is the service frequency at time period t (vehicles/hour);

Step 5: Calculate fully allocated costs.

Total annual operator cost (*TOC*) is the sum of annual operating costs and annual infrastructure costs:

$$TOC = AIC + AOC = (1 + \alpha) * (L_{track/lane} * UIC_{track/lane} + N_{station/stop} * UIC_{station/stop} + N_{depot} * UIC_{depot}) + (VH * UOC_T + \beta * VKM * UOC_D + PVR * UOC_V) \quad \textbf{(5-15)}$$

where,

AIC is the total annual infrastructure investment charge of the PT service (£/year);

AOC is the annual operating costs (£/year);

α is a factor to account for supplementary costs which can cover extra incurred costs during the construction period in reality. Ministry of Construction (2016) states that the maximum value of 'α' is 10%. Hence, this value can be calculated as 10% for the Hanoi case study;

$L_{track/lane}$ is the total length of the PT track/lane route (km).

$UIC_{track/lane}$ is the unit annual track/lane-related infrastructure cost costs (£/km).

$UIC_{station/stop}$ is the unit annual station/stop-related infrastructure cost costs (£);

$N_{station/stop}$ is the total number of stations/stops for the PT route.

N_{depot} is the total number of depots for the PT route.

UIC_{depot} is the unit annual station/stop-related infrastructure cost costs (£).

VKM is the annual vehicle-kilometres on the chosen corridor, shown in Equation (5-6);

UOC_D is the unit distance-related operating costs (£/vehicle-kilometre);

β is a factor to account for additional fuel and oil consumption due to congestion in mixed traffic. which is usually between 1 and 1.2 (Brand and Preston, 2003);

VH is the annual vehicle-hours, shown in Equation (5-5);

UOC_T is the unit time-related operating costs (£/vehicle-hour);

PVR is the maximum number of the required vehicle in service during a weekday, shown in Equation (5-7);

UOC_V is the unit vehicle-related operating costs (£/vehicle);

5.2.2 User cost

Transfer time is not considered in the PT user costs because of the following reasons. Firstly, the results of a survey sample of 2,000 households in the influence area of the Metro lines in Hanoi in

2019, which are provided by the Transport Engineering Design Incorporated, showed that the number of PT trips with transfers is minor. Secondly, this thesis focuses on only one transport infrastructure corridor rather than a complete network. The total cost of PT users is estimated as (Brand and Preston, 2003):

$$TUC = (W_{walk} * TT_{walk} + W_{wait} * TT_{wait} + TT_{IVT}) * VoT \qquad \textbf{(5-16)}$$

Where,

TUC is the total annual user cost (£/year);

W_{walk} is a factor to represent the weighting perception of walking versus in-vehicle time (IVT).

W_{wait} is a factor to represent the weighting perception of waiting versus IVT.

Asian Development Bank (2013) suggested that these factors should be equal to 1.5 for LMICs, however, a value of 2.0 is used for the walking and waiting factors in this thesis (Department for Transport, 2017b). The reason for choosing a higher value is that the existing conditions at bus stops and sidewalks seemed to be poor in Hanoi (Hansen, 2016).

TT_{walk}, TT_{wait} , TT_{IVT} are the total annual walking time, total annual wait time and total annual IVT respectively (hours);

VoT is the value of IVT for the PT users (£/hour).

5.2.2.1 In-vehicle time

The total annual in-vehicle time is calculated by using the average passenger journey length, the average operating speed of the transit service and the total passenger demand level. Note that a factor of 2 is used for both directions.

$$TT_{IVT} = 2 * a * JL * \sum_t \frac{Q_t * T_t}{V_{all}} \qquad \textbf{(5-17)}$$

where,

TT_{IVT} is the total annual in-vehicle time (hours);

JL is the average transit passenger journey length (Km);

V_{all}, Q_t , T_t and a are shown in Equation (5-10) and (5-11).

5.2.2.2 Walking time

Brand and Preston (2003) suggested an equation to evaluate the walking distance from/to stop based on the average influence width and the average distance between stops/stations as follows:

$$D_{walk} = \frac{WC + D_{stop}}{4} \tag{5-18}$$

where,

D_{walk} is the average walking distance from/to the transit stop/station (km);

WC is the average influence width of the transit corridor, or service coverage (km);

D_{stop} is the average distance between stops/stations (km).

The average walking time is calculated by the following equation:

$$T_{walk} = \frac{D_{walk}}{V_{walk}} \tag{5-19}$$

where,

T_{walk} is the average walking time per passenger (hours);

V_{walk} is the average walking speed (km/hour).

The total annual walking time is estimated by multiplying the average walking time per passenger by the total annual passengers. Note that a factor of 2 is multiplied to the average walking time to take into account for both accessing the stop/stop and getting to the destination.

$$TT_{walk} = 2 * a * Q * 2 * T_{walk} \tag{5-20}$$

where,

TT_{walk} is the total annual passenger walking time (hours);

Q is the total daily passenger demand (passenger/direction/day);

a is the annualisation factor, the default value is 261 (weekdays/year).

5.2.2.3 Waiting time

By assuming all transit passengers are evenly distributed, the passenger waiting time is calculated as a function of the service frequency and dwell time (Brand and Preston, 2003):

$$T_{wait} = \frac{1}{2*F} + \frac{T_{dwell}}{2*3600} \tag{5-21}$$

Where,

T_{wait} is the average waiting time per passenger (hours);

F is the service frequency (vehicle/hour);

T_{dwell} is the average vehicle dwell time per stop/station, is shown in Equation (5-14).

The total annual waiting time is estimated by multiplying the average waiting time per passenger by the total annual passengers.

$$TT_{wait} = 2 * a * Q * T_{wait} \tag{5-22}$$

where,

TT_{wait} is the total annual passenger waiting time (hours);

Q is the total daily passenger demand (passenger/direction/day);

a is the annualisation factor, the default value is 261 (weekdays/year).

5.2.3 External cost

The total external costs for PT include accident cost, noise pollution cost, air pollution cost and climate change cost. The total external costs are calculated by multiplying the total annual traffic volume (vehicle-kilometre) by the unit external cost value (Brand and Preston, 2003). Using vehicle occupancy rate values, unit external costs for PT technologies can be transferred from pence/vehicle-km into pence/pax-km. Therefore, the total external costs are rearranged as:

$$TEC = (UEC_{air} + UEC_{noise} + UEC_{climate} + UEC_{accident}) * 100 * PKM \tag{5-23}$$

where,

TEC is the total annual external cost (£/year);

UEC_{air}, UEC_{noise} , $UEC_{climate}$, $UEC_{accident}$ are the unit air pollution cost, unit noise pollution, unit climate change cost and unit external accident respectively (pence/pax-km);

PKM is the total annual passenger-kilometres (pax-km).

The ‘Willingness to Pay’ approach mentioned in subsection 2.3.1.3 is used for transferring of unit external costs for PT between the UK (showed in Table 2-2) and a study country.

5.2.4 Operating Procedure of public transport social cost model

Figure 5-1 shows the operating procedure of the public transport social cost model to estimate the ASC for PT for different demand levels.

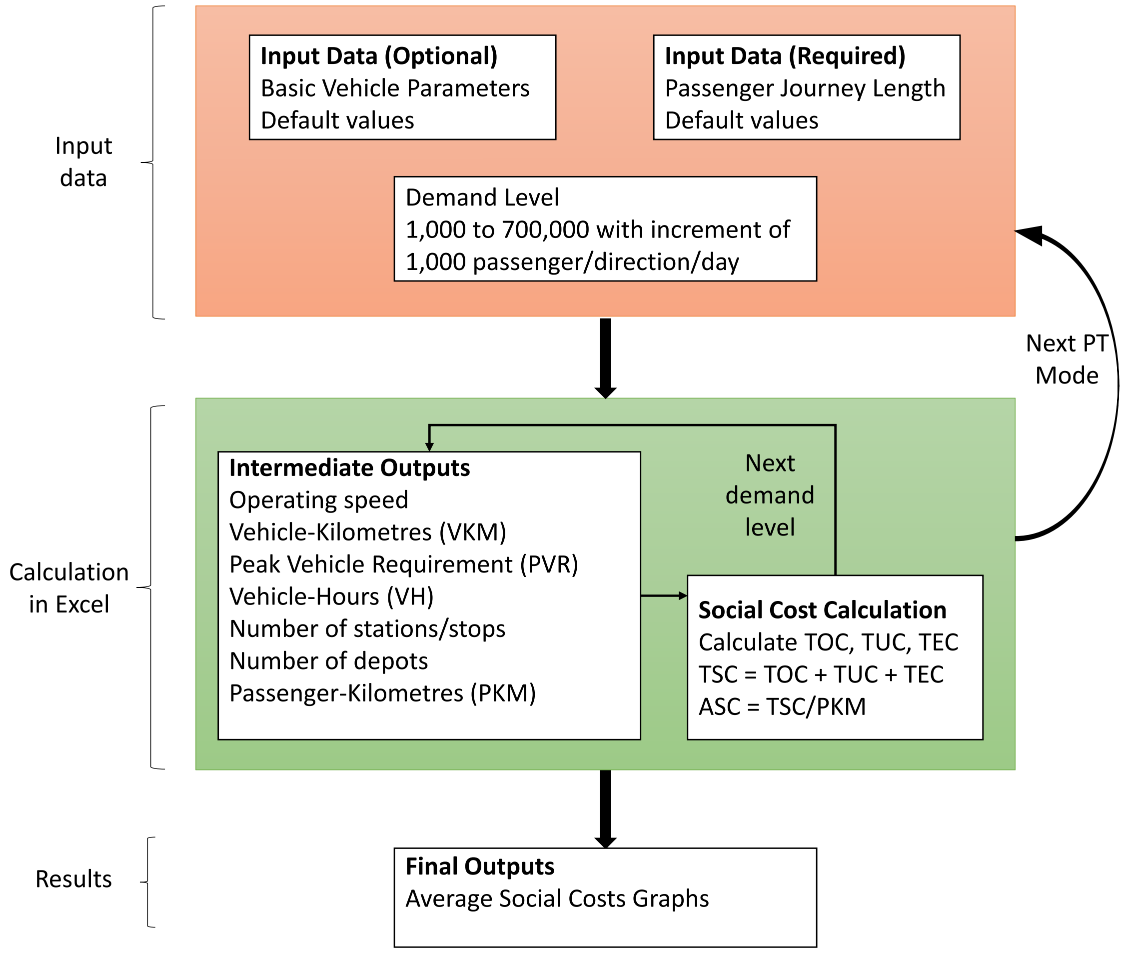


Figure 5-1 Procedure of public transport social cost model

Due to high person capacity, the daily passenger demand level for the Monorail and Metro options starts at 20,000 pdd and 30,000 pdd respectively.

5.3 Private Transport Social Cost Model

The private transport social cost model is developed based on the cost functions of PRV by Small and Verhoef (2007). The total social costs (*TSC*) of each private transport mode include the total vehicle user cost (*TUC*), the total infrastructure operator costs (*TOC*) and the total external costs (*TEC*). The TUCs for PRV consist of operating costs for users, private vehicle capital costs, travel time and congested-related delay costs. The TOCs for PRV cover maintenance costs, infrastructure costs and parking costs. The TECs cover noise pollution, air pollution, climate change and accident cost. Each cost element is illustrated below.

5.3.1 Operating cost for users

The operating costs for the PRV users include fuel and non-fuel costs. The non-fuel costs cover oil, tyres and vehicle maintenance (Department for Transport, 2017b). The road tax and insurance could be treated as costs to the private vehicle operator. However, these might be benefits to the infrastructure operator. Hence, they can be treated as transfers and ignored in the calculation of total social costs and average social costs.

Car fuel operating costs

Car fuel operating cost is the product of fuel consumption and fuel price. Fuel consumption is estimated as (Department for Transport, 2017b):

$$L = (a + b * v + c * v^2 + d * v^3) / v \tag{5-24}$$

Where,

L is the fuel consumption (litres/kilometre);

v is the average speed (km/h);

a, b, c, d are parameters defined for each vehicle category. Table 5-2 shows fuel consumption parameter values in the UK.

Table 5-2 Fuel consumption parameter values in the UK (litres per km, 2010)

Vehicle Category	Parameters			
	a	b	c	d
Petrol Car	1.180115	0.046395	-0.000086	0.000003
Diesel Car	0.518875	0.065559	-0.000623	0.000005

Source: TAG Data Book (Department for Transport, 2017a)

There is very little evidence on estimations of fuel consumption in Vietnam. Hence, it is assumed that parameters of the car fleet in a developed country (UK) in 2010 can be used for the car fleet in a developing country (Vietnam) at the present time.

Car non-fuel operating costs

These costs cover oil, tyres, maintenance and vehicle capital saving (only for vehicles in working time), which are combined in the following formula (Department for Transport, 2017b).

$$C = a_1 + b_1/\mathrm{V} \tag{5-25}$$

Where,

C is the cost in pence per kilometre travelled;

V is the average link speed (km/h);

a_1 is a parameter for distance-related costs defined for each vehicle category;

b_1 is a parameter for vehicle capital saving defined for each vehicle category (only relevant to working vehicles). This value is not considered in this thesis.

Table 5-3 shows these parameter values in the UK.

Table 5-3 Non-fuel resource vehicle operating costs (2010 prices)

Vehicle Category		Parameter Values	
		a_1 p/km	b_1 p/hr
Car	Work Petrol	4.966	135.946
	Work Diesel	4.966	135.946

Source: TAG Data Book (Department for Transport, 2017a)

Motorcycle operating costs

Sugiyanto et al. (2011) estimated the congestion cost for motorcycles users in Malioboro, Yogyakarty, Indonesia. According to Sugiyanto et al. (2010) as cited by Sugiyanto et al. (2011), the motorcycle operating cost is formulated as:

$$OC_{motorcycle} = 0.0921 * V^2 - 8.8647 * V + 555.51 \tag{5-26}$$

Where,

$OC_{motorcyle}$ is the motorcycle operating cost (IDR/km). A PPP factor is used to transfer Indonesian Rupiah (IDR) to the currency of a study country;

V is the speed of motorcycle (km/h).

After estimating the unit operating costs for PRV, the total operating costs for PRV is calculated as a function of the unit operating costs, the average journey length, the daily passenger demand on the corridor and the vehicle occupancy.

5.3.2 Private vehicle capital cost

The private vehicle capital costs can be estimated by combining interest and depreciation costs and might be averaged over the life of the private vehicle by applying the CRF to the price of a new vehicle (Small and Verhoef, 2007).

So, the average private vehicle capital cost is calculated as:

$$AVC_i = \frac{APNV_i}{AVKT_i} * \frac{r\,(1+r)^m}{(1+r)^m - 1} \qquad \textbf{(5-27)}$$

where,

AVC_i is the average capital cost of private vehicle type *i* (£/vehicle-km);

$APNV_i$ is the average price of a new private vehicle type *i* (car or motorcycle) (£);

$AVKT_i$ is the annual distance one private vehicle type *i* travelled (vehicle-km/year);

m is the median lifetime of the private vehicle (years);

r is the discount rate for capital investment (%).

The total private vehicle capital costs are calculated by multiplying the average private vehicle capital cost by the total vehicle-km. The total vehicle-km is estimated as a function of the average journey length, the daily passenger demand on the corridor and the vehicle occupancy.

5.3.3 Travel time cost

This study does not consider accessing the vehicle at parking areas and walking from parking areas to final destinations. In other words, the in-vehicle time for PRV users is treated as the travel time. The travel time for PRV users includes travel time on links and travel time at intersections. The travel time cost for each mode is calculated by multiplying the travel time and the value of time for that mode.

5.3.3.1 Travel time on links

The travel time on links with the journey length of *JL* can be estimated by the following formula:

$$TraT_{link} = \frac{JL}{V_{all}} \qquad \textbf{(5-28)}$$

Where,

$TraT_{link}$ is the travel time on a link (hours);

V_{all} is the mean operating speed of private vehicles (km/h).

The average operating speed of private vehicles on a link is calculated for two cases: traffic volume is smaller than capacity and traffic volume is higher than capacity. The equation of the average speed is shown in Equation (5-11), however, the values of V_{NoCap} are different for dissimilar modes.

For motorcycle, based on the motorcycle equivalent unit (MCU) model of Nguyen, Sano and Chu (2007), V_{NoCap} kph at a link of for one-lane per direction corridor is calculated as:

$$V_{NoCap} = 39.82 - 0.0011 * Flow \qquad \textbf{(5-29)}$$

and for a two-lane per direction corridor as (Chu, Sano and Matsumoto, 2005):

$$V_{NoCap} = 37.90 - 0.0018 * Flow \qquad \textbf{(5-30)}$$

where,

Flow is the motorcycle flow (motorcycle/direction/hour).

For car, Taxi and Uber, the average link vehicle speed V_{NoCap} kph at flow (*Flow*) is given by the following formula (Department for Transport, 2014).

$$V_{NoCap} = 39.50 - 0.003 * Flow \qquad \textbf{(5-31)}$$

Where,

Flow is the car flow (car/hour/3.65m lane).

The vehicle flow can be calculated based on passenger demand and vehicle occupancy.

5.3.3.2 In-vehicle time at intersections

Assume all intersections on the selected corridor have traffic two-phase signals. A simple approach to estimate the average travel time at signalised junctions as a quarter of signal cycle time. Hence, the IVT at intersections is calculated as:

$$Intersection\ time = INT * Cycle\_time/(4 * 3600) \qquad \textbf{(5-32)}$$

Where,

INT is the number of intersection on the corridor;

Cycle_time is an average cycle time for a signalised junction on the corridor (seconds).

5.3.4 Congested-related delay costs

The congested-related delay costs (*SDC*) for each mode is estimated by multiplying the delay time (*SDTT*) and the value of time for that mode, which is:

$$SDC = \frac{SDTT * VoT}{JL} \qquad \textbf{(5-33)}$$

Where,

VoT is the value of time (£/hour);

JL is the average length of the journey (Km).

For one study corridor, the *SDTT* is calculated by multiplying the Coefficient of Variation *CV* by the mean travel time (*MTT*) (Department for Transport, 2017a):

$$SDTT\ =\ CV * MTT \tag{5-34}$$

$$MTT = \frac{JL}{V_{all}} \tag{5-35}$$

Where,

V_{all} is the mean operating speed (km/h).

CV is calculated as Equation (2-19). Of these, the Congestion Index (*ci*) is determined as follows:

$$ci = \frac{MTT}{FLTT} \tag{5-36}$$

Where,

FLTT is the free-flow travel time in the objective corridor, which is:

$$FLTT = \frac{JL}{FLS} \tag{5-37}$$

where,

FLS is the free-flow speed in the objective corridor (km/h), which is treated as the maximum operating speed.

5.3.5 Maintenance cost

The average maintenance cost is estimated as (Small and Verhoef, 2007):

$$AVMC = \frac{AMC}{AVKT} \tag{5-38}$$

where,

AVMC is the average highway maintenance costs (£/vehicle-km);

AMC is the annual highway maintenance costs for whole networks (£/year);

AVKT is the annual all vehicles kilometre travelled (vehicle-km/year), which is calculated by the formula as follows:

$$AVKT = \sum APVKT_i \tag{5-39}$$

where,

$APVKT_i$ is the annual private vehicle type *i* kilometre travelled (km/year). These values need to be estimated according to local conditions.

The total annual maintenance cost is calculated by multiplying the average maintenance cost by the total annual vehicle-km.

5.3.6 Infrastructure cost

The infrastructure costs for PRV are fixed costs, which are the product of the infrastructure costs per km and the length of the corridor. This means that these costs are independent of passenger demand. The infrastructure costs per km must be converted to an annual basis using the Capital Recovery Factor, which is estimated as Equation (5-4). In the PRV social cost model, only one transport mode is assumed to be used infrastructure facility. Hence, the infrastructure costs for car and motorcycle are assumed to be the same if the number of lanes per direction is identical. Moreover, as road-based modes, the infrastructure costs for BRT and bus in the PT social cost models, which exclude the costs of PT stops and depots, are identical to those costs for PRV. These costs need to be estimated based on local conditions.

5.3.7 Parking cost

The average parking costs for private vehicle type *i*, PC_i in pence/vehicle-km, can be estimated as follows:

$$PC_i = \frac{Average\ cost\ of\ parking\ for\ vehicle\ type\ i}{Average\ distance\ of\ each\ trip\ by\ vehicle\ type\ i} \tag{5-40}$$

The average parking costs are estimated based on local conditions. Then, the total annual parking costs for PRV are calculated by multiplying the average parking cost in pence/vehicle-km by total annual vehicle-km.

5.3.8 External cost

The ‘Willingness to Pay’ approach is used for transferring of the unit external costs by car and motorcycle between the UK and a study country where an income elasticity of 1.0 and a PPP rate are used. The results of the unit external costs by car and motorcycle for a study country are estimated by using findings of several empirical studies by Sansom *et al.* (2001), Chen *et al.* (2003), Vu *et al.* (2013), Tsai *et al.* (2005), Maibach *et al.* (2007) and WebTAG. The findings of those studies are shown in subsection 2.3.2.7. Then, the total external costs are calculated as Equation (5-23).

5.3.9 Operating Procedure of private transport social cost model

Figure 5-2 shows the operating procedure of the private transport social cost model to estimate the ASC of each mode. This model is applied to motorcycle and car.

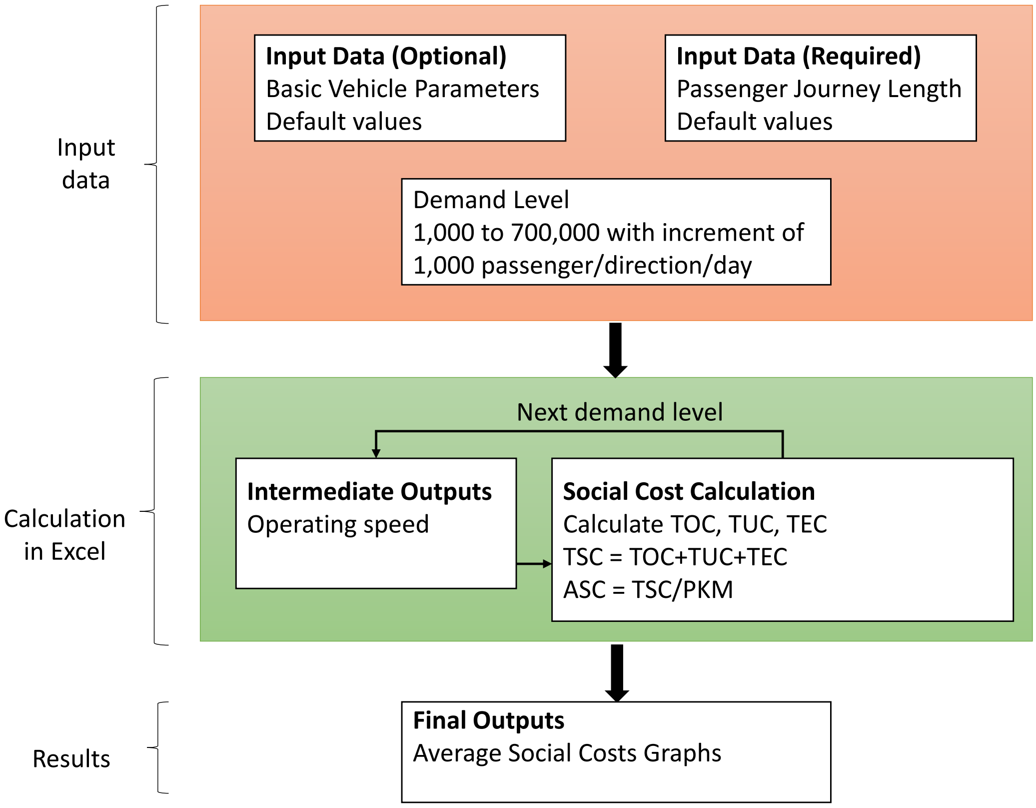


Figure 5-2 Procedure of private transport social cost model

5.4 Taxi/Uber Social Cost Model

The total social costs (*TSC*) of Taxi/Uber include the total operator costs (*TOC*), the total user costs (*TUC*) and the total external costs (*TEC*). The operator costs consist of vehicle capital cost; fuel and non-fuel operating cost; administrative cost; infrastructure costs and highway maintenance cost; and driver earnings. The total user costs cover travel time cost and congested-related delay costs. The TECs cover noise pollution, air pollution, climate change and accident cost. These cost components are described below.

5.4.1 Operator cost

5.4.1.1 Vehicle capital cost

For taxi, assume that the capital cost of taxi fleets is mostly determined by vehicle provision, hence, the average taxi capital costs are calculated as the following equations by using the Capital Recovery Factor (Rogers and Duffy, 2012):

$$ATaxiC = \frac{APTaxi}{ATaxiKm} * \frac{r\,(1+r)^{m}}{(1+r)^{m}-1} \qquad \textbf{(5-41)}$$

Where,

$ATaxiC$ is the average taxi capital unit cost (£/vehicle-km);

$APTaxi$ is the average price of a new taxi vehicle (£);

$ATaxiKm$ is the annual taxi kilometre travelled (vehicle-km/year);

m is the median lifetime of the taxi fleet (years);

It seems to be difficult to estimate Uber vehicle capital cost because an Uber driver runs for not only the Uber service but also his/her personal purpose. Hence, the Uber vehicle capital cost depends on the extent to which Uber miles are additional and the extent to which depreciation is mileage related. It is assumed that all Uber miles are additional and that capital costs are annualised using the Capital Recovery Factor and apportioned using mileage. In the United States, 53% of Uber driver-partners work 1-15 hours per week, 30% of them work 16-34 hours/week, 12% of them work 35-49 hours/week and 5% of them work more than 50 hours/week (Hall and Krueger, 2018). It is assumed that the average hours an Uber driver-partner works per week is the average of the mid-points of these values, which is estimated at around 19.28 hours per week. Moreover, Hall and Krueger (2018) stated that an Uber driver would travel about 35,000 miles in 2,000 hours of professional driving. Hence, a speed of 17.5 miles an hour is used to estimate the annual distance that an Uber driver-partner drives (around 17,544 miles per year). This compares with an average for cars in the United States of 12,375 miles in 2005 (Small and Verhoef, 2007). Therefore, in broad terms, the vehicle capital cost of Uber can be allocated 41.4 % for personal purposes and 58.6 % for Uber rides. This means Uber vehicle capital cost is estimated as 58.6% of the vehicle capital cost of a private passenger car.

The total capital costs for taxi/Uber are calculated by multiplying the average vehicle capital cost by the total vehicle-km. The total vehicle-km is estimated as a function of the average journey length, the daily passenger demand on the corridor and the vehicle occupancy.

5.4.1.2 Fuel and non-fuel operating cost

The fuel and non-fuel operating costs for Taxi and Uber are assumed as the same as car. These costs are illustrated in subsection 5.3.1.

5.4.1.3 Administrative cost

For taxi, these costs include advertising, publicity, telephone, office supplies, light, heat, power, postage etc. Each year, the Independent Pricing and Regulatory Tribunal of New South Wales was asked to review taxi fares and recommend new maximum fares to Transport for New South Wales. In 2012, the results show that for standard taxi system in urban areas, the driver labour cost is 62,673 $/taxi/year while the operator administration cost is 9,328 ($/vehicle/year) (Independent Pricing and Regulatory Tribunal of New South Wales, 2012). This means the administration cost is equal to around 15% of the driver labour costs. Therefore, the administrative cost of taxi is assumed as 15% of the taxi driver wage in this thesis.

Uber drivers using the driver app are charged the Uber Fee as a percentage of each trip fare. If surge pricing applies to a trip, the Uber Fee percentage is also deducted from the surge amount. The Uber Fee helps cover costs including technology, development of app features, marketing, and payment processing for driver-partners (Uber, 2018). The Uber Fee varies by countries and types of Uber. Indeed, Uber receives from 5% to 20% of the trip price, with the rest for the driver (Schneider, 2017). Mostly, that number is 20%, for example, as in the UK and for Uber Black in Netherland, whilst it is 25% in Vietnam. In this study, the Uber Fee is assumed as 25% of Uber driver earnings before vehicle expenses. The Taxi/Uber driving earnings are illustrated in subsection 5.4.1.5

5.4.1.4 Infrastructure cost and highway maintenance cost

The infrastructure costs and highway maintenance costs for Taxi and Uber are assumed as the same as car.

5.4.1.5 Driver earnings

Taxi driver earning unit can be calculated as follows (Transport Research Partners, 2016):

$$ASalaryC = \frac{ASalaryTaxi}{ATaxiKm} \quad \textbf{(5-42)}$$

Where,

$ASalaryC$ is the taxi driver earning unit cost (£/vehicle-km);

$ASalaryTaxi$ is the average annual taxi driver earnings (£/year);

$ATaxiKm$ is the annual taxi kilometre travelled (vehicle-km/year);

The annual taxi driver earnings and annual taxi kilometre travelled can be estimated by using available data from local taxi companies.

There seems to be difficult to obtain data for estimating directly Uber driver earnings. Hence, an indirect estimation from Taxi driver earnings is considered, because data on Taxi driver wages can be available. Based on the results of the study by Hall and Krueger (2018), it is assumed that the taxi driver wages (after vehicle expenses) are as the same as the hourly earnings of Uber driver-partners (after vehicle expenses). Hall and Krueger (2018) also find that the Uber driver-partners wages after vehicle expenses are around 2/3 of the wages before vehicle expenses and it is assumed this also applies to taxi drivers.

5.4.2 User costs

The total user costs cover travel time cost and congested-related delay costs. Taxi/Uber travel time cover in-vehicle time, walk time and wait time. In this thesis, the walk time is assumed as zero while the wait time for Taxi/Uber users is assumed as three minutes. This value is implied as an average travel time of an available Taxi/Uber between the moment a driver accepts the ride and the moment the driver pick a passenger up. The congested-related delay costs of Taxi and Uber are assumed as the same as car.

5.4.3 External costs

The external costs of Taxi and Uber are assumed as the same as car.

5.4.4 Operating procedure of Taxi/Uber social cost model

The operating procedure of the Taxi/Uber social cost model is similar to the private transport social cost model (see Figure 5-2).

5.5 Mixed Transport Cost Model

The PT, PRV and Taxi/Uber social cost models seem to be suitable in situations where only one transport use infrastructure facility. However, if conventional bus, car, motorcycle and Taxi/Uber share facilities in mixed transport systems, the mixed transport social cost model is therefore considered. These modes can include Taxi, Uber, conventional bus, car and motorcycle. Hence, the total social costs for mixed transport are the sum of the total social costs for PT, PRV and Taxi/Uber, except infrastructure costs. The infrastructure costs of mixed transport include the infrastructure costs of the segregated public transport modes (e.g. Metro and Monorail) and the infrastructure costs of mixed lane facilities. The infrastructure costs of the mixed lane facilities are allocated to transport modes sharing facilities (e.g. car, motorcycle and conventional bus). In addition, the operating speed of the exclusive public transport technology is determined as shown in Equation (5-11) while the mean operating speed of all modes sharing infrastructure facilities will be discussed below.

5.5.1 The mean stream speed on links

The PT, PRV and Taxi/Uber social cost models are developed for one single urban corridor for fixed daily passenger demand. In other words, speed and other parameters in these models are estimated based on given demand levels. Hence, it is essential to determine the speed of mixed traffic corresponding to a given traffic flow (or passenger demand). However, there are very little studies on this problem, whilst other studies show the traffic flow corresponding to the mean speed. By using a motorcycle equivalent unit (MCU) model, Nguyen and Sano (2012) produced the flow-speed relationships for three types of urban mixed traffic corridors, which are shown in Table 5-4.

Table 5-4 Flow-speed relationship for three types of mixed traffic corridors

	Four lanes per direction	Three lanes per direction	Two lanes per direction
Traffic flow (F) in MCU and mean stream speed (S) relationship	F =5,852*S*exp(-S/11.3)	F = 5,271*S*exp(-S/11.2)	F = 2,951*S*exp(-S/12.3)

Source: Nguyen and Sano (2012)

As reviewed equations of speed in subsection 2.3.2.3, the equations shown in Table 5-4 seem to be suitable for mixed transport environments with the dominance of motorcycles. However, for a given traffic flow, the speed cannot be estimated by using basic mathematics principles. To estimate the speed corresponding to a given traffic flow, Biswas, Chandra and Ghosh (2017) rearranged Greenberg’s speed-flow equation by using Lambert W function below.

Suppose that two variables *x* and *z* are related as:

$$xe^{x} = z \qquad \textbf{(5-43)}$$

Biswas, Chandra and Ghosh (2017) cited that Euler (1927) suggested a function for solving the Equation above and rearranged it as:

$$x = W(z) = \sum_{n=1}^{\infty} \frac{(-n)^{n-1}}{n!}\, z^{n} \tag{5-44}$$

Biswas, Chandra and Ghosh (2017) cited that Lambert (1758) obtained a solution of the trinomial equation $x = q + x^m$ and then Euler's work was an extension of the research of Lambert. Therefore, the function W was named as Lambert W in his honour. Speed can be expressed as (Biswas, Chandra and Ghosh, 2017):

$$v = -c\,.\,Lambert\ W\left(-\frac{q}{k_j.c}\right) \tag{5-45}$$

Where,

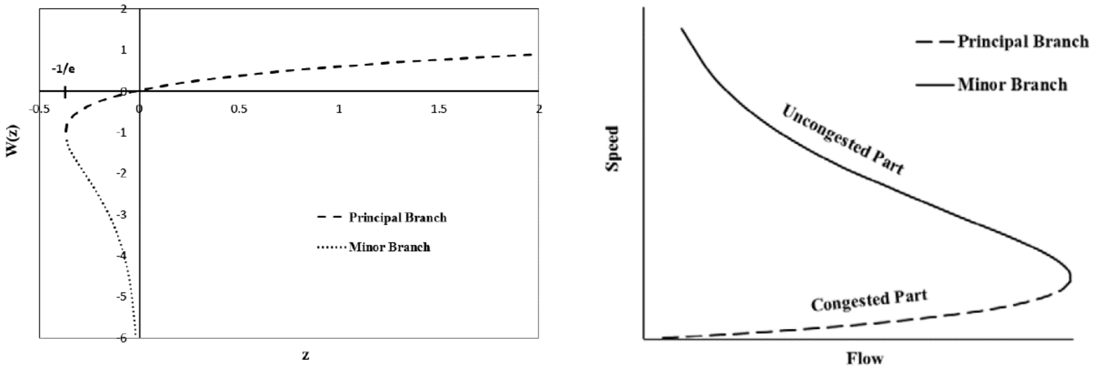
v is the speed (km/h);

q is the flow (vehicle/h);

k_j is the density for a traffic jam (or jam density) (vehicle/km);

c is a parameter shown in Equation (2-8).

The minor branch of the Lambert W function shows the speed corresponding to the uncongested part of the speed-flow curve whereas the principal branch expresses the speed in the congested part (see Figure 5-3). This means the uncongested part shows the smaller solution of the Lambert W function (Biswas, Chandra and Ghosh, 2017).



(a) (b)

Figure 5-3 (a) Two branches of Lambert W function and (b) Flow-speed relationship in Greenberg model by using Lambert W function

Source: Biswas, Chandra and Ghosh (2017)

The MATLAB program can solve Lambert W function. Indeed, for real x where $-1/e < x < 0$, the equation has exactly two real solutions. The larger solution is represented by *y = lambertW(x)* and the smaller solution by *y = lambertW(-1,x)* (Mathworks, n.d).

As a result, an application for estimating speed corresponding to a given uncongested traffic flow is suggested by using the Lambert W function in MATLAB as follows:

$$v = -c * lambertW \left(-1, -\frac{q}{k_j c}\right) \tag{5-46}$$

where,

All variables are shown in Equation (5-45).

To validate an application of this suggested speed equation, the equation for four-lane per direction corridor in Table 5-4 is chosen to test. The results of the test are shown in Appendix A.2. The results prove this application can be acceptable.

To conclude, the mean stream speed on a mixed traffic corridor is estimated for two cases below.

(i) For a two-lane divided corridor (one lane per direction) (Chu, Sano and Matsumoto, 2005):

$$V_{mean} = -0.0018 * q + 28.29 \tag{5-47}$$

where,

q is the mixed flow in MCU. Maximum flow is 5,000 MCU/direction/hour.

(ii) If there is more than one lane per direction:

$$V_{mean} = \begin{cases} min\left[-c * lambertW \left(-1, -\frac{q}{k_j.c}\right), V_{max}\right] & if\ q \le C \\ \frac{L}{\frac{L}{v_0} + \frac{1}{2} * W * \left(\frac{q}{C} - 1\right)} & if\ q > C \end{cases} \tag{5-48}$$

Where,

V_{mean} is the mean stream speed on links (km/h);

k_j is the density for a traffic jam (or jam density) (MCU/direction/km);

c is a parameter shown in Equation (2-8). This is shown in Table 2-4 for the Hanoi case study;

q is the all mixed traffic flow (MCU/direction/h);

V_{max} is the maximum operating speed on the corridor (km/h);

C is the highway capacity (MCU/direction/hour), which are shown in Table 2-4;

L is the length of the corridor (km);

W is the peak period duration in hours. In this thesis, the default value can be 1 hour.

The speeds of Taxi, Uber, motorcycle and car can be estimated as mean stream speed on links, which is shown in Equations (5-47) and (5-48). By taking time at bus stops into account, the speed of bus can be calculated based on Equation (2-4) as:

$$V_{bus} = \frac{V_{mean}*A*D_{stop}*1000}{\left(\frac{V_{mean}}{3.6}\right)^2+A*\left(D_{stop}*1000+T_{dwell}*\frac{V_{mean}}{3.6}\right)} \quad \textbf{(5-49)}$$

where,

V_{mean} is the mean stream speed, which is shown in Equations (5-47) and (5-48);

Other parameters are shown in Equation (2-4).

5.5.2 Percentage of total infrastructure cost allocated to each vehicle type

If there is an exclusive PT mode in mixed transport systems, the infrastructures costs of this PT mode are calculated separately in the PT social cost model. The infrastructure costs of mixed traffic facilities are allocated for transport modes sharing facilities such as car, motorcycle and conventional bus. The total infrastructure costs (*TIC*) for mixed transport vary from place to place and should be estimated from available data in local conditions.

Based on the study by Sansom *et al.* (2001), the percentage of the total infrastructure cost allocated to each vehicle type is shown as the following formula.

$$\sigma_i = 0.85 * \frac{\delta_i*APVKT_i}{\sum \delta_i*APVKT_i} + 0.15 * \frac{GMWPV_i*APVKT_i}{\sum GMWPV_i*APVKT_i} \quad \textbf{(5-50)}$$

where,

σ_i is the percentage of the total infrastructure cost allocated to each vehicle type *i*;

δ_i is passenger car unit (PCU) value for vehicle type *i*. These factors for motorcycle and bus/coach are 0.4 and 2.0 respectively (Transport for London, 2010). Another approach can use conversion factors from other modes into MCU (Nguyen and Sano, 2012);

$GMWPV_i$ is the gross maximum weight of vehicle type *i* (tonnes);

$APVKT_i$ is the annual vehicle type *i* kilometre travelled (km/year);

5.5.3 Total social cost for each transport mode and all transport modes

5.5.3.1 Total social cost for each transport mode

The total social costs (TSC_{public}) for each PT mode are the sum of total operator costs, total user costs and total external costs, which are shown in section 5.2. For PT modes sharing infrastructure facilities with other modes, the infrastructure costs are allocated as shown in Equation (5-50).

The estimate of the total social costs ($TSC_{private}$) for car or motorcycle is illustrated in section 5.3. The infrastructure costs allocated to car and motorcycle are calculated as shown in Equation (5-50).

The calculation of the total social costs ($TSC_{Taxi/Uber}$) for Taxi or Uber is described in section 5.4. Equation (5-50) shows how to estimate the infrastructure costs allocated to Taxi or Uber.

5.5.3.2 Total social cost for all transport modes in mixed transport

The total social costs (TSC_{all}) for all transport modes are the sum of social costs of PT (TSC_{public}), social costs of Uber/Taxi ($TSC_{Taxi/Uber}$) and private transport ($TSC_{private}$).

5.5.3.3 Average social cost for each vehicle user and all users

The ASC for each public transport user (ASC_{public}) is calculated as follows:

$$ASC_{public} = \frac{TSC_{public}}{PKM_{public}} \tag{5-51}$$

where,

PKM_{public} is the annual public transport passenger kilometres travelled.

The ASC for users of each private transport mode ($ASC_{private}$) is estimated as:

$$ASC_{private} = \frac{TSC_{private}}{PKM_{private}} \tag{5-52}$$

where,

$PKM_{private}$ is the annual private transport user kilometres travelled.

The ASC for users of Taxi or Uber ($ASC_{Taxi/Uber}$) is identified as follows:

$$ASC_{Taxi/Uber} = \frac{TSC_{Taxi/Uber}}{PKM_{Taxi/Uber}} \tag{5-53}$$

where,

$PKM_{Taxi/Uber}$ is the annual Taxi or Uber passenger kilometres travelled.

The ASC for all transport users (ASC_{all}) is calculated as follows:

$$ASC_{all} = \frac{TSC_{all}}{PKM_{all}} \tag{5-54}$$

where,

PKM_{all} is the annual passenger kilometres travelled by all transport modes.

5.5.4 Operating procedure of mixed transport social cost model

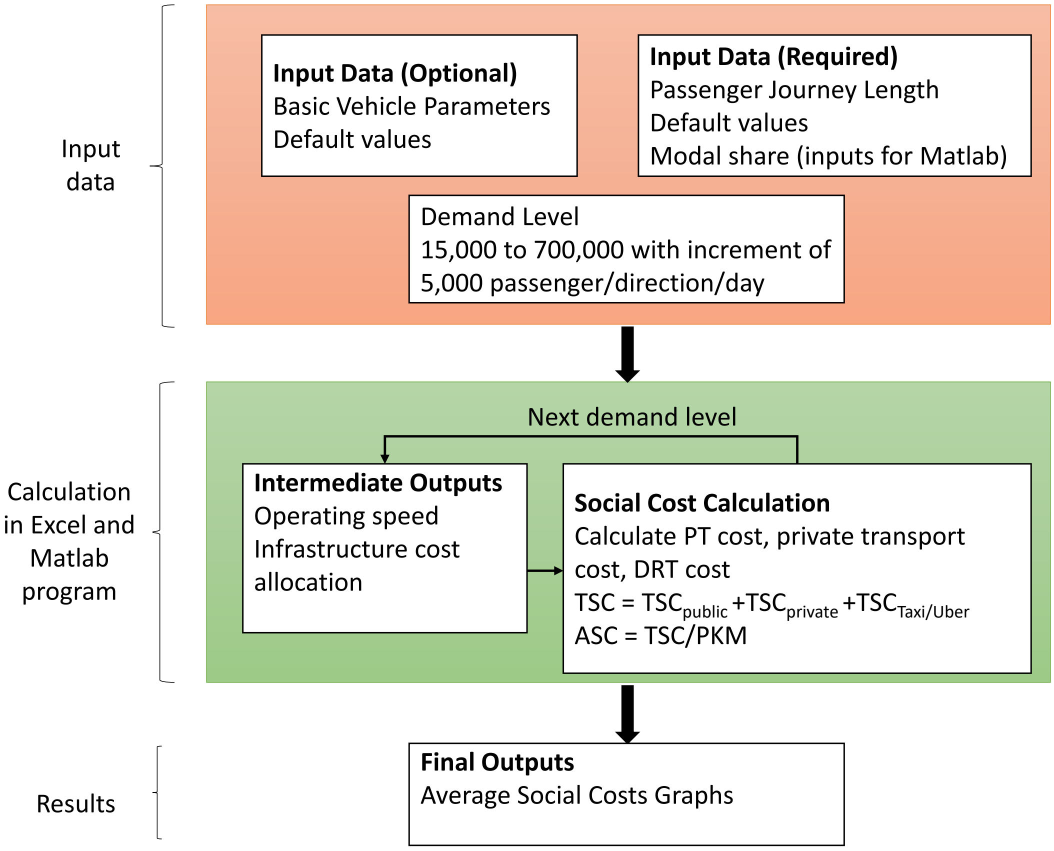


Figure 5-4 Procedure of the mixed transport social cost model

Figure 5-4 shows the operating procedure of the mixed transport social cost model to estimate ASC. To compare mixed traffic infrastructure options in terms of ASC, mixed traffic divided corridors with two, three and four lanes per direction are considered in this thesis. The main differences between the three types of corridors in the cost model are infrastructure costs and mean speed. The operating procedure of the mixed transport social cost models are run as shown in Figure 5-4 for demand levels ranging from 15,000 to 700,000 pax/day/direction. The modal share in mixed traffic environments is an important input of the mixed transport social cost model. The modal share should be adapted from available data in local transport systems. The calculations are run in the MATLAB program and Microsoft Excel. The following suggested options, which can represent situations in reality, are compared in the mixed transport social cost model at a strategic planning level.

- *Option 1:* two-lane (per direction) divided corridor for only motorcycle in a case with car ban. This can be considered if transport planners and decision makers would like to introduce a policy to reduce car dependency. The modal share of motorcycle is 100% in the mixed transport social cost model or the PRV social cost model can be used for this case.

- *Option 2:* two-lane (per direction) divided corridor for only car in a case with motorcycle ban. This can be considered if transport planners and decision makers would like to introduce a policy to reduce motorcycle dependency. The modal share of car is 100% in the mixed transport social cost model or the PRV social cost model can be used for this case.

- *Option 3:* two-lane (per direction) divided corridor for conventional bus, car and motorcycle. There are no new PT modes.

- *Option 4:* three-lane (per direction) divided corridor for conventional bus, car and motorcycle. There are no new PT modes.

- *Option 5:* four-lane (per direction) divided corridor for conventional bus, car and motorcycle. There are no new PT modes.

- *Option 6:* Combination of three-lane (per direction) divided corridor where there are an exclusive bus lane per direction and two mixed lanes per direction for car and motorcycle. There are no new PT modes, however, one existing lane is converted into an exclusive bus lane per direction.

- *Option 7:* Combination of three-lane (per direction) divided corridor where there are an exclusive BRT lane per direction and two mixed lanes per direction for car and motorcycle. In this case, BRT is introduced to replace existing bus services and one existing lane is converted into an exclusive BRT lane per direction.

- *Option 8:* Combination of four-lane (per direction) divided corridor where there are an exclusive bus lane and three mixed lanes for car and motorcycle per direction. There are no new PT modes, however, one existing lane is converted into an exclusive bus lane per direction.

- *Option 9:* Combination of four-lane (per direction) divided corridor where there are an exclusive BRT lane and three mixed lanes for car and motorcycle per direction. In this case, BRT is introduced and one existing lane is converted into an exclusive BRT lane per direction.

- *Option 10:* Combination of four-lane (per direction) divided corridor where a segregated Monorail service is introduced to replace existing bus services and four existing mixed lanes per direction are for car and motorcycle.

- *Option 11:* Combination of four-lane (per direction) divided corridor where a segregated Elevated Metro service is introduced to replace existing bus services and four existing mixed lanes per direction are for car and motorcycle.

Depending on how many mixed lanes per direction on the existing corridor, some of these options above will be compared in terms of ASC or new options can be added. For example, if an existing corridor has three mixed lanes per direction, the options 4-11 are considered. Of these, the option 5 can be a case when Right of Way is expanded from three lanes per direction to four lanes per direction.

5.5.5 Basic parameters and unit costs

Basic input parameters in the four social cost models are adapted from secondary data provided by the People's Committee of Hanoi (PCH), Transport Engineering Design Incorporated (TEDI), Hanoi Transport Management and Operation Centre (TRAMOC), Hanoi Metro Company (HMC), T&D Vietnam Highway Consultancy Companies (T&D) and TTS Group. Considering the price dissimilarity concerning labour costs and material costs between the UK and Vietnam, the PPP rate from the World Bank (WB) is used. The PPP rate in 2015 for the UK was 0.69 while that number for Vietnam was 7,576.25 (World Bank, 2015b). Hence, a factor of 0.00009 (0.69/7,576.25) is used to convert the Vietnamese currency (VND) into the British currency (GBP). Similarly, the PPP factors are used to convert US$ and IDR into GBP. The main input parameters are illustrated in details below and all prices are calculated in GBP in 2015 prices. Eight transport modes are modelled in this study. The characteristics, default unit capital costs and life expectancies of these modes are summarised in Table 5-5.

Table 5-5 Vehicle characteristics, default unit capital costs and life expectancies

Transport modes	Person capacity[1] (pax)	Occupancy[2] (pax)	Vehicle length (m)	Max. speed (km/h)	Infrastructure capacity (vehicles/h)	Vehicle costs (£ 000/ vehicle)	Life expectancies in years (Vehicle/ Infrastructure)	Infrastructure costs[3] (£ million/km)
Conventional bus[4]	80	33	12	55	225 (340)[5]	182.1	20/20	9.0 (15.0)[5]
BRT[6]	90	41	12.3	60	240	455.4	20/20	9.0
Elevated Metro[7] (4-car unit)	820	287	80	80	138	3,045.3	25/50	-
Monorail[8] (4-car unit)	360	126	50	80	156	2,000	25/50	-
Passenger car[9]	5	1.57	-	55	1,800	15.6	20/20	9.0 (15.0)[5]
Motorcycle[9] (125cc)	2	1.22	-	50	5,000 (9,000)[5]	1.5	13.3/20	9.0 (15.0)[5]
Taxi[10]	5	1.57	-	55	1,800	17.3	20/20	9.0
Uber	5	1.57	-	55	1,800	7.8	20/20	9.0

Notes:

All costs are in 2015 prices.

[1] Based on data which are provided by Hanoi Metro Company and Hanoi Transport Management and Operation Centre.

[2] Monorail and Metro occupancy rates are assumed as 35% of vehicle person capacity (European Environment Agency, 2015). Motorcycle and bus occupancies are shown in the report of Transport Engineering Design Incorporated (2013). BRT occupancy in 2017 was provided by TRAMOC. Passenger car occupancy is assumed as 1.57 (Department for Transport, 2017b). It is assumed that occupancies of Taxi/Uber (excluding the driver) and car (including the driver) are the same.

[3] Based on data provided by the PCH and T&D.

[4] Based on the report of Hanoi Transport Management and Operation Centre (2011).

[5] Values in bracket () are for the two-lane per direction corridor.

[6] Based on the report of Hanoi Transport Management and Operation Centre (2011).

[7] Based on data on URT line 1, 2A and 3, which are provided by Hanoi Metro Company.

[8] Based on the study of DMJM Harris (2001).

[9] Based on the studies by Bray and Holyoak (2015) and Nguyen, Sano and Chu (2007).

[10] Taxi vehicle cost is adapted from data showed on a Taxi Group website (Taxi Group, 2018). Other parameters are assumed as those numbers of car.

5.5.5.1 Parameters for the public transport cost model

Table 5-6 shows unit PT operator costs for the Hanoi case study. Appendix A.1 illustrates more detailed calculations of the FAC for each PT mode.

Table 5-6 Default unit PT operator costs

Cost components	Vehicle Hours	Vehicle Distance	Peak Vehicle Requirement	Track/lane Distance	Station / Stop	Depot
Units	£2015 per VH	£2015 per VKM	£2015 per PVR pa	£2015 per track/lane distance pa	£2015 per Station/stop pa	£2015 per depot pa
Conventional bus[1]	21.14	0.55	15,384.70	1,204,909.02	182.89	60,964.43
BRT[2]	17.66	0.55	62,355.85	1,204,909.02	109,948.03	60,964.43
Elevated Metro[3]	444.42	7.87	442,502.85	1,836,945.18	2,243,595.49	5,483,418.43
Monorail[4]	331.09	5.51	178,499.96	1,806,249.95		

Notes:

[1] Based on data provided by TRAMOC and the report of Hanoi Transport Management and Operation Centre (2011).

[2] Based on the report of Hanoi Transport Management and Operation Centre (2011).

[3] Based on data on URT line 1, 2A and 3, which are provided by Hanoi Metro Company.

[4] Based on the study of DMJM Harris (2001). The study summarised characteristics and parameters of Bombardier technology as follows. The capital construction cost is around $50 million per track mile. Assume that Annual Vehicle-Hours and Vehicle-Kilometre are equal to 70 % of Metro Vehicle-Hours and Vehicle-Kilometre. Infrastructure costs cover capital costs of track, station and depot, which are per Route Km.

Hanoi Transport Management and Operation Centre (2011) showed that the average distance between bus stops in Hanoi is 0.5 km. For urban rail transit services, the average distance between stations is around 1.1 km (Government of Vietnam, 2016). Molt (2016) stated that the average walking speed of Hanoi citizens is 4.0 km/h.

5.5.5.2 Parameters for the private transport cost model

The capital cost for a typical motorcycle, including taxes and delivery charges, is around US$ 2,200 in 2014 prices (Bray and Holyoak, 2015). Whilst the capital cost for a typical car is approximately from US$ 20,000 to US$ 25,000, which covers all taxes and road use fee (Hansen and Nielsen, 2014). Hence, US$ 22,500 is assumed as the price of a new passenger car.

According to the Decree No.95/2009/ND-CP issued by the Government of Vietnam (2009), the maximum lifetime of a coach and a freight vehicle is 20 years and 25 years correspondingly whilst there are no regulations about the lifetime of car and motorcycle. Hence, the lifetime of a car is assumed as the same bus. Because the mean disposal age of motorcycles in Taiwan was about 13.3 years (Chang and Yeh, 2006), 13.3 years can be therefore used as the lifetime of a motorcycle in this thesis.

Average car parking price is VND20,000 for a 2-hour slot while the price for motorcycle is VND3,000 (Hanoi Transport & Services Corporation, 2017).

Fuel price is VND19,000 per litre in 2015 prices, which was shown in the Unique Petro Group in Vietnam.

Using available data on modal share in Hanoi and total bus passengers for the whole year of 2015, the average highway maintenance cost for bus, car or motorcycle is estimated as 0.21 (pence/vehicle-km).

Trang, Van and Oanh (2015) carried out a survey of car fleet in Hanoi. The results of the survey show that petrol cars and diesel cars account for 93% and 7% respectively. Hence, the values for petrol cars shown in Table 5-2 are assumed to calculate operating costs for cars.

5.5.5.3 Parameters for Taxi/Uber cost models

Available data for the Hanoi case study are shown as follows: (i) The taxi life time is 12 years (Government of Vietnam, 2014); and (ii) The average monthly salary of a taxi driver is VND8 million and average 4,000 km driven with taxi's passenger per month (Taxi Group, 2018).

5.5.5.4 Other key parameters

The length of the study corridor

The length of the NT-TP-QT corridor is 7 Km.

Average passenger journey length

The average passenger journey length is a required input data for the social cost model. This value is either set by the user or used default value as 4 km for urban corridors.

Unit infrastructure cost for 6-lane and 8-lane divided arterials

Based on data provided by the People's Committee of Hanoi and T&D Vietnam Highway Consultancy Company, the unit infrastructure costs for 6-lane and 8-lane divided arterials are calculated as 22 and 30 million £/km respectively.

Daily demand split into different times

Based on results of a traffic survey in 2016 provided by the TTS Group, data on passenger split by time at several roads in Hanoi are collated. The core operating day time services are assumed to be from 06:00 to 21:00 and daily passenger demand is split into the four periods including the peak hours (2 hours), peak periods (3 hours), mid-day off-peak (7 hours) and early morning-late evening off-peak (3 hours), which are described in Table 5-7.

Table 5-7 Passenger demand split into different times in the Hanoi case study

Periods	Time-time	Period duration (hours)	Split rate for one hour period	Daily split
Early morning off-peak	6:00-7:00	1	4.0%	4.0%
Morning peak hour	7:00-8:00	1	10.0%	10.0%
Morning peak period	8:00-9:00	1	7.5%	7.5%
Mid-day off-peak	9:00-16:00	7	6.5%	45.5%
Afternoon peak period	16:00-17:00	1	7.5%	7.5%
Afternoon peak hour	17:00-18:00	1	10.0%	10.0%
Evening peak period	18:00-19:00	1	7.5%	7.5%
Late evening off-peak	19:00-21:00	2	4.0%	8.0%

Source: data collated from the TTS Group.

The value of time

The value of time seems to be sensitive to estimate the user costs, therefore the total social cost and average social cost. There are few empirical estimates of the value of time (VOT) in Vietnamese cities. Hence, this study considers the two following approaches. The transfer approach from the UK into Vietnam should be used in the first place, based on available data on modal splits in the case study. Empirical evidence on the VoT in Vietnam can be then analysed. Both approaches are compared to evaluate the reliability of the implied value of time and the sensitivity of the VoT is then tested to impact on results of the social cost models.

Firstly, due to available data on modal splits in Hanoi in 2010, transferring of the value of time in the UK to Vietnam is suggested. The comparable value of time in the UK ($VOT_{UK2010,COMP}$) in 2010 prices (£/hour) is estimated as:

By using modal splits in Hanoi travel survey, comparable the value of time in the UK is estimated by the following equation:

$$VOT_{UK2010,COMP} = VOT_{UK2010,WT} * P_{WT} + VOT_{UK2010,C} * P_C + VOT_{UK2010,O} * P_O \qquad \textbf{(5-55)}$$

Where,

$VOT_{UK2010,COMP}$ is the comparable value of time in the UK, in 2010 prices (£/hour);

$VOT_{UK2010,WT}, VOT_{UK2010,C}, VOT_{UK2010,O}$ are the value of working time, by commuting and non-working time in the UK respectively, in 2010 prices (£/hour);

P_{WT}, P_C, P_O are the proportions of travellers in course of work, travellers commuting and travellers for other purposes in the Hanoi travel survey (%).

Then, the value of time in Vietnam is calculated as follows:

$$VOT_{VN2010} = VOT_{UK2010,COMP} * \frac{Mean\ Income_{VN2010}}{Mean\ Income_{UK2010}} \qquad \textbf{(5-56)}$$

Where,

VOT_{VN2010} is the value of time in Vietnam in 2010 price (£/hour);

$Mean\ Income_{VN2010}$ is the mean income in Vietnam in 2010 (PPP £);

$Mean\ Income_{UK2010}$ is the mean income in the UK in 2010 (£).

Using data on modal share by purpose of journey (Transport Engineering Design Incorporated, 2013), GDP deflator and values of time in the UK in WebTAG, the value of IVT for car in Vietnam (in

2015 prices) is calculated as 0.77 (£/hour). In addition, based on the study of Wardman, Chintakayala and de Jong (2016), it is assumed that the values of IVT by mode are as follows. Those numbers for PT and Uber/Taxi are the same, which are equal to 0.7 times than the value for car, while the number for motorcycle is twice than the value of IVT for car.

Secondly, the value of time for the Hanoi case study for different modes are estimated based on utility functions of dissimilar modes in the study by Bray and Holyoak (2015), which is shown in subsection 3.2.1. The work and non-work values of time are assumed to increase with income over time with an elasticity of 1.0 (Department for Transport, 2017b). GPD per capita in Vietnam for years of 2014 and 2015 are \$2,030.262 and \$2,085.101 respectively (World Bank, https://data.worldbank.org/indicator/NY.GDP.PCAP.CD?locations=VN, accessed 26 June 2020). The results of the VoT for different modes are shown in Table 5-8.

Table 5-8 Value of in-vehicle time for different modes for the Hanoi case study

Modes	Coefficient of IVT	Coefficient of fuel cost	Coefficient of PT fare	Value of time (VND/hour), 2014 prices	Value of time (PPP £/hour), 2014 prices	Value of time (PPP £/hour), 2015 prices
Motorcycle	-0.0100	-0.00021		20,516	1.87	1.92
Car	-0.0045	-0.00016		12,023	1.09	1.12
Bus	-0.0051		-0.0146	21,091	1.92	1.97
New PT	-0.0045		-0.0146	18,415	1.68	1.72

Notes: The average journey length of 7.2 km is taken into account for estimating the value of time for private transport users because the unit of fuel cost is per km. The units of the in-vehicle time, fuel cost and PT fare in the utility functions are minute, VND/km and VND/1,000 respectively.

The value of time for car in the transfer method above is £0.77 in 2015 prices while the value adapted from the study by Bray and Holyoak (2015) is £1.12 shown in Table 5-8. The difference between these two values is not significantly high. Moreover, the value of time for motorcycle are £1.54 and £1.92 correspondingly. However, the value of in-vehicle time for both existing conventional bus and proposed PT technology seems to be high compared to the value of time for private transport. The reason for that can relate to characteristics of the existing bus systems during the time that the surveys were carried out in 2014 while new PT modes (e.g. BRT) were not operated. Bray and Holyoak (2015) suggested that people in Hanoi were concerned about the bus system, which includes safety and personal security, over-crowding, service reliability and air conditioning. Similarly, Molt (2016) and Vu (2015) showed that there were poor bus services in Hanoi around that time. These factors can lead to increases in the value of in-vehicle time unit for bus passenger (Litman, 2020). Those values can be used in the total social cost models to test how the results of these models change.

The discount rate for capital investment

The discount rate (DR) for capital investment is set at 12% for the Hanoi case study (Duong, 2005; Asian Development Bank, 2013;2014; World Bank, 2015a). To illustrate how the cost comparisons are impacted by the discount rate, a sensitivity analysis is implemented with other two different DRs (8% and 16%).

Unit external costs

The results of unit external costs by different modes for the Hanoi case study are estimated by using findings of several empirical studies by Sansom *et al.* (2001), Chen *et al.* (2003), Tsai *et al.* (2005), Maibach *et al.* (2007), Wang (2011), Vu *et al.* (2013), Li and Preston (2015), Manoratna, Kawata and Yoshida (2017) and WebTAG. For most unit external costs by dissimilar modes, the 'Willingness to Pay' approach mentioned in subsection 2.3.1.3 is used for transferring unit external costs between the UK (showed in Table 2-2) and Vietnam. Moreover, the air pollution cost for motorcycle is estimated based on data on air pollutants in Hanoi in the study of Vu *et al.* (2013). The climate change cost for motorcycle is calculated from evidence in Taiwan in the study of Chen *et al.* (2003) and Tsai *et al.* (2005). In order to take into account of the vehicle occupancy, unit external costs of each mode are transferred from pence/vehicle-distance into pence/passenger-distance. The central values are used rather than low and high values in this study, which are shown in Table 5-9.

Table 5-9 Default external unit costs by impact category in the Hanoi case study, 2015 prices

Transport modes	Air pollution (p/pax km)	Noise pollution (p/pax km)	Climate change (p/pax km)	Accidents cost (p/pax km)
Bus	0.10[1]	0.04[1]	0.0089[1]	0.01[1]
BRT	0.10[1]	0.04[1]	0.0078[1]	0.01[1]
Monorail	0.0008[1]	0.0014[1]	0.0009[2]	0.0001[3]
Elevated Metro	0.0008[1]	0.0017[1]	0.0005[1]	0.0001[3]
Car/Uber/Taxi	0.11[4]	0.06[4]	0.06[4]	0.10[4]
Motorcycle	0.12[5]	0.15[6]	0.03[7]	1.92[8]

Sources:[4] Sansom *et al.* (2001), [5] Chen *et al.* (2003), [5,7] Tsai *et al.* (2005), [5,6,8] Maibach *et al.* (2007), [3] Wang (2011), [5] Vu *et al.* (2013),[1] Li and Preston (2015), [2] Manoratna, Kawata and Yoshida (2017) and [2,7] WebTAG.

Notes:

- External costs of Uber and Taxi are assumed as the same as car.
- External costs of BRT are assumed as the same as a single bus on busway.
- Air and noise pollution costs of Monorail are assumed as those of modern light rail.
- Air pollution, noise pollution and climate change costs of elevated Metro are assumed as the same as suburban heavy rail.
- Assume that accidents cost of Monorail and elevated Metro are the same.

5.6 Case Study

As discussed in Chapter 4, the Nguyen Trai - Tran Phu - Quang Trung corridor with the length of 7 km, one main arterial in Hanoi, Vietnam, is chosen as a case study for this study. Basic parameters and unit costs in the four social cost models are described below. The results of these cost models for the Hanoi case study are then discussed.

5.6.1 Results of transport social cost models

5.6.1.1 PT, PRV and Taxi/Uber social cost models

One-lane per direction corridor

To compare the ASCs of different transport modes, the PT, PRV and Taxi/Uber social cost models are calculated for a 1-lane (per direction) corridor with the length of 7 km and average passenger journey length of 4 km. Figure 5-5 shows the results of the ASCs of PT, PRV and Taxi/Uber modes for 1-lane (per direction) corridor in the Hanoi case study. Two example calculations for the one exclusive motorcycle lane option and the elevated Metro option are shown in Appendix A.3.

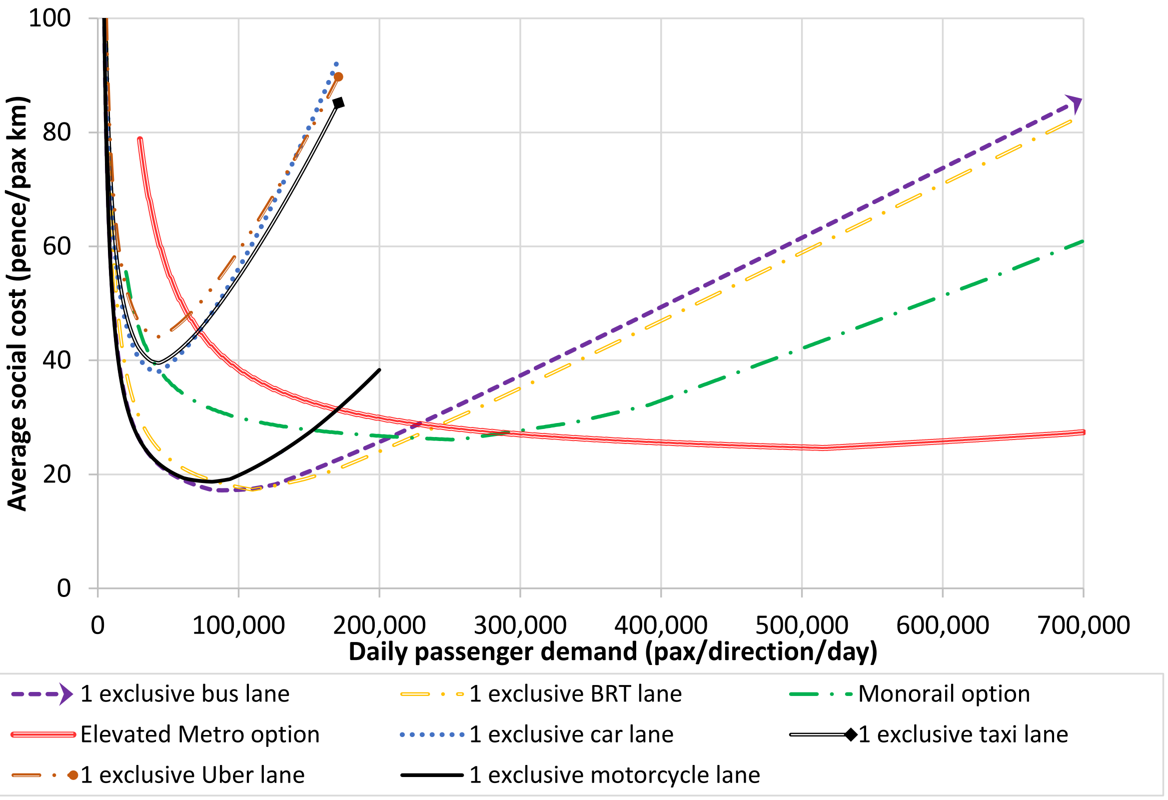


Figure 5-5 The ASC as a function of demand for 1-lane (per direction) divided corridor, 2015 prices

As can be seen from Figure 5-5, the relationships between the ASC and demand level for all transport modes are shown as U-shape curves. The explanation can be that while fixed costs per passenger are high at low demand levels, these reduce as they are spread across higher levels of demand. By contrast, route capacity constraints have a significant impact on speeds, and therefore costs, at higher demand levels. When demand reaches route capacity, speeds decrease dramatically. In addition, Figure 5-5 shows that the slopes of the curves for PRV and Taxi/Uber are much steeper than those for PT due to low person occupancy of PRV and Taxi/Uber.

Figure 5-5 shows that when the daily demand levels range from 1,000 to 35,000 pdd, the ASC of the motorcycle option is the smallest. The reasons for this might be:

- Motorcycle speed is quite high at low demands due to small size and flexibility, as well as motorcyclists do not appear to stop during their journeys.

- Operating costs of motorcycle is lower than those costs of bus-based technologies, which seems to have advantages at low demand levels.

However, the ASC of the motorcycle option is only slightly lower than the ASC of the conventional bus option at low demand levels, because infrastructure costs for road-based options including motorcycle, car, Uber/Taxi and conventional bus are the same, and this accounts for a major portion of total social costs at low demand levels. When the daily demand is from 35,000 to 107,000 pdd, conventional bus shows the smallest ASC. When compared to motorcycle, the significantly higher person capacity of bus is an advantage. Moreover, compared to rail-based technologies, infrastructure costs and operator costs of bus-based technologies are significantly smaller. This seems to be a benefit for conventional bus at low and medium demand levels. BRT is the best mode for a daily demand range of between 107,000 and 220,000 pdd although the ASCs of BRT and bus can be similar due to insignificant differences in vehicle capital costs and person capacity of vehicles. This can be reasonably consistent with several successful BRT systems in the world such as Transmilenio in Bogota, Sao Paulo, Porto Alegre, and Curitiba with 20,000 passengers per hour per direction (Hensher and Golob, 2008). Indeed, the peak hour demand is assumed as 10% of the daily demand in this study, which is shown in Table 5-7. Obviously, conventional bus in mixed traffic with private transport modes would change this similarity dramatically as conventional bus would not be dedicated anymore and, consequently, there would be lower average speed and higher waiting and in-vehicle time for bus users.

When daily demand level is between 220,000 and 290,000 pdd, the ASC of Monorail is the lowest while Metro has advantages with demand higher than 290,000 pdd. This might prove the BTS Sky Train in Bangkok, Thailand is a successful elevated Metro line with average March weekday ridership of 749,180 passengers in both directions in 2018 (Bangkok Mass Transit System Public Company Limited, 2018). The higher capacity than bus-based technologies, and the lower capital investment for vehicles and infrastructure than Metro, make Monorail achieve the lowest ASC within the demand level from 220,000 pdd to 290,000 pdd.

The ASC for car and Taxi/Uber are similar if their occupancy are the same. The ASCs of these options are considerably higher than those numbers for conventional bus, BRT and motorcycle. The reasons for this might be:

- Compared to motorcycle with the similar occupancy, capital vehicle costs for car, Taxi and Uber are much higher, as well as greater taxes for these vehicles. For the Hanoi case study, the new prices of these vehicles include a value added tax (VAT) of 10 percent; an import duty of between 15 percent and 60 percent; a special consumption tax that ranges from 45 percent to 60 percent (depending on engine capacity); and an ownership registration tax and a one-off first time registration fee that are together a little over 20 percent (Bray and Holyoak, 2015). Because only one Vietnamese car brand has started to operate since 2019, most of cars running in Vietnam are imported from other countries. A sensitivity test was performed to investigate the differences if these taxes are not included in the SCMs. Based on the results of the sensitivity test, the curves for car, Taxi and Uber in Figure 5-5 shift downwards for around 7 pence/pax-km. This does not essentially impact on the basic results of the analysis.

- Compared to PT modes, lower occupancy is a drawback whist these modes appear to have advantages of minor higher average speed.

Two-lane per direction corridor

These comparisons above are measured for the one-lane per direction corridor. However, this seems to be insufficient for road-based arterials in urban areas, where there are normally more than one lane per direction. In addition, buses are not allowed to overtake in the one-lane per direction corridor, which can cause congestion rapidly when demand increases and reaches capacity, whilst motorcycles can overtake easily in the one-lane per direction corridor. As a result, a two-lane per direction corridor is considered for motorcycle, car and bus options, and is then compared with rail-based systems. The results of ASCs of these options are shown in Figure 5-6.

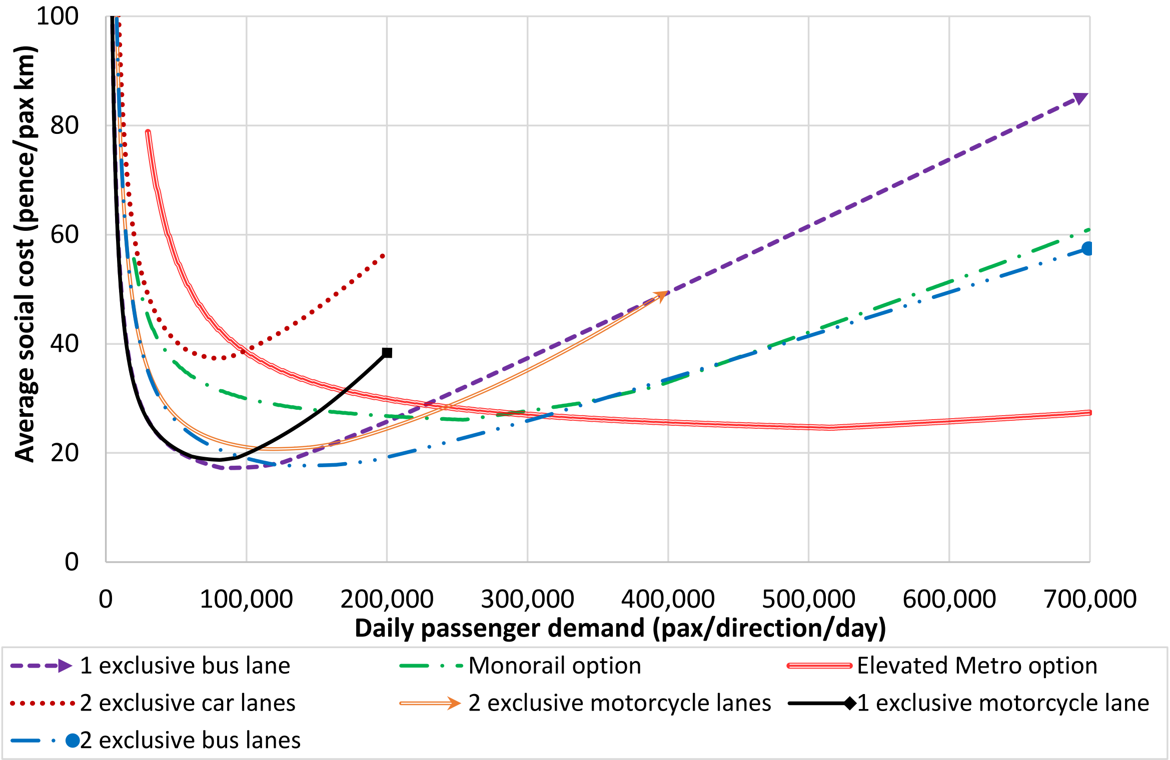


Figure 5-6 ASCs of different road-based and rail-based modes, DR=12%, 2015 prices

Figure 5-6 describes that when one more lane per direction for motorcycle or bus is expanded, the curves for motorcycle or bus shift to the right side. This means that higher demand levels can be supplied at the same ASC when Right of Way (RoW) is expanded. Therefore, an expansion of RoW can be a feasible option when the demand levels of one single mode increase. However, the expanding option should be compared to other options for different modes. This can be illustrated below.

The one exclusive motorcycle lane per direction corridor is the best option at demand levels below 35,000 pdd. When demand levels increase, expanding one motorcycle lane per direction does not appear to be appropriate because this option cannot be as competitive as the one exclusive bus lane or two exclusive bus lanes per direction options. When demand is higher than 220,000 pdd, expanding one bus lane per direction can be better than Monorail. However, when demand reaches 315,000 pdd and above, bus-based technologies are not sufficient. The reason for that is that the costs are extremely high as the number of vehicles required becomes more than the infrastructure capacity and congestion causes the user costs to be much higher. Hence, Metro is the most appropriate option for those high demand levels due to high person capacity.

The results show that external costs account for a small proportion of total social costs for all modes, compared to the operator and user costs. This is consistent to the study of Wang (2011). Most external unit costs for all modes are less than 0.1 p/pax-km (except the accident costs of motorcycle), which are minor components of the ASC. Hence, a sensitivity analysis for external costs can be ignored in this study. A sensitivity test with respect to the discount rate is carried out to analyse how the cost comparisons are affected by the discount rate. The baseline estimate of the discount rate is 12% and alternative values are 8% and 16%. In addition, a sensitivity test with respect to the value of time is conducted to analyse how the cost comparisons are affected by the value of time.

A sensitivity test with respect to the discount rate

Figure 5-6, Figure 5-7 and Figure 5-8 show the results under three dissimilar DRs. In general, when the DR rises from 8% to 16%, the cost curves of all modes shift upward due to increases in infrastructure costs and capital vehicle costs. Moreover, the cost curves of car with low occupancy move upward at a faster rate than those of other modes. Additionally, the costs of the more capital-intensive elevated Metro is the most sensitive to changes in the DRs, particularly significant changes occur at low demand levels. However, the options having the minimum ASC are broadly unchanged for the range of demand levels studied. There are only insignificant changes at critical points of demand levels, where the lowest ASC switches from one mode to another mode. The changes from the two bus lanes per direction option to the elevated Metro option is an example. Critical points of demands levels are at 305,000; 315,000 and 320,000 pdd with respect to the DRs of 8%, 12% and 16% respectively. To conclude, this sensitivity test demonstrates that DRs do not materially impact on the basic results of the analysis because of the main following reason. Firstly, the DRs impact on the infrastructure costs and vehicle capital costs, which are elements of the total social costs. Secondly, the basic results are about comparisons of the ASC between different transport infrastructure options, which mainly occur from a demand level where the ASC of the motorcycle option is minimum (the upwards portion of the U-shape curve). On the upwards portion of the U-shape curve, the ASCs are significantly impacted by the user costs. The reason is that the user costs are major parts of the total social cost when the traffic conditions are more congested.

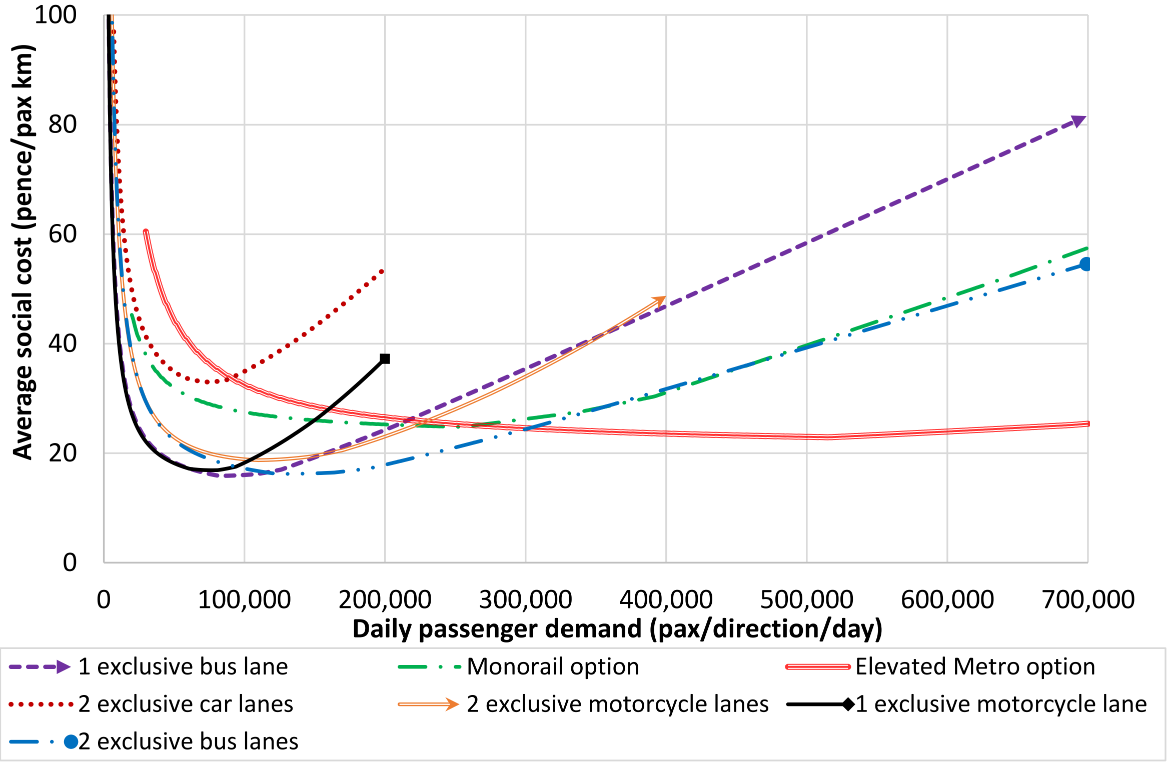


Figure 5-7 ASCs of different road-based and rail-based modes, DR=8%, 2015 prices

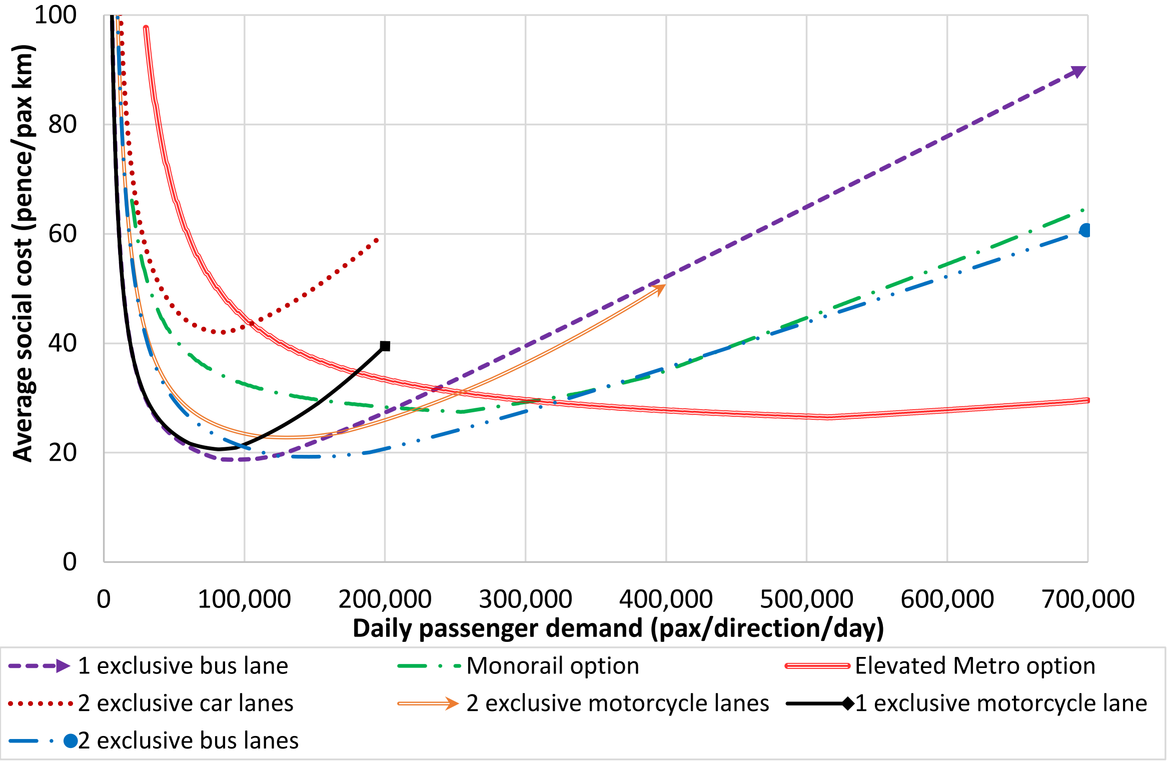


Figure 5-8 ASCs of different road-based and rail-based modes, DR=16%, 2015 prices

A sensitivity test with respect to the value of time

The value of time for different transport modes shown in Table 5-8 are used in the social cost models to analyse how the results of these models change, compared to outcomes in Figure 5-6. The values of time for all modes adapted from the study by Bray and Holyoak (2015) are higher than those numbers adapt from the transfer approach from the UK. The new ASCs of different road-based and rail-based modes are shown in Figure 5-9.

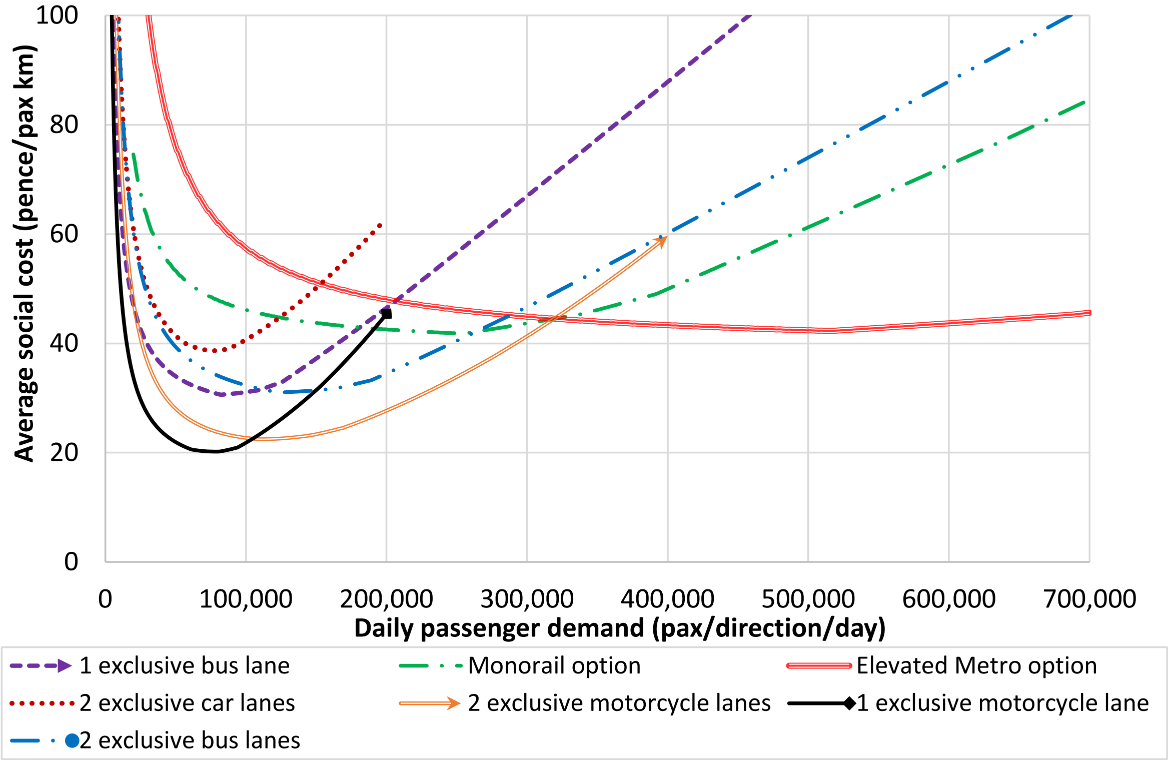


Figure 5-9 New ASCs of different road-based and rail-based modes for different VoT, DR=12%, 2015 prices

Figure 5-6 and Figure 5-9 show that the cost curves of all transport modes shift upward when the value of time increases. The reason can be that the total user costs account for between around 30% and 50% of the total social costs for all modes. Additionally, the cost curves of bus move upward at a faster rate than those of other modes because the value of time for bus users rise at the highest rate. Compared to the cost curves of motorcycle and car, the cost curves of new PT modes shift up at a higher rate because the rates of increases in VoT for private transport are smaller than those rates for the new PT modes. There seems to be no change in that Metro is still the best mode at highest demand levels, above around 320,000 pdd. However, the options having the minimum ASC are changed for medium demand levels, ranging from 100,000 to 320,000 pdd. The bus and Monorail cannot be as competitive as the motorcycle options. Hence, the value of time appears to be sensitive to choosing the best option at medium demand levels.

5.6.1.2 Mixed transport social cost model

The mixed transport social cost model is applied for the Hanoi case study where the chosen corridor has four lanes per direction. Modal shares of motorcycle, car and bus are 77.47%, 13.72% and 8.81% respectively. The detailed calculation of these values is shown in section 6.2. Of all options shown in subsection 5.5.4, option 5, as a base option, represents the existing situation for the NT-TP-QT corridor. Hence, option 5 is compared to the following options. Options 8 and 9 are cases, where one lane per direction is converted to an exclusive bus and BRT lane correspondingly while three lanes per direction are for motorcycle and car. Options 10 and 11 are cases where there is a segregated Monorail service and an elevated Metro line correspondingly while four existing lanes per direction are for motorcycle and car. The main assumptions are: (i) the new modal share of the PT mode increases to 20%, compared to the modal share of the existing bus of 8.81% and (ii) according to the existing modal share, the modal shares of motorcycle and car in mixed traffic lanes without PT are 67.96% and 12.04% of the total demand respectively. Based on all required data for the Hanoi case study, the results of the ASCs of five options are calculated and shown in Figure 5-10.

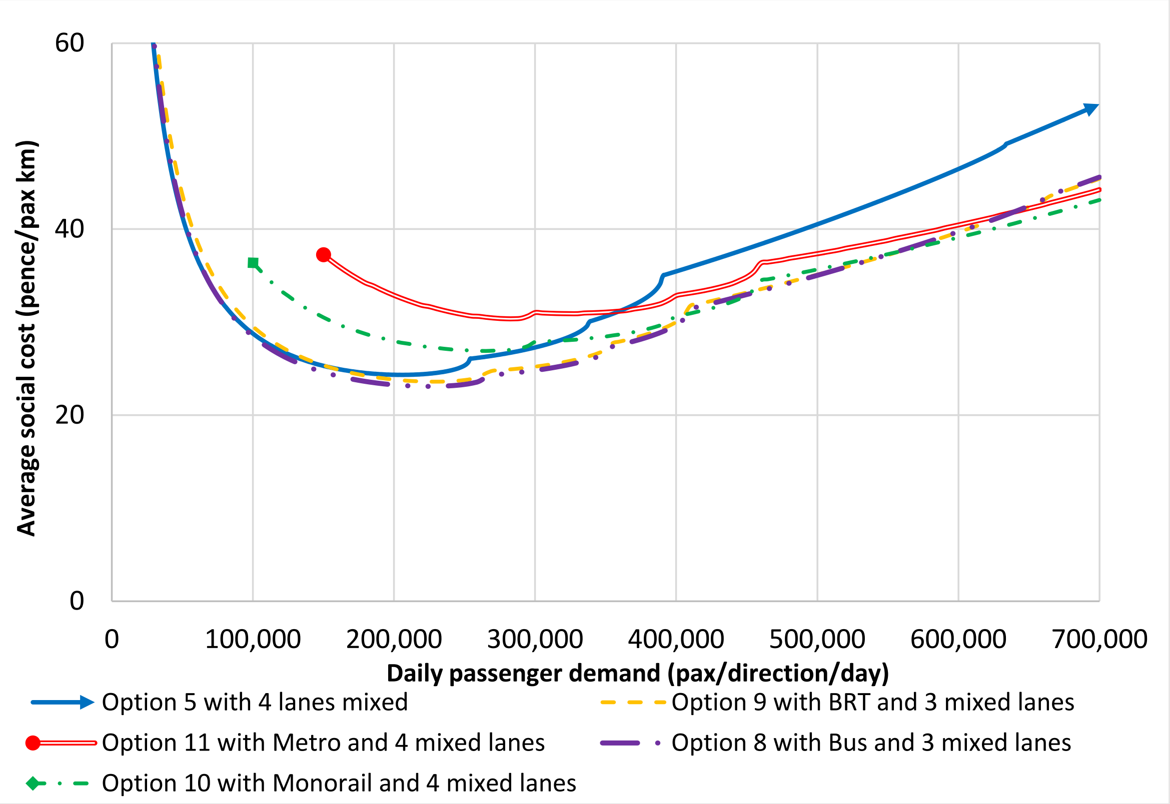


Figure 5-10 Average social costs of five mixed traffic options, DR=12%, 2015 prices

As can be seen from Figure 5-10, there are four kinks on each cost curve. These kinks appear at demand levels where traffic flows reach infrastructure capacity, vehicle speeds therefore decreased dramatically. As a result, the ASC increases considerably around these demand levels. Four kinks on each cost curve are relevant to four time periods of a day, which are shown in Table 5-7. For example, on the curve of the option 5, a kink appears at a demand level of around 250,000 pdd at which the demand for the peak hour is 25,000 passengers/direction/hour. The traffic flow, which is converted to the motorcycle unit, reaches the capacity of 24,335 MCU/direction/hour. This value of capacity is shown in Table 2-4.

In general, with the assumptions of the modal share above, option 8 with exclusive bus lane has the smallest ASC at low and medium demand levels. However, the ASC of option 9 with BRT is only slightly lower than the ASC of option 8 at any demand levels. Option 8 with bus, option 9 with BRT and option 10 with Monorail have very similar ASCs within the demand level from around 300,000 pdd to 550,000 pdd. When daily demand level is higher than 550,000, option 10 with Monorail has advantages. The ASCs of the existing option and option 11 with Metro are very high at any demand levels.

The total existing demand of this corridor, which is shown in details in section 6.2, is 407,700 pdd. All other options seem to be better than the existing option in terms of ASC. As a result, in order to improve the performance of the current situation, transport planners and decision makers might consider these four options to analyse their feasibility and comparisons. However, the main drawback of the mixed transport social cost model is that demand is exogenous and modal share is fixed. The mixed transport social cost model cannot estimate changes to the existing transport conditions when a new PT mode is introduced. The incremental demand models, the traffic simulation model and the comparative economic assessment are developed to overcome this disadvantage.

5.6.2 Summary

The social cost models are applied to the Hanoi case study. All basic parameters and unit costs are adapted from primary and secondary data for the case study. The PT, PRV and Taxi/Uber social cost models, which can be used for homogeneous traffic, evaluate several transport modes in terms of ASC. Then these models might identify the most cost-effective transport mode with respect to different passenger demand levels at a strategic planning level. In addition, the mixed transport cost model, which might be used for mixed traffic environments, can determine whether or not options with a new PT mode are better than the existing situation at a strategic planning level. In other words, the mixed transport social cost model is for use in strategic analysis of public transport technology choices. Then, the chosen options will be analysed for a more detailed assessment. When these cost models are implemented, sensitivity tests with respect to the discount rate and value of time are considered. For the sensitivity tests with respect to the discount rate, the options having the minimum ASC are broadly unchanged for the range of demand levels studied. On the contrary, the lowest ASC option seems to be sensitive to the value of time at medium demand levels.

5.7 Conclusion

This chapter illustrates the development of the social cost models for one single urban corridor. These social cost models can evaluate the total operator costs (or infrastructure operator costs for PRV), total user costs (or vehicle user costs for PRV), total external costs and hence TSC and ASC for individual transport mode and mixed transport from daily passenger demand of 1,000 pdd to 700,000 pdd.

For all modes, the total external costs include accident cost, noise pollution cost, air pollution cost and climate change cost. Elements of total operator costs and total user costs and their calculations are different for dissimilar modes. Firstly, the operator costs of the PT service include both operating cost and capital investment cost, which are estimated in the Fully Allocated Costs model. The PT user costs cover walking time, waiting time and in-vehicle time. Secondly, the infrastructure operator costs for PRV cover infrastructure costs, maintenance costs and parking costs. The vehicle user costs for PRV consists of operating costs for users, private vehicle capital costs, travel time and congested-related delay costs. Thirdly, the Taxi/Uber operator costs cover capital cost; non-fuel operating cost; fuel cost; administrative cost; infrastructure costs and highway maintenance cost; and driver earnings. The Taxi/Uber user costs cover in-vehicle time and waiting time.

The PT, PRV and Taxi/Uber social cost models are initially considered in situations where only one transport mode uses the infrastructure facility. To calculate the costs in these models, the intermediate outputs must be obtained in the first place. For the PT social cost model, these intermediate outputs are operating speed, Vehicle-Kilometres, Peak Vehicle Requirement, Vehicle-Hours, number of stations/stops, number of depots, passenger-kilometres. For the PRV and Taxi/Uber social cost models, the key intermediate output is operating speed. This study improves the calculation of the speed based on previous studies to consider all types of transport modes.

The mixed transport social cost model is considered if several modes share facilities in mixed transport systems with the dominance of motorcycles. The total social costs for mixed transport include the total social costs for PT, PRV and Taxi/Uber, except the infrastructure costs. The infrastructure costs cover the infrastructure costs of the exclusive PT mode and the infrastructure costs of mixed lane facilities. The latter is allocated to transport modes sharing infrastructure facilities based on the study by Sansom *et al.* (2001). To estimate average speed in mixed transport environments, the flow-speed relationships in exponential function by Nguyen and Sano (2012) are chosen. However, these flow-speed relationships are improved by using the Lambert W function to determine the speed of mixed traffic corresponding to a given traffic flow.

The social cost models are applied to Nguyen Trai - Tran Phu - Quang Trung corridor with a length of 7 km, a main arterial in Hanoi, Vietnam. The PT, PRV and Taxi/Uber social cost models can be used for homogeneous traffic while the mixed transport cost model might be used for mixed traffic. The results of the Hanoi case study prove that these social cost models can be useful for transport planners and decision makers to determine the most cost-effective transport mode with respect to different passenger demand levels at the strategic planning level. Furthermore, to improve the performance of the existing mixed transport conditions, potential new PT modes can be considered for analysing their feasibility and therefore for a more detailed assessment. Moreover, with optional inputs and the flexibility of the cost functions, the social cost models are able to be modified to suit other local conditions.

However, the main drawback of the mixed transport social cost model is that demand is exogenous and modal share is fixed. The transport social cost model cannot estimate changes to the existing transport conditions after an introduction of a new PT mode. Moreover, these cost models might not reflect interactions between vehicles at links and junctions, compared to the real network. This means that the social cost model cannot evaluate congestion effects in the multimodal models. Hence, the traffic simulation model, the incremental demand models and the comparative economic assessment are developed to overcome these disadvantages in the following chapters. Chapter 6 is going to show the development of the traffic simulation model for the case study. Chapter 7 will describe incremental demand models. Chapter 8 illustrate the comparative economic assessment integrating the social cost models, demand models and traffic simulation models.

Chapter 6 Traffic Microscopic Simulation Model

6.1 Introduction

Chapter 4 describes the methodology of the comparative economic assessment, which compares existing mixed transport systems and potential options with an introduction of a new PT mode and/or transport policy in terms of ASC. The core model of the comparative economic assessment, which is the social cost model, is developed in Chapter 5. However, as a strategic level model, the social cost model is built for a stand-alone corridor without any interaction between vehicles. Therefore, a traffic simulation model is required in the comparative economic assessment to reflect real transport networks. As discussed in Chapter 3, VISSIM is chosen to develop the microscopic simulation model for mixed transport systems. This chapter is going to demonstrate the VISSIM simulation model as one component of the completed assessment.

As mentioned in section 4.3, the Nguyen Trai – Tran Phu – Quang Trung (NT-TP-QT) corridor with a length of 7.0 km is selected for the Hanoi case study. The next part of this chapter describes the data collection process on the selected corridor in Hanoi. The third part of this chapter demonstrates the development of the simulation model in VISSIM, which is based on infrastructure data, signal data and traffic data. To test the accuracy of the simulation model, the calibration and validation process is implemented and shown in the fourth part of the chapter.

6.2 Data Collection and Analysis

The data collection process was carried out from 10 February 2018 to 25 June 2018 by the author and around 100 undergraduate students at the National University of Civil Engineering in Hanoi, Vietnam. Ethics number 40105 for this project including the data collection process was approved by the Ethics Committee of Faculty of Engineering and Physical Sciences. The data were collected on the Nguyen Trai - Tran Phu - Quang Trung corridor, which is shown in Figure 6-1. Types of collected data include traffic volume, bus passenger demand, bus arrival/departure time, signalised data at intersections, infrastructure geometry, data for simulation model calibration and validation and local acceleration data. Note that all collected data are not only for the microscopic simulation model but also for the incremental demand models and the social cost models.

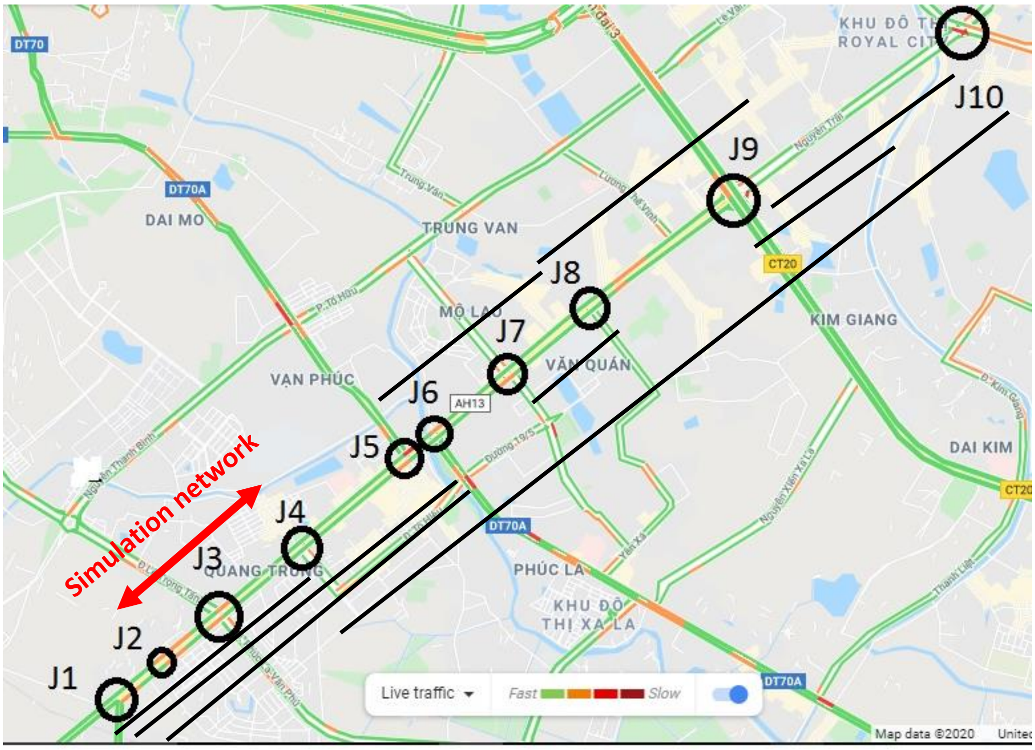


Figure 6-1 Location of Nguyen Trai - Tran Phu - Quang Trung corridor

Source:

https://www.google.com/maps/@20.9817054,105.7890439,16.79z/data=!5m1!1e1?hl=en

Notes: Width of green lines and size of black circles show a high level of traffic level at links and junctions correspondingly. Nine existing bus services, which are operated on segments of the corridor, are shown in black lines. Moreover, four bus services run on the whole corridor.

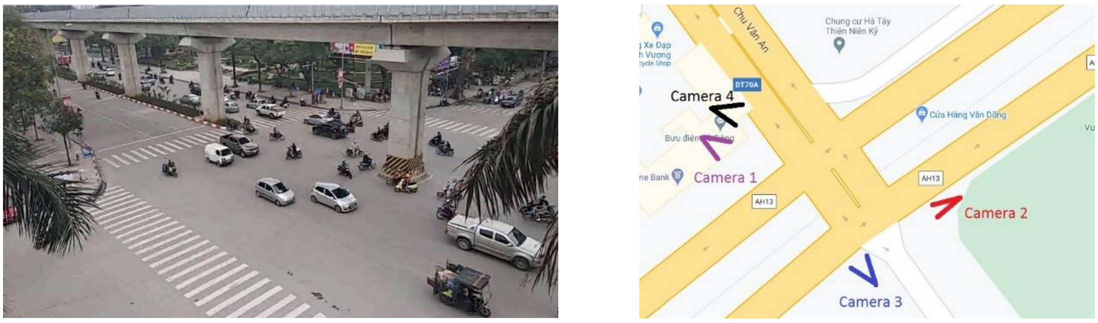
The VISSIM package with student version 6.0, which was available in 2018, is able to simulate a maximum corridor of 1.5 km. Hence, the segment from the junction J2 to the junction J4 on the corridor ('Quang Trung' road) was selected for the simulation model because of the following reasons. Firstly, this segment can represent the average traffic volume and the average bus passenger demand level of the entire corridor. Secondly, this segment with a length of less than 1.5 km includes three junctions. Representing the whole corridor by a segment of three junctions seems to be better than a segment of two junctions. Thirdly, there can be potentially available video recordings at the junctions J2 and J3, which are provided by the Hanoi Police Department. This can avoid collecting a huge amount of data on-site. Collected data for the calibration and validation process are focussed on the selected segment.

6.2.1 Traffic volume data

6.2.1.1 Primary data

The traffic volume data cover car, motorcycle and bus at junctions for the peak period. The real surveys at ten junctions (J1-J10) on the chosen corridor shown in Figure 6-1 were carried out from 16:30 to 18:30 on Monday 16 April 2018. Required data include volumes of car, motorcycle and bus for all movements at each junction, for example, twelve movements consist of turning left, turning right and going straight for four approaches at a crossroad. It is very difficult to count manually traffic volume on-site in real time. Hence, the method for collecting data is that one group of undergraduate students at each junction used cameras to record all movements of vehicles. Then, the traffic volume of each mode for each movement had been counted in-house by using video recordings. For example, four cameras were located at the junction J5 to record all movements of vehicles, which are shown in Figure 6-2.

Camera 1 Camera 2 Camera 3



Camera 4 Junction layout with cameras

Figure 6-2 Location of recording cameras at junction J5

6.2.1.2 Secondary data

The Hanoi Police Department (HPD) manages cameras in real time at the junctions J2 and J3 on the corridor. Video recordings at these junctions (7:00-9:00, 12:00-13:00 and 17:00-19:00) on Monday 19 March and Thursday 22 March 2018 were provided by the HPD. These data can be used for developing the simulation models and the simulation model calibration and validation.

6.2.1.3 Counting data in-house from video recordings

For the peak period, video recordings for the ten junctions were stored and volumes of each vehicle type in an interval of 15 minutes were counted in-house by the undergraduate students and the author. Volumes of each vehicle type for each movement in an hour were then calculated. The results are separately obtained for the period from 16:30 to 17:30 and the period from 17:30 to 18:30 on Monday 16 April 2018. The reason for that is that two different sets of data are for the calibration and validation process of the simulation model. For example, Figure 6-3 shows the results of motorcycle and car volumes at the junction J3. Bus volumes are counted separately. Other results are summarised in Appendix B.1.2.

For the off-peak period, video recordings of the period from 12:00 to 13:00 for the junctions J2 and J3 were provided by the HPD. The data were recorded on Monday 19 March and Thursday 22 March 2018. The method for counting traffic volume for the off-peak period is the same as the peak period. Two different sets of data on both days are used for the calibration and validation process of the simulation model. Results are summarised in Appendix B.1.3.

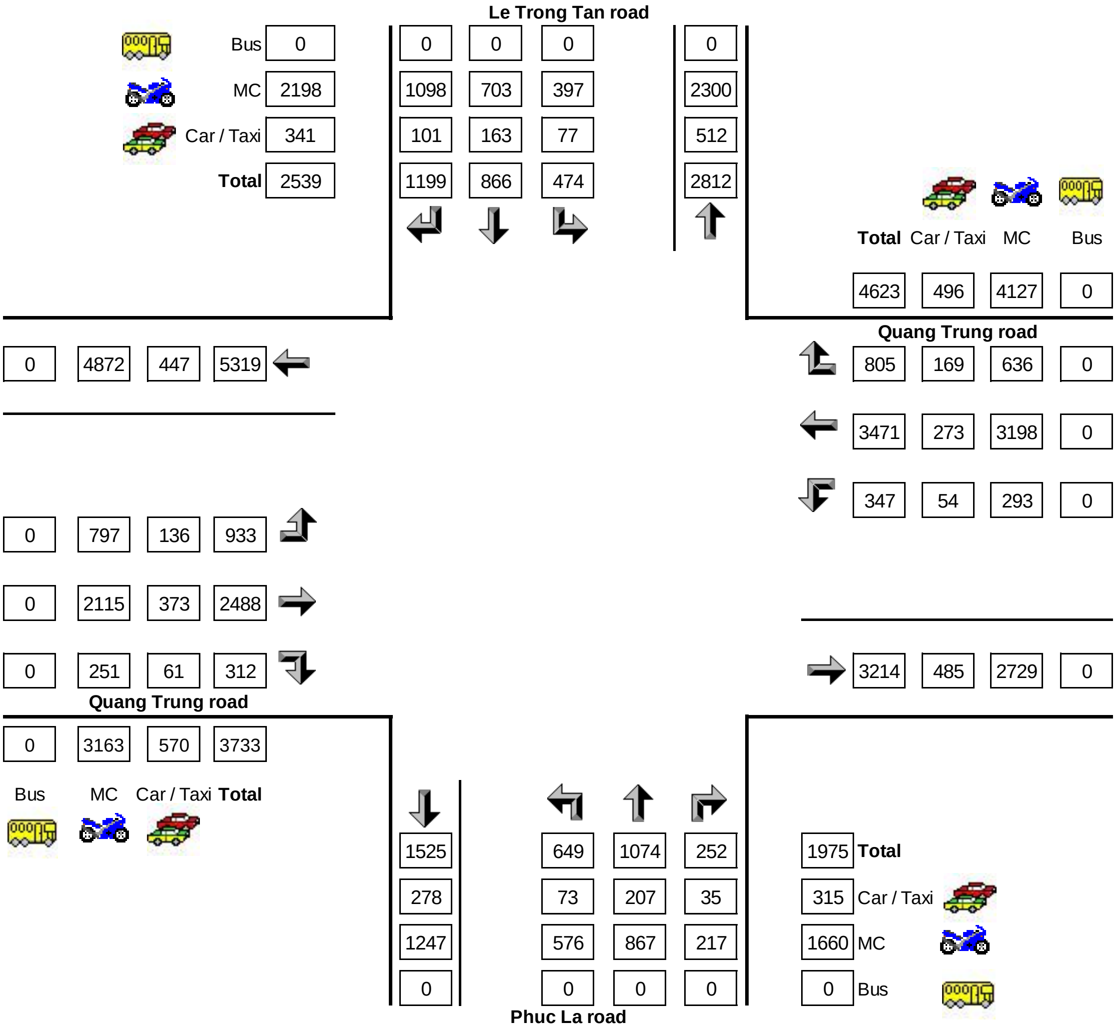


Figure 6-3 Volumes of car and motorcycle at the junction J3 from 17:30 to 18:30 on 16 April 2018

6.2.2 Bus data

The real surveys at thirty bus stops on the whole corridor were implemented from 16:30 to 18:30 on Thursday 19 April 2018. The types of data were collected for all bus services running on the corridor, which include: (i) number of boardings and alightings at all bus stops; (ii) bus occupancy; (iii) arrival/departure time and stopping time; and (iv) boarding/alighting time per passenger. Four bus services run on the whole corridor while nine existing bus services are operated on different segments of the corridor. The locations of the nine bus services are shown in Figure 6-1. Two methods for collecting these data were used as (i) one group of the undergraduate students at each bus stop used cameras to record all movements of bus passengers and bus vehicles; and (ii) the surveyors used survey forms to count manually on-site. The combination of the two methods ensures that the results are accurate enough. Appendix B.2 summarises results of bus data.

6.2.3 Control data

To get signal data, surveys at the ten junctions on the whole corridor were carried out on-site by the undergraduate students and the author. All junctions are controlled by a signal with the traditional “Red – Green – Amber” phase and traffic lights show phasing time in seconds. Moreover, all signal timings are fixed and there is no difference between the peak and off-peak period. Signposts on links were collected to determine their locations.

6.2.4 Infrastructure

Geometric measurement surveys at all junctions and links on the corridor were carried out on-site by the undergraduate students and the author. Geometric data of links include the number of lanes, lane width and gradient while the data at junctions consist of the number of lanes, lane width and gradient of each approach and curb curvature radius for turning right and turning left.

6.2.5 Local acceleration of motorcycle for inputs of VISSIM

As discussed in subsection 4.3.2, acceleration surveys were carried out by using the speed gun (see Figure 4-2). Samples of 200 motorcycles were obtained at different speeds ranging from 0 km/h to a speed limit of 50 km/h. The undergraduate students and the author chose suitable segments on the corridor and suitable time of a day to implement these surveys. For example, very low speeds were observed at junctions whilst high speeds were observed at links at off-peak morning periods.

Long (2000) suggested that the linearly decreasing model of acceleration related to speed of travel performs successfully for both maximum vehicle acceleration and normal motorist-chosen acceleration, for both cars and trucks. The results showed that the acceleration is not constant during speed changes, but the rate of change in acceleration is constant. Long (2000) reviewed some research on vehicle acceleration, which based on observation of vehicle speed increments. Firstly, Long (2000) reviewed the study by Loutzenheiser (1937) that conducted a series of tests on six- and eight-cylinder passenger cars. The acceleration results from repeated trials at full acceleration with all six vehicles and different drivers were averaged together in successive 8.05 km/h (5-mph) speed increments. Secondly, Long (2000) reviewed the study by Beakey (1938) that reported the acceleration results for each vehicle separately for 16.1-km/h (10-mph) speed increments.

As a result, in this thesis, a 5-km/h speed increment is chosen for estimating motorcycle acceleration. A mid-point of acceleration, which represents for a speed band, will be inserted in VISSIM. The acceleration at 0 km/h represents for the smallest speed band of 0-2.5 km/h while the acceleration at 5 km/h represents for the next speed band of 2.5-7.5 km/h. The highest speed band of 47.5-50 km/h is represented by the acceleration at 50 km/h. Hence, for each speed increment, the acceleration of observed motorcycles is estimated. Then a function of motorcycle acceleration is produced for a range speed between 0 and 50 km/h.

There are six steps for estimating motorcycle acceleration for each speed band, which include: (i) observed motorcycle were selected for one speed band; (ii) for raw data of each motorcycle from Stalker ATS 5.0, biased points, which show speeds of other vehicles nearby the objective vehicle, need to be eliminated; (iii) speed-time values for each vehicle from Stalker ATS 5.0 are exported to an Excel file; (iv) a linear model is made for speed-time relationship for each observed motorcycle where a correlation coefficient and equation of the fitted line are determined for this motorcycle; (v) if the speed-time linear model appears to be consistent, the acceleration of each observed vehicle can be calculated from the slope of the fitted line; and (vi) Maximum, minimum and median values of acceleration are determined for each speed increment. To minimise impacts of outliers, an approach is to use a 5 per cent trimmed median, where the 5 per cent of observations in each tail of the distribution are removed from the sample (Long, 2000). Then, 95th percentiles, 5th percentiles and trimmed median of motorcycle acceleration are used as maximum, minimum and median values respectively. The threes values are inserted in VISSIM for one speed band. The detailed six-step process is shown in Appendix B.3.

Using observation data in the Hanoi case study, the results show that the speed-time relationship is a linear function for all speed bands because all sample correction coefficients are higher than 0.85. The six-step process above is conducted for all speed bands from 0 to 50 km/h. Figure 6-4 shows upper bound, lower bound and median of desired acceleration of motorcycle in successive

5-km/h speed increments, which are 95th percentiles, 5th percentiles and trimmed median of motorcycle acceleration. Three curves in Figure 6-4, which are used as 'desired acceleration functions' of motorcycle, are inserted in VISSIM.

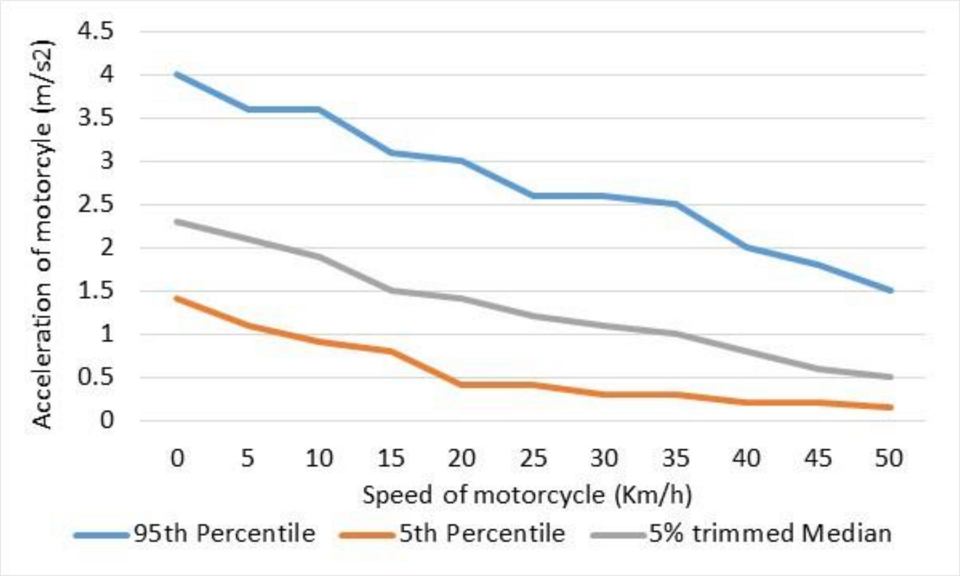


Figure 6-4 Upper bound, lower bound and median of desired acceleration of motorcycle for the Hanoi case study

6.2.6 Data for simulation model calibration and validation

As mentioned in subsection 3.3.5, the nine-step procedure for the microscopic simulation model calibration and validation is used in this thesis. Travel time is chosen as a measure of effectiveness. Therefore, travel time of bus, motorcycle and car needs to be collected on-site for the peak period. For the off-peak period between 12:00 and 13:00, data can be extracted from video recordings provided by the HPD.

6.2.6.1 Travel time of bus

Travel time of conventional bus between two given points on the chosen segment from the junction J2 to the junction J4. The real surveys were carried out from 15:00 to 19:00 on 17 May 2018 at eight bus stops (four successive bus stops each direction). The locations of eight bus stops are shown in Figure 6-5. Two surveyors at a stop counted manually information including bus service number, bus plate number and bus arrival/departure time. This set of data is different from the set of data collected on 19 April 2018, which is shown in subsection 6.2.2.

Similarly, travel time of conventional bus can be determined from video recordings provided by the HPD when bus service number and time recorded can be identified. These data are used for the off-peak period.

6.2.6.2 Travel time of the car

Travel time of cars between two given points on the study corridor. It is difficult to chase and see a car from video recordings at the two points. As a result, one surveyor and the author ride a car between the two points on different weekdays during the collection data period. A sample of 100 cars was carried out between the 182 Quang Trung bus stop and 418 Quang Trung bus stop for the period from 16:30 to 17:30 and another sample of 100 cars was implemented between the 705 Quang Trung stop and the 267 Quang Trung bus stop for the period from 17:30 to 18:30. These are two different sets of data in terms of time periods and directions. This is necessary for the calibration and validation process.

6.2.6.3 Travel time of the motorcycle

Travel time of motorcycles between two given points on the chosen corridor. Ten surveyors including the author ride motorcycles of two people between the two points on different weekdays during the collection data period. A sample of 200 motorcycles was carried out between the 182 Quang Trung bus stop and 418 Quang Trung bus stop for the period from 16:30 to 17:30 and another sample of 200 motorcycles was implemented between the 705 Quang Trung stop and the 267 Quang Trung bus stop for the period from 17:30 to 18:30. These are two different sets of data in terms of time periods and directions.

6.2.7 Summary

The required collected data for the microscopic simulation model include both primary data and secondary data. The primary data were collected by the author and around 100 undergraduate students while secondary data were provided by the Hanoi Police Department. The data were collected for both the peak and off-peak periods. Moreover, the data cover traffic volume data at junctions, data on bus, data on signals at junctions, infrastructure geometry, motorcycle acceleration, vehicle travel time. Traffic volume and data on bus passenger are collected by using cameras and then counted in-house. Data on local motorcycle acceleration are analysed to get local parameters for inputs of the VISSIM simulation.

6.3 Developing Simulation Model

As mentioned in Chapter 3 and Chapter 4, the microscopic simulation model is based on VISSIM to develop an urban mixed traffic corridor where bus, car and motorcycle share facilities. This model is integrated with the social cost model and incremental demand models to form the comparative economic assessment to analyse the feasibility of proposed public transport modes on the selected corridor and identify the best mixed transport option. The VISSIM model simulates the Quang Trung segment of the chosen corridor in Hanoi. To develop the VISSIM model, infrastructure, signalised control data and traffic data are input in the VISSIM package.

The results of traffic data provided by the HPD show that there are significant differences in general traffic volume and bus travel time between the peak and off-peak period. These results are summarised in Figure B-2 and Figure B-7 in Appendix B. This is consistent with data on passenger demand split in the different time provided by the TTS Group, which are shown in Table 5-7. Hence, the simulation models are developed for the peak and off-peak periods separately. The VISSIM model for the peak period simulates a segment between the junctions J2 and J4 while the VISSIM model for the off-peak period is developed for a segment between the junctions J2 and J3 in Figure 6-1 due to lack of data for the junction J4. The process for building infrastructure and signal data in VISSIM for both peak and off-peak periods are the same whilst general traffic data of both periods are different. The junctions J2, J3 and J4 are named for the Van La – Quang Trung intersection, Le Trong Tan – Phuc La – Quang Trung intersection and Ngo Thi Nham – To Hieu – Quang Trung intersection respectively.

6.3.1 Infrastructure

There are two ways to build an infrastructure network in VISSIM. The first way is based on geographic data in VISSIM, which is named as ‘bing maps’. The ‘bing maps’ can be switched ‘on’ or ‘off’ in VISSIM. The second way is that VISSIM users can build the network manually. However, there are some differences of updated data between ‘bing maps’ and the corridor condition due to the time gap between release data of the VISSIM package and data collection time. Hence, a combination of two ways is used to develop the VISSIM model in this thesis. Based on ‘bing maps' and collected data at all links and junctions (on geometric data, post, one-way lane, etc.), the infrastructure network of the segment between the junction J2 and J4 is built. The VISSIM infrastructure network contains the geometry of the selected segment and the other roads intersecting at the junctions J2-J4. Additionally, the VISSIM network includes any existing signposts on the real network. Figure 6-5 shows the simulated segment for the peak period. To build the simulated network, each junction needs to be developed in VISSIM based on the collected data. Figure B-11 in Appendix B.4 shows an example of the detailed layout of the junction J3 that is imported in VISSIM.

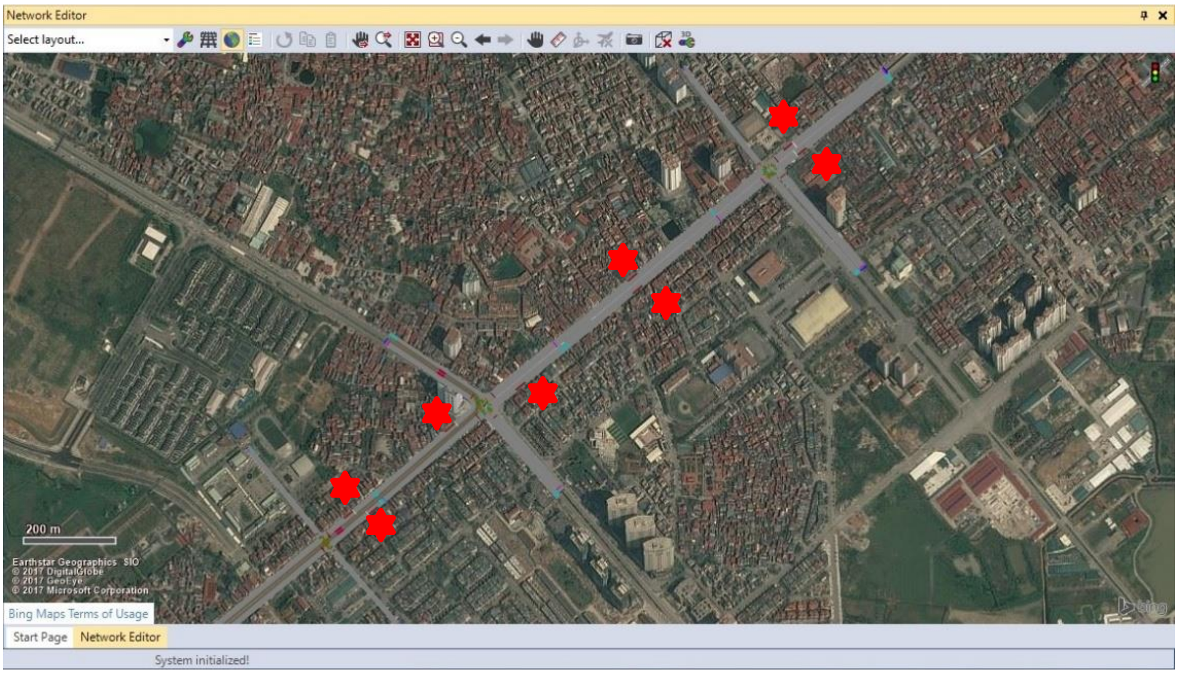
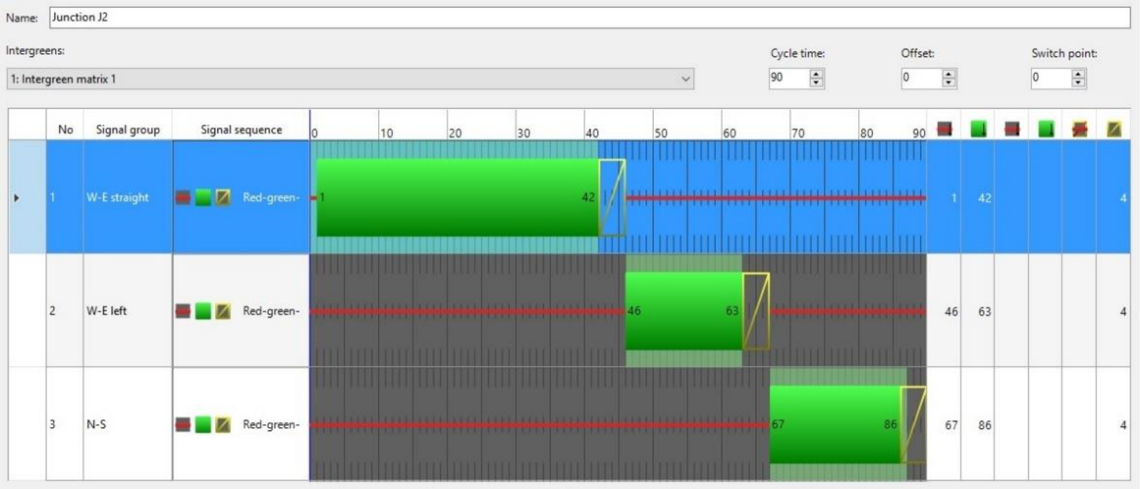


Figure 6-5 Simulated traffic network of the study corridor in VISSIM

Notes: Eight bus stops on the selected segment are shown in red stars.

6.3.2 Signalised control data

In Hanoi, the signal phases are fixed without any priority for public transport modes at junctions. The collected signalised data for the junctions J2-J4 were inserted into the VISSIM model by using the signal control input interface, that are shown in Figure 6-6, Figure 6-7 and Figure 6-8. Pedestrian stages were not inputted into the control data because traffic signals for pedestrian follow the three stages for the general traffic.



Name: Junction J2

Intergreens: 1: Intergreen matrix 1

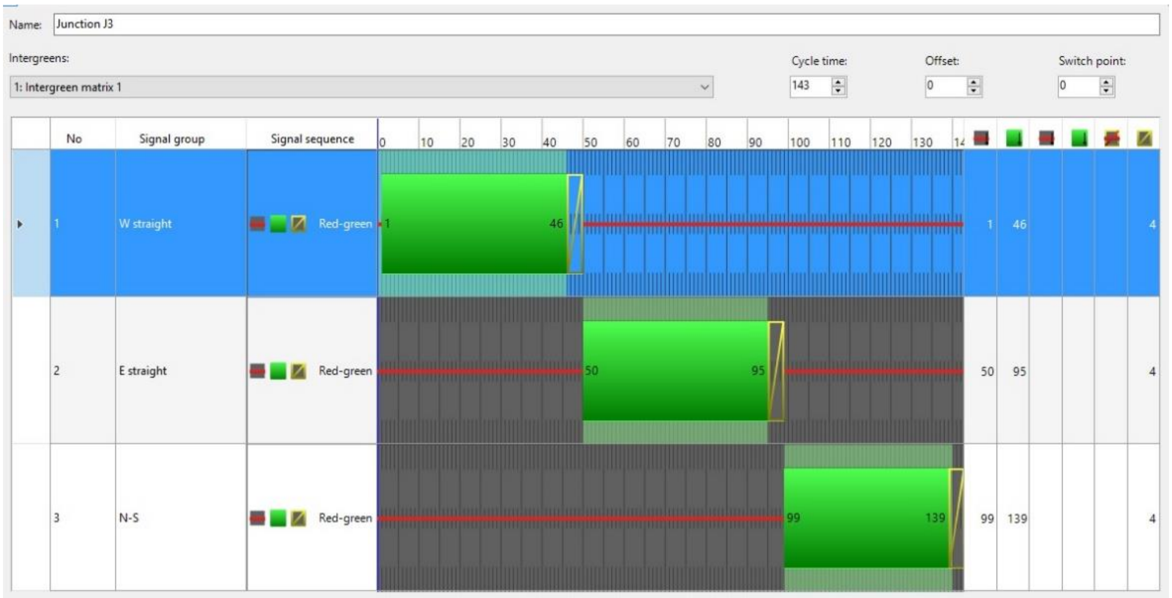
Cycle time: 90

Offset: 0

Switch point: 0

No	Signal group	Signal sequence	🟥	🟩	🟥	🟩	🟥	▨
1	W-E straight	Red-green-	1	42				4
2	W-E left	Red-green-	46	63				4
3	N-S	Red-green-	67	86				4

Figure 6-6 Signalised control data for the junction J2



Name: Junction J3

Intergreens: 1: Intergreen matrix 1

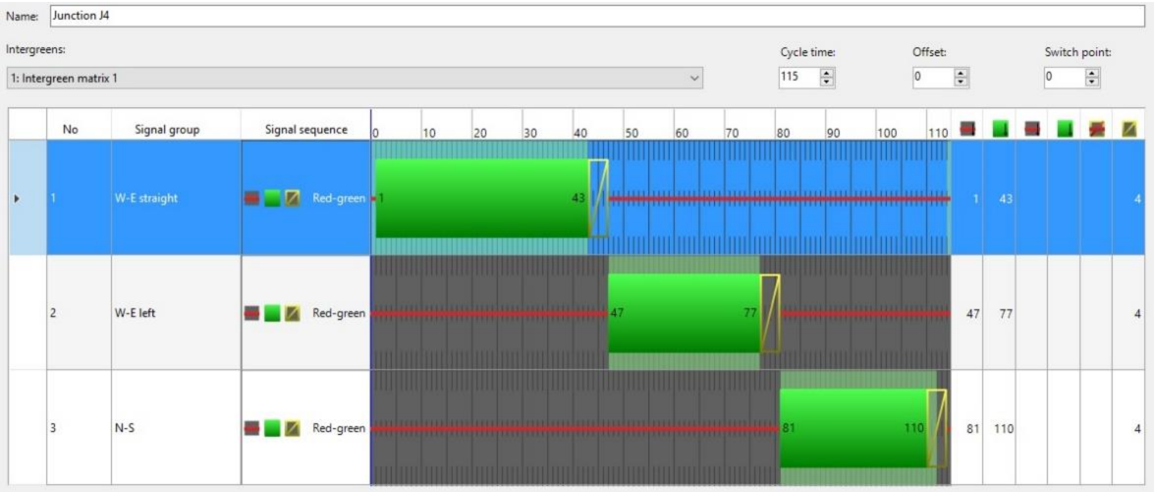
Cycle time: 143

Offset: 0

Switch point: 0

No	Signal group	Signal sequence	🟥	🟩	🟥	🟩	🟥	▨
1	W straight	Red-green	1	46				4
2	E straight	Red-green	50	95				4
3	N-S	Red-green	99	139				4

Figure 6-7 Signalised control data for the junction J3



Name: Junction J4

Intergreens: 1: Intergreen matrix 1

Cycle time: 115

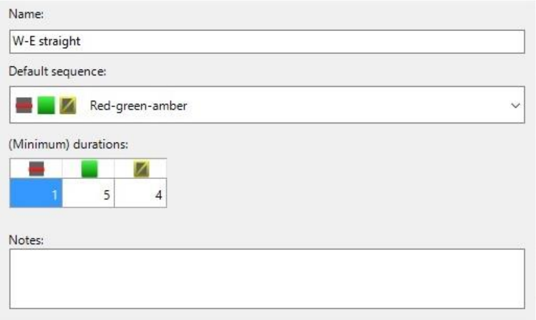
Offset: 0

Switch point: 0

No	Signal group	Signal sequence	🟥	🟩	🟥	🟩	🟥	▨
1	W-E straight	Red-green	1	43				4
2	W-E left	Red-green	47	77				4
3	N-S	Red-green	81	110				4

Figure 6-8 Signalised control data for the junction J4

A signal sequence for each phase in each signal cycle is “Red-Green-Amber” for all junctions. The durations for each sequence are based on the collected data on-site. The signal sequence for one phase in the junction J4 is shown in Figure 6-9.



Name: W-E straight

Default sequence: Red-green-amber

(Minimum) durations:

🟥	🟩	▨
1	5	4

Notes:

Figure 6-9 Signal sequence setting for ‘W-E straight’ phase in VISSIM

6.3.3 General traffic input

Traffic input data need to represent the traffic network of the chosen segment in Hanoi. The traffic input data, which include private transport and public transport, represent the characteristics of all vehicles, the origin-destination movements, bus routes and bus stops. In this study, general traffic cover motorcycle, car and bus while HGVs and bicycles are not considered due to very minor volumes. This subsection is going to demonstrate general traffic input for cars and motorcycles in the first place, followed by public transport input.

6.3.3.1 General traffic input

General traffic inputs in VISSIM consist of vehicle volumes, vehicle compositions and origin-destination movements at each junction. Vehicle volumes are input by using the ‘Vehicle Inputs’ setting in VISSIM. The ‘Vehicle Compositions / Relative Flows’ attribute is used for vehicle composition inputs while the ‘Static Vehicle Routing Decisions / Static Vehicle Routes’ attribute is used for origin-destination movements at each junction. Traffic volumes of car and motorcycle at each junction (e.g. values shown in Figure 6-3) are required to input in the VISSIM simulation. An example of this process for general traffic input in VISSIM is shown in Appendix B.4.2.

6.3.3.2 Public transport input data

Public transport data are input in VISSIM by using the Public Transport Lines and Public Transport Stops settings.

To create each bus line through the Public Transport Line setting in VISSIM, the bus origin, bus destination, bus route and the activated public transport stops must be defined. The starting time of each bus vehicle on the simulated corridor needs to be input through the ‘departure times’ attribute, which can be set either by service frequency or by entering an exact starting time. Because the start point and end point of the simulated corridor are not terminations of the bus routes, the starting time of each bus in the VISSIM simulation model is used from collected data on-site. In addition, the occupancy of each bus vehicle, which is the number of passengers on board when this vehicle enters the VISSIM network, needs to be input through the ‘occupancy’ attribute in the Public Transport Line setting. This value, which is calculated by dividing the total initial passengers on board at the first bus stop of each direction by the total number of bus vehicle entering the VISSIM network, is inserted for each bus service separately.

Data on each public transport stop are input in VISSIM through the Public Transport Stops setting in VISSIM. The locations of each bus stop were identified based on the collected data on-site. Boarding passenger of each bus line at each bus stop, which is boarding passenger volume per hour, is inserted through the ‘Volume’ attribute. Alighting percentage of each bus line at one bus stop is input through the Public Transport Line setting and ‘PT line stop’ attribute. Based on the boarding passengers, occupancy and alighting percentage, the dwell time data are calculated automatically in VISSIM. An example of this process of public transport input in VISSIM is shown in Appendix B.4.3.

6.3.4 Summary

The VISSIM simulation models are developed for the peak and off-peak periods separately because there are significant differences in general traffic volume and bus travel time between these periods. The peak period is between 16:30 and 18:30 while the off-peak period is from 12:00 to 13:00. To develop the VISSIM models, infrastructure, signalised control data and traffic data are input in VISSIM. The infrastructure geometry, which includes links and junctions are input in the first place. Secondly, signals data are set for all junctions. Finally, traffic data including general traffic and bus data are inserted in the VISSIM simulation model.

6.4 Model Calibration and Validation

The previous section illustrates the development of the VISSIM simulation models for the peak and off-peak periods. The VISSIM simulation models were developed based on the data collected from the Quang Trung segment on the selected corridor. Calibration and validation of the model need to be implemented to ensure the outputs of the VISSIM simulation model represent the transport network in reality. This is a process to adjust parameters in the model and test the accuracy of the model by comparing with the data collected in the field.

Chapter 3 discusses the model calibration and validation process by Park and Schneeberger (2003), which is a comprehensive and standardised calibration and validation procedure for the microscopic simulation model. This nine-step procedure includes: (1) measure of effectiveness selection; (2) data collection; (3) calibration parameter identification; (4) experimental design; (5) run simulation; (6) surface function development; (7) candidate parameter set generation; (8) evaluation; and (9) validation with new data collection. This process is demonstrated for the both peak and off-peak periods.

6.4.1 Calibration and validation process for the peak period

6.4.1.1 Measure of effectiveness selection

The first step is to determine the key performance indicators as the measure of effectiveness. The key performance indicators are considered in not only the simulation model but also the social cost models and incremental demand models in the comparative economic assessment. In addition, the key performance indicators need to be collected from the VISSIM simulation model and from the fields to test the accuracy. In this thesis, motorcycle, car and bus are considered for the existing transport condition. As a result, the travel time of motorcycle, car and bus are chosen as key performance indicators. Two travel time evaluation points were identified on the selected segment on-site to collect data. These points were also placed on the VISSIM network. The distance between the two points is 1.5 km.

6.4.1.2 Data collection

Section 6.2 describes the data collection process. The collected data for calibration and validation are summarised below.

The field data for the 16:30-17:30 period for the calibration process include: (i) Traffic volume at three junctions were collected on Monday, 16 April 2018; (ii) Data on bus passenger demand were collected on Thursday, 19 April 2018; (iii) Data on bus travel time were collected on Thursday, 19 April 2018; (iv) Data on car and motorcycle travel time were collected on different weekdays during the collection data period (February to June 2018); (v) Data on acceleration motorcycle were collected on different weekdays during the collection data period (February to June 2018).

The field data for the 17:30-18:30 period for the validation process include: (i) Traffic volume at three junctions were collected on Monday, 16 April 2018; (ii) Data on bus passenger demand were collected on Thursday, 19 April 2018; (iii) Data on bus travel time were collected on Thursday, 17 May 2018; and (iv) Data on car and motorcycle travel time were collected on different weekdays during the collection data period (February to June 2018).

Travel times of vehicles on the westbound corridor were selected for the calibration process whilst travel times of vehicles on the eastbound corridor were selected for the validation process.

6.4.1.3 Calibration parameters

Seven calibration parameters were considered in the study by Park and Schneeberger (2003), which are the emergency stopping distance, lane-change distance, desired speed, number of observed preceding vehicles, average standstill distance, additive part of desired safety distance, waiting time before diffusion, and minimum headway. Furthermore, bus desired speed, bus acceleration and bus deceleration are chosen as three calibration Parameters (Li, 2015).

As discussed in subsections 4.3.2 and 6.2.5, data on acceleration motorcycle were collected and analysed. The motorcycle acceleration parameters are then used as direct input data for the VISSIM simulation without calibration. Due to time limits, four calibration parameters are selected as (i) desired speed of car and bus; (ii) desired speed of motorcycle; (iii) minimum lateral distance driving when overtaking vehicles on the same lane; and (iv) average standstill distance. Because these parameters might have significant impacts on vehicle travel time in mixed transport systems with the dominance of motorcycles. The base values of the four parameters are chosen based on the default values in VISSIM and regulations of the speed limit in Hanoi. Other possible values, which are smaller than the base values, are also selected because of the following reasons. Firstly, the base value of the speed is the speed limit in Hanoi. Secondly, volumes of motorcycles in the Hanoi roads are high, therefore, other possible values of average standstill distance and minimum lateral distance driving should be smaller than the default values. All possible values of these parameters are shown in Table 6-1.

Table 6-1 Model calibration parameters

Parameters	Possible values		
Desired speed distribution of bus and car (km/h)	60 (base value)	50	40
Motorcycle desired speed distribution (km/h)	50 (base value)	40	30
Average standstill distance (m)	2 (base value)	1	0.5
Minimum lateral distance driving at 50 km/h (m)	1 (base value)	0.8	0.6

Note that *minimum lateral distance driving* at 50 km/h is the minimum distance between vehicles when overtaking at 50 km/h within the lane and keeping the distance to vehicles in the adjacent lanes. The minimum distance is linearly interpolated for other speeds between 0 km/h and 50 km/h (PTV AG, 2011). Minimum lateral distance driving at 0 km/h is chosen as 0.2 m.

The *distribution function of desired speeds* is a particularly important parameter, as it has an impact on link capacity and achievable travel times. If not hindered by other vehicles or network objects, e.g. signal controls, a driver will travel at his/her desired speed. Desired speed takes the permissible speed into account, the upper limit of its distribution, however, mostly exceeds the permissible speed. This is not the case though if the route examined is equipped with a permanently installed speed trap (PTV AG, 2011).

Average standstill distance is defined as the average desired distance between two stopped cars; and cars and stop lines (PTV AG, 2011).

6.4.1.4 Experimental Design

In order to obtain the parameter set that produces the vehicle travel time values that match the data collected from a field survey, different combinations of the four parameters were tested. There are 81 possible combinations for the four calibration parameters in Table 6-1.

6.4.1.5 Run Simulation

To ensure the variability of the simulation results and to reduce the randomness, each parameter combination case has been run five times with different random seeds. Therefore, a total of 405 runs were performed in VISSIM to obtain the vehicle travel times of the westbound traffic. The total simulation time in VISSIM has been set to 60 minutes (3,600 seconds), which include 15 minutes system warming up period and 45 minutes of travel time collecting period.

6.4.1.6 Surface function development

The surface function was created to estimate the relationships between the calibration parameters and the vehicle travel times obtained from the simulation model. A linear regression model was built in the SPSS program with the four calibration parameters as the independent variables and the vehicle travel time as the dependent variable (Park and Schneeberger, 2003; Li, 2015). The linear regression model is implemented for travel time of bus, car and motorcycle.

6.4.1.6.1 Bus travel time

Bus travel time is a criterion (or dependent variable). Motorcycle desired speed distribution (MCSpeed), desired speed distribution of car and bus (BusCarSpeed), minimum lateral distance driving (LateralDistance) and average standstill distance (AvgStandstillDistance) are the predictors (or independent variables). Table 6-2 shows the outputs from the SPSS program.

Table 6-2 Results of a linear regression model for bus travel time

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.984[a]	.968	.967	78.03346
a. Predictors: (Constant), MCSpeed, BusCarSpeed, LateralDistance, AvgStandstillDistance				

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	14208328.758	4	3552082.190	583.339	.000[b]
	Residual	462780.819	76	6089.221		
	Total	14671109.578	80			
a. Dependent Variable: BusTraveltime						
b. Predictors: (Constant), MCSpeed, BusCarSpeed, LateralDistance, AvgStandstillDistance						

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	118.546	82.254		1.441	.154
	AvgStandstillDistance	670.840	13.904	.983	48.250	.000
	LateralDistance	-120.472	53.095	-.046	-2.269	.026
	BusCarSpeed	-.460	1.062	-.009	-.434	.666
	MCSpeed	-.019	1.062	.000	-.018	.986
a. Dependent Variable: BusTraveltime						

As can be seen from Table 6-2, *p-values* for *average standstill distance* and *minimum lateral distance driving* are smaller than 0.05. This means that these parameters have significant impacts on the average bus travel time based on a significance level of 5%.

Moreover, the *b* coefficient for *average standstill distance* is a positive number. This indicates that higher average standstill distance is associated with higher average bus travel time. This seems to be sensible because higher average distance between two vehicles can cause lower capacity in the VISSIM simulation, therefore higher travel time with the same existing traffic volume.

By contrast, the *b* coefficient *for minimum lateral distance driving* is a negative number. This means that higher minimum lateral distance driving is associated with smaller average bus travel time. This appears to be consistent with the study by Nguyen and Sano (2012). Those authors suggested that the relationship between speed and effective space is an increasing one in the peak period. Higher minimum lateral distance driving can lead to higher effective space, which is a product of lateral distance of running vehicle and longitudinal distance of the running vehicle. Therefore, higher minimum lateral distance driving results from larger mean speed, and then, lower average travel time.

Additionally, Table 6-2 shows the *p*-values for the desired speed distribution of bus, car and motorcycle are much higher than 0.05. This means that these parameters do not have a significant impact on the average bus travel time based on a significance level of 5%. The reason for that can be explained that car, bus and motorcycle cannot reach desired speed (or around speed limit) in the peak period where traffic volume is high and any vehicle might be hindered by other vehicles or network objects. As a result, a driver cannot travel at his/her desired speed.

6.4.1.6.2 Car travel time

Similarly, the results of a linear regression model for car travel time are shown in Table 6-3 displays that the relationships between the car travel time obtained from the simulation model and the calibration parameters are similar to the relationship between the bus travel time and calibration parameters, which are mentioned in subsection 6.4.1.6.2. This means that there is significant evidence that *average standstill distance* and *minimum lateral distance driving* have significant impacts on the car travel times whilst *speed distribution of motorcycle, car and bus* do not have significant impacts on the car travel times. As mentioned in subsection 6.4.1.6.2, car, bus and motorcycle cannot reach desired speed (or around speed limit) in the peak period when traffic volume is high.

Table 6-3 Results of a linear regression model for car travel time

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.969[a]	.940	.937	96.97482

a. Predictors: (Constant), MCSpeed, BusCarSpeed, LateralDistance, AvgStandstillDistance

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	11154287.792	4	2788571.948	296.527	.000[b]
	Residual	714712.821	76	9404.116		
	Total	11869000.614	80			

a. Dependent Variable: CarTraveltime

b. Predictors: (Constant), MCSpeed, BusCarSpeed, LateralDistance, AvgStandstillDistance

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	162.179	102.220		1.587	.117
	AvgStandstillDistance	593.910	17.278	.968	34.373	.000
	LateralDistance	-134.789	65.983	-.058	-2.043	.045
	BusCarSpeed	-.591	1.320	-.013	-.448	.656
	MCSpeed	-.635	1.320	-.014	-.481	.632

a. Dependent Variable: CarTraveltime

6.4.1.6.3 Motorcycle travel time

Results of a linear regression model for motorcycle travel time are shown in Table 6-4.

Table 6-4 Results of a linear regression model for motorcycle time

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.963[a]	.928	.924	91.61382

a. Predictors: (Constant), MCSpeed, BusCarSpeed, LateralDistance, AvgStandstillDistance

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	8250968.390	4	2062742.097	245.767	.000[b]
	Residual	637874.927	76	8393.091		
	Total	8888843.317	80			

a. Dependent Variable: MCTraveltime

b. Predictors: (Constant), MCSpeed, BusCarSpeed, LateralDistance, AvgStandstillDistance

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	207.842	96.569		2.152	.035
	AvgStandstillDistance	510.430	16.323	.961	31.270	.000
	LateralDistance	-128.220	62.335	-.063	-2.057	.043
	BusCarSpeed	-.469	1.247	-.012	-.377	.708
	MCSpeed	-1.162	1.247	-.029	-.932	.354

a. Dependent Variable: MCTraveltime

Table 6-4 shows that there is significant evidence that *average standstill distance* and *minimum lateral distance driving* have significant impacts on the motorcycle travel times whilst *speed* *distribution of motorcycle, car and bus* do not have significant impacts on the motorcycle travel times.

6.4.1.7 Candidate parameter sets

This step aims to identify an optimal parameter set that provides a close match with the field performance measure. Candidate parameter sets were created with the linear regression model. There is significant evidence that *average standstill distance* and *minimum lateral distance driving* have significant impacts on the vehicles travel times but *speed distribution of bus, car and motorcycle* do not. However, the linear regression model was created from the results of five VISSIM simulation runs for each candidate parameter set. A sample of five runs seems to be not large enough. Hence, to cover all possibilities, *speed distribution of bus, car and motorcycle* should be still considered for choosing the candidate parameter set, which can be the one with an estimated travel time close to the observation value from the field are selected for the evaluation step. Forty simulation runs rather than five runs are conducted for this evaluation step.

For the period from 16:45 to 17:30, the average bus, car and motorcycle travel times observed from the field are 288.14, 220.17 and 213.59 seconds respectively. A parameter set is chosen if the differences between vehicle travel times on both directions obtained from the VISSIM simulation and the field are less than six seconds[2]. As a result, five combinations of parameters were selected and are presented in Table 6-5.

Table 6-5 Candidate parameter sets

Case	Average standstill distance (m)	Minimum lateral distance driving (m)	Desired speed distribution of bus and car (km/h)	Motorcycle desired speed distribution (km/h)	Average bus travel time in 5 simulation runs	Average car travel time in 5 simulation runs	Average motorcycle travel time in 5 simulation runs
1	0.5	0.6	60	40	283.07	212.78	213.94
2	0.5	0.6	50	40	283.44	220.75	216.73
3	0.5	0.6	40	40	284.35	226.85	216.78
4	0.5	0.8	40	40	283.04	224.03	216.42
5	0.5	1.0	60	50	282.69	220.01	215.63

---

[2] Due to time limits, the number of parameter sets should not large, therefore six seconds is chosen and then the number of possibilities is five.

6.4.1.8 Candidate Parameter Set Evaluation

Forty random seeded runs were made for each of five candidate parameter sets and each set is evaluated based on two criteria. The first criterion is visualisation. The second evaluation criterion is distribution of vehicle travel times produced from VISSIM.

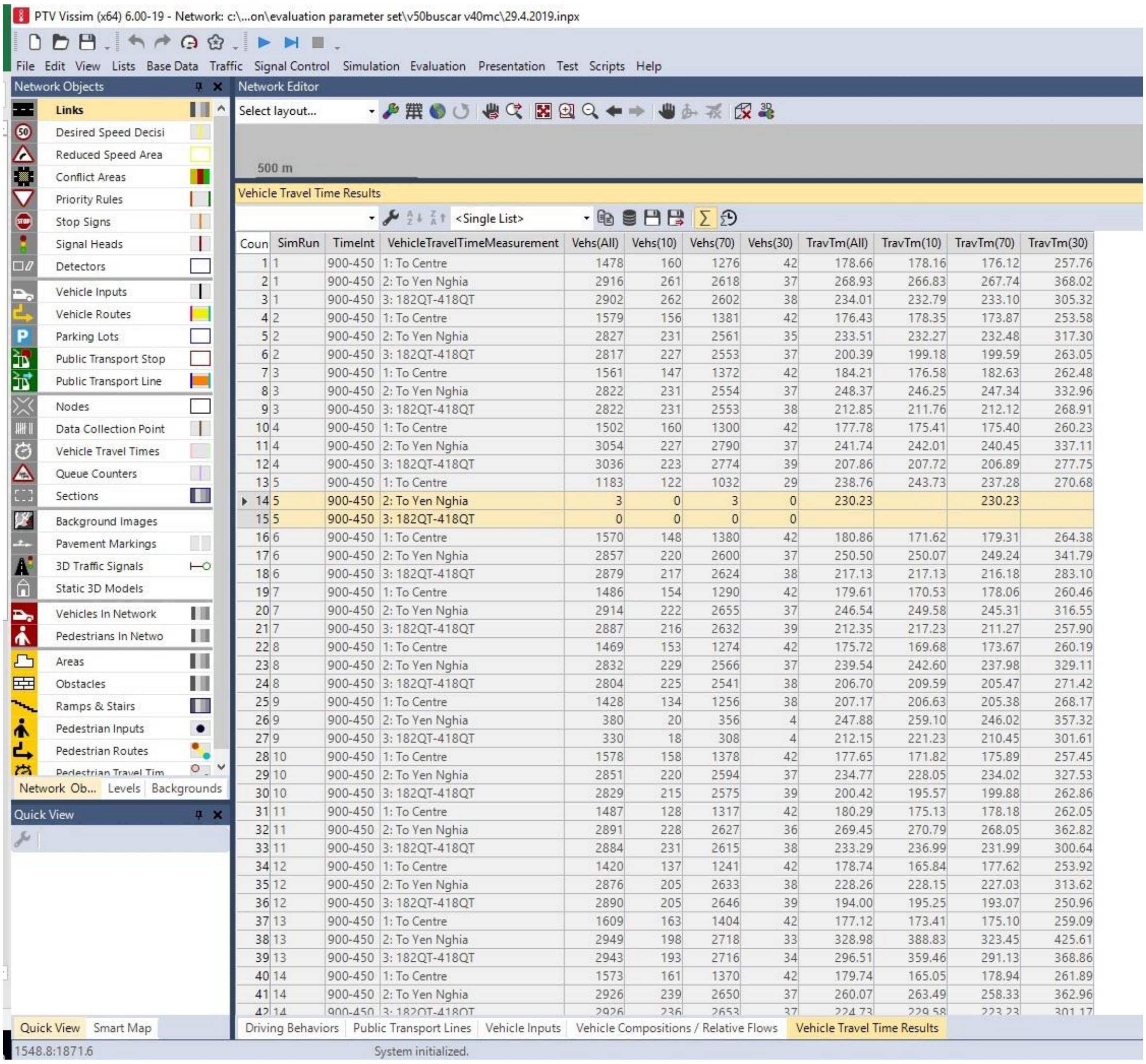
6.4.1.8.1 Visualisation

Visualisation is a necessary performance measurement to validate microscopic simulation models. If the values of the parameters are not realistic, errors will be produced during the simulation runs, which might be in the error output file or from the visualisation. Hence, visualisation is checked during the simulation runs as well as the error files to ensure the parameters are realistic. After implementing 40 simulation runs, errors occur in outputs of Case 1, Case 2 and Case 5. For example, Figure 6-10 shows a result error of the simulation run number five for Case 2. The same error occurs for the simulation run 27 and the simulation run 28 for Case 1 and Case 5 respectively. The simulated network is totally blocked in those simulations, therefore, all vehicles cannot move until the end of the simulation period. The reason can relate to a lane change problem where vehicles were not able to change their desired lane. For example, two vehicles at two adjacent lanes at the stop line tried to change to the other lane. The block did not occur in a day when the survey was carried out. Hence, Case 1, Case 2 and Case 5 are ignored whilst Case 3 and Case 4 are tested with the second criterion.

6.4.1.8.2 Travel time distributions

Travel times of bus, car and motorcycle on the westbound direction were collected from 40 random seeded runs. For each simulation run, the average bus, car and motorcycle travel times are collected and then used to compare vehicle travel times collected from the field. The field bus data, which was collected in one single day, might represent the average travel time on the corridor but might not. Therefore, the bus data collected on-site can be average or lower or higher than the true mean. In addition, the field car and motorcycle data were collected in different weekdays. Hence, both comparisons of mean travel time and travel time distribution from the field and the simulation are tested.

Firstly, an independent two-tailed Student's t-test was run to see if the means of vehicle travel time obtained from the field observation and the simulation are equal. Secondly, the Kolmogorov-Smirnov (K-S) test was used to evaluate the goodness-of-fit of the two probability distributions of vehicle travel times. For each candidate parameter set passing the t-test, one simulation run is chosen and travel time of every single vehicle in the chosen simulation run is obtained from outputs of VISSIM. Consequently, the distribution of the vehicle travel times for the chosen simulation run is compared with the distribution of the field sample. One candidate parameter set will pass the K-S test if at least one simulation run (out of 40 runs) passes the K-S test. This proves that at least once the distribution of vehicle travel time for the simulation and the field are the same.



Coun	SimRun	TimeInt	VehicleTravelTimeMeasurement	Vehs(All)	Vehs(10)	Vehs(70)	Vehs(30)	TravTm(All)	TravTm(10)	TravTm(70)	TravTm(30)
1	1	900-450	1: To Centre	1478	160	1276	42	178.66	178.16	176.12	257.76
2	1	900-450	2: To Yen Nghia	2916	261	2618	37	268.93	266.83	267.74	368.02
3	1	900-450	3: 182QT-418QT	2902	262	2602	38	234.01	232.79	233.10	305.32
4	2	900-450	1: To Centre	1579	156	1381	42	176.43	178.35	173.87	253.58
5	2	900-450	2: To Yen Nghia	2827	231	2561	35	233.51	232.27	232.48	317.30
6	2	900-450	3: 182QT-418QT	2817	227	2553	37	200.39	199.18	199.59	263.05
7	3	900-450	1: To Centre	1561	147	1372	42	184.21	176.58	182.63	262.48
8	3	900-450	2: To Yen Nghia	2822	231	2554	37	248.37	246.25	247.34	332.96
9	3	900-450	3: 182QT-418QT	2822	231	2553	38	212.85	211.76	212.12	268.91
10	4	900-450	1: To Centre	1502	160	1300	42	177.78	175.41	175.40	260.23
11	4	900-450	2: To Yen Nghia	3054	227	2790	37	241.74	242.01	240.45	337.11
12	4	900-450	3: 182QT-418QT	3036	223	2774	39	207.86	207.72	206.89	277.75
13	5	900-450	1: To Centre	1183	122	1032	29	238.76	243.73	237.28	270.68
14	5	900-450	2: To Yen Nghia	3	0	3	0	230.23		230.23	
15	5	900-450	3: 182QT-418QT	0	0	0	0				
16	6	900-450	1: To Centre	1570	148	1380	42	180.86	171.62	179.31	264.38
17	6	900-450	2: To Yen Nghia	2857	220	2600	37	250.50	250.07	249.24	341.79
18	6	900-450	3: 182QT-418QT	2879	217	2624	38	217.13	217.13	216.18	283.10
19	7	900-450	1: To Centre	1486	154	1290	42	179.61	170.53	178.06	260.46
20	7	900-450	2: To Yen Nghia	2914	222	2655	37	246.54	249.58	245.31	316.55
21	7	900-450	3: 182QT-418QT	2887	216	2632	39	212.35	217.23	211.27	257.90
22	8	900-450	1: To Centre	1469	153	1274	42	175.72	169.68	173.67	260.19
23	8	900-450	2: To Yen Nghia	2832	229	2566	37	239.54	242.60	237.98	329.11
24	8	900-450	3: 182QT-418QT	2804	225	2541	38	206.70	209.59	205.47	271.42
25	9	900-450	1: To Centre	1428	134	1256	38	207.17	206.63	205.38	268.17
26	9	900-450	2: To Yen Nghia	380	20	356	4	247.88	259.10	246.02	357.32
27	9	900-450	3: 182QT-418QT	330	18	308	4	212.15	221.23	210.45	301.61
28	10	900-450	1: To Centre	1578	158	1378	42	177.65	171.82	175.89	257.45
29	10	900-450	2: To Yen Nghia	2851	220	2594	37	234.77	228.05	234.02	327.53
30	10	900-450	3: 182QT-418QT	2829	215	2575	39	200.42	195.57	199.88	262.86
31	11	900-450	1: To Centre	1487	128	1317	42	180.29	175.13	178.18	262.05
32	11	900-450	2: To Yen Nghia	2891	228	2627	36	269.45	270.79	268.05	362.82
33	11	900-450	3: 182QT-418QT	2884	231	2615	38	233.29	236.99	231.99	300.64
34	12	900-450	1: To Centre	1420	137	1241	42	178.74	165.84	177.62	253.92
35	12	900-450	2: To Yen Nghia	2876	205	2633	38	228.26	228.15	227.03	313.62
36	12	900-450	3: 182QT-418QT	2890	205	2646	39	194.00	195.25	193.07	250.96
37	13	900-450	1: To Centre	1609	163	1404	42	177.12	173.41	175.10	259.09
38	13	900-450	2: To Yen Nghia	2949	198	2718	33	328.98	388.83	323.45	425.61
39	13	900-450	3: 182QT-418QT	2943	193	2716	34	296.51	359.46	291.13	368.86
40	14	900-450	1: To Centre	1573	161	1370	42	179.74	165.05	178.94	261.89
41	14	900-450	2: To Yen Nghia	2926	239	2650	37	260.07	263.49	258.33	362.96
42	14	900-450	3: 182QT-418QT	2926	236	2653	37	224.73	229.58	223.23	301.17

Figure 6-10 An example of an error in VISSIM outputs

a) Student's t test

The test hypotheses are:

H_0: Null Hypothesis is that the means of vehicle travel time from the field survey and the simulation model are the same.

H_1: the means of vehicle travel time from the field survey and the simulation model are not the same.

a.1) Student's t test for bus

Thirty-nine buses were observed at the 182 Quang Trung and 418 Quang Trung stop on the westbound corridor from 16:45 to 17:30 on Monday, 16 April 2018. Then bus travel times from the 182 Quang Trung stop to the 418 Quang Trung stop were explored. In each Vissim simulation for Case 3 and Case 4, the average bus travel times from the 182 Quang Trung stop to 418 Quang Trung stop on the westbound corridor were obtained. Hence, for each Case there are 40 values of the average bus travel times were collected from 40 VISSIM random seeded runs. The independent two-tailed Student's t-test was run to see if the means of bus travel time obtained from the field observation and the simulation for each Case are equal.

However, Levene's Test for equality of variances should be tested along with Student's t-test. Levene's test is an inferential statistic used to assess the equality of variances for a variable calculated for two or more samples. It tests the null hypothesis that the population variances are equal. If the significance value of Levene's test is less than some significance level (typically 0.05), the obtained differences in sample variances are unlikely to have occurred based on random sampling from a population with equal variances. Thus, the null hypothesis of equal variances is rejected and it is concluded that there is a difference between the variances in the population. Both tests for Case 3 and Case 4 are run in SPSS program and the results are shown in Table 6-6.

Table 6-6 Results of Student's t test and Levene's Test for two Cases with respect to bus travel time

Group Statistics

	GroupBus	N	Mean	Std. Deviation	Std. Error Mean
BusTravelTimeCase3	Simulation	40	289.9502	41.19036	6.51277
	Observation	39	288.1538	56.57996	9.06004
BusTravelTimeCase4	Simulation	40	276.5608	14.31796	2.26387
	Observation	39	288.1538	56.57996	9.06004

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
BusTravel TimeCase3	Equal variances assumed	9.156	.003	.162	77	.872	1.79633	11.11411	-20.33470	23.92735
	Equal variances not assumed			.161	69.371	.873	1.79633	11.15798	-20.46111	24.05377
BusTravel TimeCase4	Equal variances assumed	38.755	.000	-1.255	77	.213	-11.59307	9.23384	-29.98000	6.79386
	Equal variances not assumed			-1.241	42.731	.221	-11.59307	9.33860	-30.42958	7.24345

As can be seen from Table 6-6, the *sig.* values in the Levene's test for the two cases are smaller than 0.05, this means there is significant evidence to reject the null hypothesis of equal variances. Then, the *sig.* value in the Student's t test is selected in a situation where equal variances not assumed (in Table 6-6). Obviously, the *sig.* values in the Student's t test for Case 3 and Case 4 are higher than 0.05, this indicates that the null hypothesis that the means of bus travel time for the observation and simulation are the same cannot be rejected.

a.2) Student’s t test for car

Undergraduate students and the author ride cars from the 182 Quang Trung stop to the 418 Quang Trung stop on the westbound corridor from 16:30 to 17:30 on different weekdays during the collection data period (February to June 2018). As the evaluation period is from 16:45 to 17:30, a sample of 76 cars was carried out and 76 values of car travel times were explored. In each Vissim simulation for Case 3 and Case 4, the average car travel time from the 182 Quang Trung stop to the 418 Quang Trung stop on the westbound corridor in the period between 16:45 and 17:30 was obtained. Therefore, for each Case there are 40 values of the average car travel times were collected from 40 VISSIM random seeded runs. The independent two-tailed Student’s t-test was run to see if the means of car travel time obtained from the field observation and the simulation are equal. The Student’s t test and Levene's Test for Case 3 and Case 4 are run in SPSS program and the results are shown in Table 6-7.

Table 6-7 Results of Student’s t test and Levene's Test for two Cases with respect to car travel time

Group Statistics

	GroupCar	N	Mean	Std. Deviation	Std. Error Mean
CarTravelTimeCase3	Simulation	40	229.6156	42.70356	6.75203
	Observation	76	220.1711	39.32137	4.51047
CarTravelTimeCase4	Simulation	40	216.8972	12.67850	2.00465
	Observation	76	220.1711	39.32137	4.51047

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
CarTravel TimeCase3	Equal variances assumed	1.117	.293	1.194	114	.235	9.44458	7.91329	-6.23158	25.12074
	Equal variances not assumed			1.163	73.919	.249	9.44458	8.11999	-6.73514	25.62430
CarTravel TimeCase4	Equal variances assumed	16.621	.000	-.512	114	.610	-3.27383	6.39635	-15.94494	9.39728
	Equal variances not assumed			-.663	100.049	.509	-3.27383	4.93588	-13.06643	6.51877

As can be seen from Table 6-7, the *sig.* value in the Levene's test for Case 4 is smaller than 0.05, this means there is significant evidence to reject the null hypothesis of equal variances. Hence, the *sig.* value in the Student's t test is selected in a situation where equal variances not assumed (in Table 6-7). Then, the *sig.* value in the Student's t test for Case 4 is higher than 0.05, this indicates that the null hypothesis that the means of car travel time for the observation and simulation are the same cannot be rejected.

Moreover, the *sig.* value in the Levene's test for Case 3 is higher than 0.05, this means the null hypothesis of equal variances cannot be rejected. Therefore, the *sig.* value in the Student's t test is selected in a situation where equal variances assumed (in Table 6-7). Then, the *sig.* value in the Student's t test for Case 3 is higher than 0.05, this indicates that the null hypothesis that the means of car travel time for the observation and simulation are the same cannot be rejected.

a.3) Student’s t test for motorcycle

Undergraduate students and the author ride motorcycles from the 182 Quang Trung stop to the 418 Quang Trung stop on the westbound corridor from 16:30 to 17:30 on different weekdays during the collection data period (February to June 2018). As the evaluation period is from 16:45 to 17:30, a sample of 153 motorcycles was carried out and 153 values of motorcycle travel times were explored. In each Vissim simulation for Case 3 and Case 4, the average motorcycle travel time from the 182 Quang Trung stop to the 418 Quang Trung stop on the westbound corridor in the period between 16:45 and 17:30 was obtained. Hence, for each Case there are 40 values of the average motorcycle travel times were collected from 40 VISSIM random seeded runs. The independent two-tailed Student’s t-test was run to see if the means of motorcycle travel time obtained from the field observation and the simulation for each Case are equal. The Student’s t test and Levene's Test for Case 3 and Case 4 are run in SPSS and the results are shown in Table 6-8.

As can be seen from Table 6-8, the *sig.* value in the Levene's test for Case 4 is smaller than 0.05, this means there is significant evidence to reject the null hypothesis of equal variances. Therefore, the *sig.* value in the Student's t test is selected in a situation where equal variances not assumed (in Table 6-8). Then, the *sig.* value in the Student's t test for Case 4 is higher than 0.05, this indicates that the null hypothesis that the means of motorcycle travel time for the observation and simulation are the same cannot be rejected.

Moreover, the *sig.* value in the Levene's test for Case 3 is higher than 0.05, this means the null hypothesis of equal variances cannot be rejected. As a result, the *sig.* value in the Student's t test is selected in a situation where equal variances assumed (in Table 6-8). Then, the *sig.* value in the

Student's t test for Case 3 is higher than 0.05, this indicates that the null hypothesis that the means of motorcycle travel time for the observation and simulation are the same cannot be rejected.

Table 6-8 Results of Student’s t and Levene's Test for two Cases with respect to motorcycle travel time

Group Statistics					
	GroupMC	N	Mean	Std. Deviation	Std. Error Mean
MCTravelTimeCase3	Simulation	40	220.4811	40.90875	6.46824
	Observation	153	213.5948	41.50800	3.35572
MCTravelTimeCase4	Simulation	40	210.1418	11.40831	1.80381
	Observation	153	213.5948	41.50800	3.35572

Independent Samples Test										
		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
MCTravel TimeCase3	Equal variances assumed	2.375	.125	.937	191	.350	6.88637	7.34954	-7.61032	21.38305
	Equal variances not assumed			.945	61.673	.348	6.88637	7.28691	-7.68149	21.45422
MCTravel TimeCase4	Equal variances assumed	14.897	.000	-.520	191	.604	-3.45299	6.63909	-16.5483	9.64235
	Equal variances not assumed			-.906	190.53	.366	-3.45299	3.80980	-10.9678	4.06182

To conclude, both Case 3 and Case 4 have passed the Student’s t test.

b) Two-sample Kolmogorov-Smirnov test

The independent two-tailed Student’s t-test was run to see if the means of vehicle travel time obtained from the field observation and the simulation are equal, which does not look at the whole vehicle travel time distribution of the result while the two-sample Kolmogorov-Smirnov (K-S) test evaluates the goodness-of-fit of the two probability distributions of vehicle travel times. Therefore, it is necessary to ensure the candidate parameter set that has passed both tests before the model validation process. One simulation run, which has the smallest difference in average bus travel time with the field data, will be chosen initially for the K-S test. The distribution of travel time of all bus vehicles in this simulation run (given name as *c1*) is compared with the distribution of the field sample. The test is implemented for each vehicle type. Therefore, the test hypotheses are:

H_0: the vehicle travel time distributions from field survey and the simulation model are the same.

H_1: the vehicle travel time distributions from field survey and the simulation model are not the same.

For the two-sample K-S test, the critical d-value was calculated as:

$$d_{critical} = c(\alpha) * \sqrt{\frac{n+m}{n*m}}$$

where,

n and *m* are the sample sizes of the simulation runs and field samples respectively;

c(α) is a factor for the selected level of significance, which is equal to 1.36 at the 5% significance level.

If Kolmogorov–Smirnov statistic (the most extreme difference) $D > D_{critical}$, the Null Hypothesis can be rejected.

If the Null Hypothesis for the simulation run *c1* is rejected, among the rest of thirty-nine simulation runs, another simulation run, which has the smallest difference in average bus travel time with the field data, will be chosen for the K-S test. The process of choosing one simulation run will be implemented until the Null Hypothesis for a simulation run cannot be rejected. If the Null Hypothesis for all forty runs is rejected, the candidate parameter set cannot pass the K-S test.

b.1) Candidate parameter set Case 3

For Case 3, the simulation run number eight is chosen initially for K-S test as the differences in bus travel times between the simulation and the field for both direction are smallest, which are both smaller than five seconds. In the simulation run number eight, 39 buses, 153 cars and 1881 motorcycles are explored to identify travel times on the westbound direction by using a *RSR* file. Indeed, one *RSR* file is written in direct outputs of VISSIM by setting up in the Evaluation Configuration setting. Then, the *RSR* file is imported in the Excel package to read travel times of every single vehicle during the evaluation period between 16:45 and 17:30. As a result, the sizes of samples for bus, car and motorcycle in the simulation number eight are estimated as 39, 153 and 1881 respectively. While the sizes of field samples for bus, car and motorcycle are 39, 76 and 153 correspondingly, the size of motorcycle sample in the simulation is huge and around twelve times higher than the size of the field sample. In other words, an average of around 42 motorcycles pass observed points in the simulated network in each minute and this implies non-lane-based movements of these vehicles on the corridor at the same time. However, data on 153 motorcycles, which were ridden by the author and surveyors between 16:45 and 17:30, cannot represent this characteristic. Hence, the K-S test is not run for the motorcycle samples. As a result, the K-S test is implemented for the car and bus samples. Critical *d*-values in the K-S tests for bus and car are 0.308 and 0.191 correspondingly. The results of the K-S test for the simulation run number eight with respect to bus and car travel time are shown in Table 6-9 and Table 6-10 respectively.

Table 6-9 The results of the K-S test for the simulation run number eight with respect to bus travel time

Test Statistics[a]		
		BusTravelTimeCase3
Most Extreme Differences	Absolute	.154
	Positive	.103
	Negative	-.154
Kolmogorov-Smirnov Z		.679
Asymp. Sig. (2-tailed)		.745
a. Grouping Variable: GroupBus		
critical *d*-value = 0.308		

As can be seen from Table 6-9, the most extreme difference of 0.154 is smaller than critical d-value of 0.308, the null hypothesis that the bus travel time distributions from field survey and the simulation number eight are the same cannot be rejected.

Table 6-10 The results of the K-S test for the simulation run number eight with respect to car travel time

Test Statistics[a]		
		CarTravelTimeCase3
Most Extreme Differences	Absolute	.155
	Positive	.027
	Negative	-.155
Kolmogorov-Smirnov Z		1.101
Asymp. Sig. (2-tailed)		.177
a. Grouping Variable: GroupCarCase3		
critical *d*-value = 0.191		

As can be seen from Table 6-10, for the most extreme difference of 0.155 is smaller than critical d-value of 0.191, the null hypothesis that the car travel time distributions from field survey and the simulation number eight are the same cannot be rejected.

b.2) Candidate parameter set case 4

For Case 4, the simulation run number twenty-one is chosen initially for K-S test as differences in bus travel times between the simulation and the field for both direction are smallest, which are both smaller than three seconds. In the simulation run number twenty-one, 39 buses, 168 cars and 1926 motorcycles are explored to identify travel times on the westbound direction by using a *RSR* file. While the sizes of field samples for bus, car and motorcycle are 39, 76 and 153 correspondingly, the size of motorcycle sample in the simulation is huge and around twelve times higher than the size of the field sample. As mentioned above, the K-S test is not run for the motorcycle samples. Hence, the K-S test is implemented for the car and bus samples. Critical *d*-values in the K-S tests for bus and car are 0.308 and 0.188 correspondingly.

The results of the K-S test for the simulation run number 21 with respect to bus and car travel time are shown in Table 6-11 and Table 6-12 correspondingly.

As can be seen from Table 6-11, the most extreme difference of 0.077 is smaller than critical d-value of 0.308, the null hypothesis that the bus travel time distributions from field survey and the simulation number 21 are the same cannot be rejected.

As can be seen from Table 6-12, for the most extreme difference of 0.166 is smaller than critical d-value of 0.188, the null hypothesis that the car travel time distributions from field survey and the simulation number 21 are the same cannot be rejected.

Table 6-11 The results of the K-S test for the simulation run number 21 with respect to bus travel time

Test Statistics[a]		
		BusTravelTimeCase4
Most Extreme Differences	Absolute	.077
	Positive	.077
	Negative	-.077
Kolmogorov-Smirnov Z		.340
Asymp. Sig. (2-tailed)		1.000
a. Grouping Variable: GroupBus		
critical *d*-value = 0.308		

Table 6-12 The results of the K-S test for the simulation run number 21 with respect to car travel time

Test Statistics[a]		
		CarTravelTimeCase4
Most Extreme Differences	Absolute	.166
	Positive	.107
	Negative	-.166
Kolmogorov-Smirnov Z		1.201
Asymp. Sig. (2-tailed)		.112
a. Grouping Variable: GroupCar		
critical *d*-value = 0.188		

To conclude, both the parameter set Case 3 and Case 4 have passed two criteria. Therefore, both Cases are chosen for the validation process below.

6.4.1.9 Validation process

To perform validation of the microscopic simulation model, a new set of field data under untried conditions were collected. This means validation data were collected for different time periods or conditions. Travel times of vehicles on the westbound corridor were collected from 16:30 to 17:30

for the calibration process whilst travel times of vehicles on the eastbound corridor were collected from 17:30 to 18:30 for the validation process. Thirty-nine buses were observed at the 705 Quang Trung and 267 Quang Trung stops on the eastbound corridor from 17:45 to 18:30 on Thursday, 17 May 2018. Then bus travel times from the 705 Quang Trung stop to the 267 Quang Trung stop were explored. Additionally, undergraduate students and the author ride cars from the 705 Quang Trung stop to the 267 Quang Trung stop on the eastbound corridor from 17:30 to 18:30 on different weekdays during the collection data period (February to June 2018). As the evaluation period is from 17:45 to 18:30, a sample of 72 cars was carried out and 72 values of car travel times were then explored. Similarly, undergraduate students and the author ride motorcycles from the 705 Quang Trung stop to the 267 Quang Trung stop on the eastbound corridor from 17:30 to 18:30 on different weekdays during collection data period (February to June 2018). As the evaluation period is from 17:45 to 18:30, a sample of 142 motorcycles was carried out and 142 values of motorcycle travel times were then explored. The average bus, car and motorcycle travel times observed from the field and their sizes are shown in Table 6-13.

Table 6-13 Average vehicle travel times and sample size from the field data

Samples	Bus	Car	Motorcycle
Sample size	39	72	142
Average travel time (s)	259.57	177.23	180.21

In terms of input data for the calibrated VISSIM simulation, traffic volume at three junctions were collected from 17:30 to 18:30 on Monday, 16 April 2018 while data on bus passenger demand were collected from 17:30 to 18:30 on Thursday, 19 April 2018. The calibrated VISSIM models with parameters set Case 3 and Case 4 were conducted for another forty different random seeded runs to obtain average bus, car and motorcycle travel times from the 705 Quang Trung stop to the 267 Quang Trung stop on the eastbound corridor. With 15 minutes system warming up, forty values of the average bus, car and motorcycle travel times were collected from these runs for the period from 17:45 to 18:30. The two-tailed Student’s t test is conducted for the model validation process with respect to bus, car and motorcycle travel times.

a) Bus travel time

The results of Student’s t test with respect to bus travel time are shown Table 6-14.

Table 6-14 The results of Student's t test with respect to bus travel time

Independent Samples Test										
		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
BusTravelTime Case3	Equal variances assumed	27.066	.000	1.906	80	.060	8.13711	4.26983	-.36012	16.63434
	Equal variances not assumed			1.948	45.725	.058	8.13711	4.17645	-.27102	16.54525
BusTravelTime Case4	Equal variances assumed	29.859	.000	1.581	80	.118	6.68488	4.22918	-1.73147	15.10122
	Equal variances not assumed			1.618	43.937	.113	6.68488	4.13278	-1.64453	15.01428

As can be seen from Table 6-14, the *sig.* values in the Levene's test for both Cases are smaller than 0.05, this means there is significant evidence to reject the null hypothesis of equal variances. As a result, the *sig.* value in the Student's t test is selected in a situation where equal variances not assumed (in Table 6-14). Then, the *sig.* values for both Cases are higher than 0.05, this indicates that the null hypothesis that the means of bus travel time for the observation and simulation are the same cannot be rejected for both Cases.

b) Car travel time

The results of Student's t test with respect to car travel time are shown in Table 6-15.

Table 6-15 The results of Student's t test with respect to car travel time

Independent Samples Test										
		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
CarTravelTime Case3	Equal variances assumed	15.639	.000	.986	110	.326	6.03747	6.12476	-6.10036	18.17530
	Equal variances not assumed			1.211	103.679	.228	6.03747	4.98362	-3.84560	15.92054
CarTravelTime Case4	Equal variances assumed	27.861	.000	.479	110	.633	2.81226	5.86772	-8.81617	14.44070
	Equal variances not assumed			.641	73.103	.524	2.81226	4.38717	-5.93115	11.55567

As can be seen from Table 6-15, the *sig.* values in the Levene's test for both Cases are smaller than 0.05, this means there is significant evidence to reject the null hypothesis of equal variances. Therefore, the *sig.* value in the Student's t test is selected in a situation where equal variances not assumed (in Table 6-15). Then, the *sig.* values in the Student's t test for both Cases are higher than

0.05, this indicates that the null hypothesis that the means of car travel time for the observation and simulation are the same cannot be rejected for both Cases.

c) Motorcycle travel time

The results of Student’s t test with respect to motorcycle travel time are shown in Table 6-16. As can be seen from Table 6-16, the *sig.* value in the Levene's test for both Cases are smaller than 0.05, this means there is significant evidence to reject the null hypothesis of equal variances. Hence, the *sig.* value in the Student's t test is selected in a situation where equal variances not assumed (in Table 6-16). Then, the *sig.* values in the Student's t test for both Cases are higher than 0.05, this indicates that the null hypothesis that the means of motorcycle travel time for the observation and simulation are the same cannot be rejected for both Cases.

Table 6-16 The results of Student’s t test with respect to motorcycle travel time

Independent Samples Test										
		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
MCTravelTime Case3	Equal variances assumed	17.394	.000	-.526	180	.599	-2.45227	4.66086	-11.64923	6.74469
	Equal variances not assumed			-.764	138.290	.446	-2.45227	3.20979	-8.79888	3.89434
MCTravelTime Case4	Equal variances assumed	34.917	.000	-1.034	180	.303	-4.67696	4.52445	-13.60475	4.25083
	Equal variances not assumed			-1.944	143.487	.054	-4.67696	2.40639	-9.43351	.07959

Hence, both Cases have passed the t test. The validated models are sufficiently reliable to produce similar bus, car and motorcycle travel time results compared with the real results on-site. However, only one Case should be chosen for the comparative economic assessment. A Case, which has smaller differences in average vehicle travel time compared to the field data will be chosen Table 6-14, Table 6-15 and Table 6-16 show that the highest difference in travel time occurred with car samples in Case 3, which is 8.14 seconds. Therefore, the calibration parameters set of Case 4 are used in the VISSIM simulation model for the peak period for the Hanoi case study.

6.4.2 Calibration and validation process for the off-peak period

The calibration and validation process of the simulation model for the off-peak period is implemented as for the peak period. This subsection summarises the main differences of the process between the peak and off-peak periods while the detailed process for the off-peak period is illustrated in Appendix B.5. Firstly, due to time limits, data on only bus travel time could be collected from the real network, therefore the travel time of bus was selected as a key performance indicator for the process of calibration and validation. Secondly, data for this process were extracted from video recordings provided by the Hanoi Police Department. The data, which were recorded at the junctions J2 and J3 on Monday, 19 March 2018, are used for the calibration stages while the data recorded on Thursday, 22 March 2018 are used for the validation stage. The results of the process for the off-peak period are shown as (i) the desired speed of car and bus is 50 km/h; (ii) the desired speed of motorcycle is 50 km/h; (iii) the minimum lateral distance driving is 1.0 m; and (iv) the average standstill distance is 0.5 m.

6.4.3 Summary

After building the VISSIM simulation models for both the peak and off-peak periods, the calibration and validation processes have been implemented to ensure that the VISSIM simulation model truly represents the real transport network. The nine-step process by Park and Schneeberger (2003) is used for this thesis. The first step is to determine the key performance indicators as the measures of effectiveness. The travel time of motorcycle, car and bus were chosen as key performance indicators because these indicators are important in not only the simulation model but also in the social cost models and incremental demand models. In addition, these indicators can be collected from the VISSIM simulation model and from the fields to test the accuracy. Another important step is to choose calibration parameters in VISSIM. As the VISSIM model simulates the mixed transport system with motorcycle, the local acceleration parameter of motorcycle was analysed and inserted directly in VISSIM without calibration. The acceleration default value, which is for typical motorcycles used in Europe, was replaced. Four parameters in VISSIM are calibrated as (i) desired speed of car and bus; (ii) desired speed of motorcycle; (iii) minimum lateral distance driving when overtaking vehicles on the same lane; and (iv) average standstill distance. Based on a significance level of 5%, these four parameters have significant impacts on the travel time of bus, car and motorcycle. The relationship between these calibration parameters and the vehicle travel times are summarised in Table 6-17. This proves that choosing the four parameters is consistent and acceptable. The calibration parameters set for the VISSIM models of peak and off-peak periods are described in Table 6-18.

Table 6-17 Relationships between the calibration parameters and the vehicle travel times obtained from the VISSIM model

Periods	Average standstill distance (m)	Minimum lateral distance driving (m)	Desired speed distribution of bus and car (km/h)	Motorcycle desired speed distribution (km/h)
Off-peak	Significant impact	No significant impact	Significant impact	Significant impact
Peak	Significant impact	Significant impact	No significant impact	No significant impact

Table 6-18 Chosen calibration parameter sets for the simulation models

Period	Average standstill distance (m)	Minimum lateral distance driving (m)	Desired speed distribution of bus and car (km/h)	Motorcycle desired speed distribution (km/h)
Off-peak	0.5	1.0	50	50
Peak	0.5	0.8	40	40

6.5 Conclusion

This chapter described the development of the microscopic simulation model, which includes the data collection process, the creation of the VISSIM simulation model and the calibration and validation process. Firstly, primary data and secondary data were collected for the chosen corridor in Hanoi in both peak and off-peak periods. The data include traffic volume data at junctions, data on bus, data on signals at junctions, infrastructure geometry, motorcycle acceleration, vehicle travel time. Secondly, collected data on infrastructure, signalised control data and traffic data are inserted in VISSIM to develop the VISSIM simulation models for the peak and off-peak periods.

After building the VISSIM simulation model for both the peak and off-peak periods, the calibration and validation process is conducted by using the nine-step procedure by Park and Schneeberger (2003). Two different sets of data are used for the model calibration and the model validation. The travel time of motorcycle, car and bus are selected as key performance indicators for this process. The local acceleration parameter of motorcycle is collected, analysed and inserted directly in VISSIM without calibration because the acceleration default value is for typical motorcycles used in Europe. Moreover, four parameters in VISSIM are chosen to calibrate the simulation model. The best parameter sets are determined by using one set of data collected on-site. The validation process is conducted to test the accuracy of the parameter sets by comparing the outputs of the VISSIM simulation and another set of vehicle travel times collected on-site. Two statistical tests are performed in the calibration and validation process to test the reliability of the simulation model Firstly, the independent two-tailed Student’s t-test was run to see if the means of vehicle travel times obtained from the field observation and the simulation are equal. Secondly, the Kolmogorov-Smirnov test was used to evaluate the goodness-of-fit of the two probability distributions of vehicle travel times. The results of these statistical tests prove that the VISSIM simulation models are sufficiently reliable to represent the real mixed traffic with motorcycle.

The aim of the comparative economic assessment is to evaluate proposed options when a new PT mode and/or transport policy are introduced in an existing transport network. The social cost model cannot consider interactions among vehicles at links and junctions. To overcome this issue, the VISSIM simulation model represents vehicle interactions on the transport network. However, the social cost and VISSIM models cannot evaluate any changes in total demand and modal share when the existing transport condition changes. The incremental demand models can solve this issue. Hence, the next chapter is going to develop the incremental elasticity analysis and incremental logit model to complete the comparative economic assessment.

Chapter 7 Incremental Demand Model

7.1 Introduction

The comparative economic assessment is created to compare an existing mixed transport situation and proposed options with an introduction of new PT technologies and/or transport policy, in terms of ASC. Chapter 5 develops the social cost model, which is the core model of the comparative economic assessment. The social cost model evaluates ASCs for individual transport mode and mixed transport in one urban corridor based on fixed daily passenger demand. The VISSIM simulation model, which is described in Chapter 6, simulates the existing transport network in reality to obtain key performance indicators such as vehicle travel time. However, these two models cannot evaluate any changes in total demand and modal share according to any change to the existing transport condition. Hence, incremental demand models are required to develop in the comparative economic assessment to overcome this problem.

A new PT mode (e.g. BRT, Metro or Monorail) is introduced to replace either all or partial existing bus services on one mixed traffic corridor where bus, car and motorcycle share infrastructure facilities. This can depend on local regulated or deregulated environments. Firstly, if the new PT technology replaces all bus services running on the partial and whole corridor, these bus routes can be adjusted to not overlap the new PT route in reality. Therefore, they become feeder systems transport passengers to new PT stations/stops. This means that the new PT mode is run exclusively whilst car and motorcycle share the mixed environment. The incremental multinomial logit model is used for this case, which is described in detail in the next part of this chapter. Secondly, if the new PT mode replaces only bus services running on the whole corridor, existing bus services running on segments of the corridor are still operated. The incremental nested logit model is used for this case and illustrated in the third part of this chapter. These two incremental logit models estimate changes in modal share but cannot evaluate endogenous growth of total demand when the existing transport condition changes. As a result, the incremental elasticity analysis is also required to solve this issue of the incremental logit models and therefore complete the comparative economic assessment. The fourth part of this chapter is going to develop the incremental elasticity analysis. Finally, the fifth part of the chapter describes key components of the three incremental demand models for the Hanoi case study.

7.2 Incremental Multinomial Logit Model

When a new PT technology replaces all bus services running on the partial and whole corridor where bus, car and motorcycle share facilities, the incremental multinomial logit model is used to estimate probabilities of choosing new PT, car and motorcycle. The structure of the incremental multinomial logit model for this situation is shown in Figure 7-1.

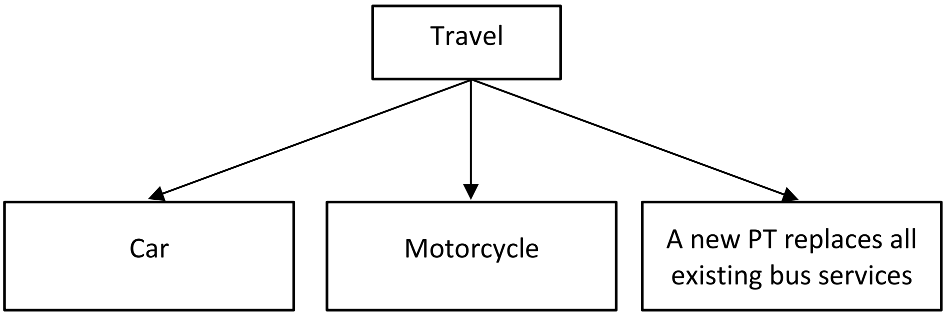


Figure 7-1 Incremental multinomial logit model structure

The probability of choosing each mode is calculated as (Department for Transport, 2017d):

$$P_{car} = \frac{P^0_{car}\exp(\Delta U_{car})}{P^0_{car}\exp(\Delta U_{car}) + P^0_{mc}\exp(\Delta U_{mc}) + P^0_{PT}\exp(\Delta U_{PT})} \tag{7-1}$$

$$P_{mc} = \frac{P^0_{mc}\exp(\Delta U_{mc})}{P^0_{car}\exp(\Delta U_{car}) + P^0_{mc}\exp(\Delta U_{mc}) + P^0_{PT}\exp(\Delta U_{PT})} \tag{7-2}$$

$$P_{PT} = \frac{P^0_{PT}\exp(\Delta U_{PT})}{P^0_{car}\exp(\Delta U_{car}) + P^0_{mc}\exp(\Delta U_{mc}) + P^0_{PT}\exp(\Delta U_{PT})} \tag{7-3}$$

where,

P_{car}, P_{mc}, P_{PT} are the forecast probability of choosing car, motorcycle and PT respectively;

P^0_{car}, P^0_{mc}, P^0_{PT} are the reference case probability of choosing car, motorcycle and PT respectively;

ΔU_{car}, ΔU_{mc}, ΔU_{PT} are the changes in the utilities of car, motorcycle and PT respectively.

After the introduction of the new PT mode, the change in the utility of PT is calculated as:

$$\Delta U_{PT} = U_{NewPT} - U_{bus} \tag{7-4}$$

where,

U_{NewPT}, U_{bus} are the utilities of the new PT mode and existing bus.

After the new PT mode is operated, any changes to the transport conditions on the chosen corridor cause changes in the utilities of the new PT mode, car and motorcycle because the conventional bus is no longer to run on the corridor. To estimate the modal shares in the incremental multinomial logit model, the utility of each transport mode needs to be identified.

7.3 Incremental Nested Logit Model

When a new PT mode replaces only bus services running on the whole corridor while the existing bus services running on segments of the corridor are still operated and shared the infrastructure facilities with car and motorcycle, the incremental nested logit model is used to estimate probabilities of choosing new PT, bus, car and motorcycle. The structure of the incremental nested logit model for this situation is shown in Figure 7-2.

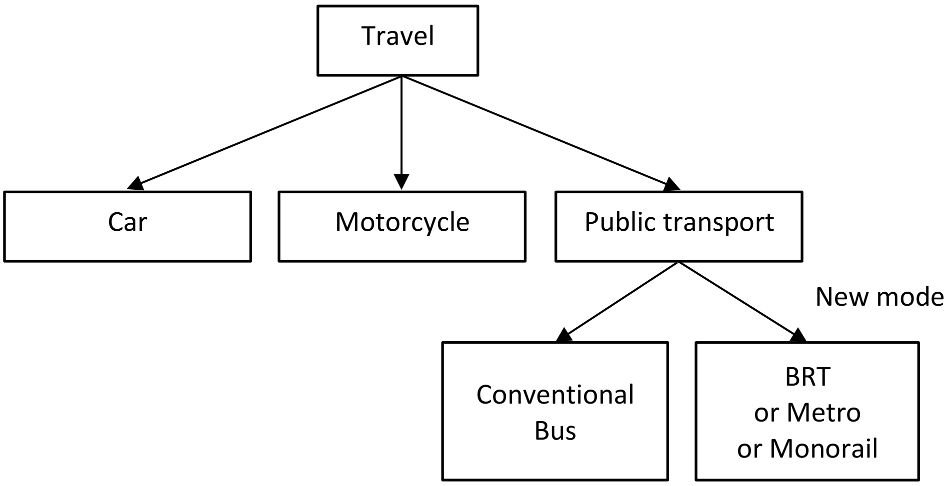


Figure 7-2 Incremental nested logit model structure

Based on the equation in the study of Preston (1991), the share of public transport in the upper nest is given by:

$$P_{PT\_1} = \frac{P_{PT\_0}\left[\exp(U_{newPT\_1} - U_{bus\_0}) + \exp(U_{bus\_1} - U_{bus\_0})\right]^{\emptyset}}{P_{PT\_0}\left[\exp(U_{newPT\_1} - U_{bus\_0}) + \exp(U_{bus\_1} - U_{bus\_0})\right]^{\emptyset} + [1 - P_{PT\_0}]} \qquad \textbf{(7-5)}$$

where,

P_{PT_1} (P_{PT_0}) is the proportion of choosing public transport in the after (before) situation. P_{PT_0} is the modal share of the existing bus;

U_{bus_1} (U_{bus_0}) is the utility of bus in the after (before) situation;

U_{newPT_1} is the utility of the new PT mode in the after situation;

$\emptyset$ is the expected maximum utility.

Hensher and Rose (2007) introduced state-of-the-art stated choice designs to parameterise modal choice models for commuting and non-commuting travel futures in the introduction of new public transport infrastructure in the north-west section of metropolitan Sydney such as new heavy rail, light rail and segregated busway systems. The choice sets include all existing main modes (bus, heavy rail, car and busway) and access modes (subsets of walk, bus and car) plus two of the new transport modes from the sample (new heavy rail, new light rail and new busway). A two-level nested logit model with a competition between car and all PT modes is run for both work trip and non-work trip segments. The results show that the structural parameter for public transport nest for the work trip segment is 0.6775 while that number for the non-work trip segment is 0.8813. The modal share of work and non-work trips in Hanoi were 62.84% and 37.26% (Japan International Cooperation Agency, 2007). To simplify the analysis in this study, the average of work and non-work values is calculated as 0.7532 (0.6775*62.84% + 0.8813*37.26%). As a result, the utility of PT in the higher level is estimated as:

$$U_{PT\_1} = 0.7532 \times \ln (e^{U_{newPT\_1}} + e^{U_{bus\_1}}) \quad \textbf{(7-6)}$$

The possibility of the new PT mode (P_{newPT_1}) and existing bus (P_{bus_1}) in the lower nest are therefore:

$$P_{newPT\_1} = \frac{\exp(U_{newPT\_1} - U_{bus\_0})}{\exp(U_{newPT\_1} - U_{bus\_0}) + \exp(U_{bus\_1} - U_{bus\_0})} . P_{PT\_1} \quad \textbf{(7-7)}$$

and

$$P_{bus\_1} = \frac{\exp(U_{bus\_1} - U_{bus\_0})}{\exp(U_{newPT\_1} - U_{bus\_0}) + \exp(U_{bus\_1} - U_{bus\_0})} . P_{PT\_1} \quad \textbf{(7-8)}$$

The probability for motorcycle (P_{mc_1}) and car (P_{car_1}) in the upper nest are estimated as:

$$P_{mc\_1} = P_{mc\_0} \frac{1 - P_{PT\_1}}{1 - P_{PT\_0}} \quad \textbf{(7-9)}$$

$$P_{car\_1} = P_{car\_0} \frac{1 - P_{PT\_1}}{1 - P_{PT\_0}} \quad \textbf{(7-10)}$$

where,

P_{mc_0}, P_{car_0} are the existing modal share of motorcycle and car.

After the new PT mode is operated, any changes to transport conditions on the chosen corridor cause changes in the utilities of the new PT mode and bus in the lower nest, as well as changes in the utilities of the combination of PT, car and motorcycle in the higher nest. Introduction of a congestion charge scheme can be an example of this change. This can be named as the ‘second change’ to the transport condition while the ‘first change’ is the introduction of the new PT mode. Hence, the notations for the before and after situation are ‘1’ and ‘2’. Then, the changes in utilities of the new PT and bus at the lower level are:

$\Delta U_{newPT\_2} = U_{newPT\_2} - U_{newPT\_1}$ **(7-11)**

$\Delta U_{bus\_2} = U_{bus\_2} - U_{bus\_1}$ **(7-12)**

where,

U_{bus_2} (U_{bus_1}) is the utility of bus in the after (before) situation;

U_{newPT_2} (U_{newPT_1}) is the utility of the new PT mode in the after (before) situation.

Therefore, the utility of PT in the higher level is estimated as:

$U_{PT\_2} = 0.7532 \times ln\,(e^{UnewPT\_2} + e^{Ubus\_2})$ **(7-13)**

The change in the utility of public transport at the highest level is as:

$\Delta U_{PT\_2} = U_{PT\_2} - U_{PT\_1}$ **(7-14)**

The changes in utilities of motorcycle and car at the highest level are as:

$\Delta U_{mc\_2} = U_{mc\_2} - U_{mc\_1}$ **(7-15)**

$\Delta U_{car\_2} = U_{car\_2} - U_{car\_1}$ **(7-16)**

Probabilities of choosing PT, car and motorcycle in the higher split are estimated as (Department for Transport, 2017d):

$$P_{PT\_2} = \frac{P_{PT\_1}\exp(\Delta U_{PT\_2})}{P_{PT\_1}\exp(\Delta U_{PT\_2}) + P_{car\_1}\exp(\Delta U_{car\_2}) + P_{mc\_1}\exp(\Delta U_{mc\_2})} \qquad \textbf{(7-17)}$$

$$P_{car\_2} = \frac{P_{car\_1}\exp(\Delta U_{car\_2})}{P_{PT\_1}\exp(\Delta U_{PT\_2}) + P_{car\_1}\exp(\Delta U_{car\_2}) + P_{mc\_1}\exp(\Delta U_{mc\_2})} \qquad \textbf{(7-18)}$$

$$P_{mc\_2} = 1 - P_{PT\_2} - P_{car\_2} \qquad \textbf{(7-19)}$$

where,

P_{PT_1}, P_{mc_1}, P_{car_1} are shown in Equations (7-5), (7-9), (7-10) respectively;

ΔU_{PT_2}, ΔU_{mc_2}, ΔU_{car_2} are shown in Equations (7-14), (7-15), (7-16) correspondingly.

Probabilities of choosing the new PT mode or bus at the lower split are estimated as:

$$P_{newPT\_2} = P_{PT\_2}.\frac{P_{newPT\_1}*\exp(\Delta U_{newPT\_2})}{P_{newPT\_1}*\exp(\Delta U_{newPT\_2}) + P_{bus\_1}*\exp(\Delta U_{bus\_2})} \qquad \textbf{(7-20)}$$

and

$$P_{bus\_2} = P_{PT\_2} - P_{newPT\_2} \quad \textbf{(7-21)}$$

where,

P_{PT_2} is shown in Equation (7-17);

P_{newPT_1}, P_{bus_1} are shown in Equations (7-7), (7-8);

ΔU_{newPT_2}, ΔU_{bus_2} are shown in Equations (7-11), (7-12).

To estimate modal shares in the incremental nested logit model, the utility of each transport mode needs to be determined.

7.4 Incremental Elasticity Analysis

The incremental multinomial logit model and incremental nested logit model, which are described above, evaluate changes in modal shares when the existing transport condition changes. This section is going to develop the incremental elasticity analysis, which estimates endogenous changes in the total demand by using the demand elasticity with respect to a logsum. A general utility function in logit models is shown as:

$$U = MSC + a * Time + b * Cost \quad \textbf{(7-22)}$$

where,

MSC is the mode specific constant;

a, b are the time and cost coefficients respectively.

The logsum of general traffic including car, motorcycle and PT is calculated as (De Jong *et al.*, 2007):

$$logsum = \frac{1}{-b}\, Ln\, (e^{U_{car}} + e^{U_{mc}} + e^{U_{PT}}) \quad \textbf{(7-23)}$$

where,

b is shown in Equation (7-22);

U_{car}, U_{mc}, U_{PT} are the utilities of car, motorcycle and PT respectively;

For the incremental multinomial logit model, existing bus represents the before situation while a new PT mode represents the after situation. For the incremental nested logit model, existing bus represents the before situation while the new PT mode and bus (in the lower nest) represent the after situation.

The demand elasticity (E) with respect to the logsum is defined as:

$$E = \frac{\Delta Q}{\mathrm{Q}} \frac{logsum}{\Delta logsum} \tag{7-24}$$

where,

Q is the total demand for general traffic.

Litman (2019) reviewed several studies, which have investigated transport elasticities. Those studies have measured various types of transport, prices, users and travel conditions by using many analysis methods. Some studies simply measure how changes in a single variable (i.e. fuel prices or transit fares) impact on a single outcome (i.e. fuel consumption or transit riders). However, more recent studies tend to use more sophisticated evaluation techniques, which consider a variety of variables and statistical analyses. Additionally, Balcombe *et al.* (2004) stated the elasticities with respect to generalised costs that include PT fare, in-vehicle time, walking time and waiting times. The generalised costs elasticities range between -0.4 and -1.7 for buses, -0.4 and -1.85 for London Underground, and -0.6 and -2.0 for national railways. Moreover, Lee (2000) estimated the elasticity of vehicle travel with respect to total price, which consists of fuel cost, tolls, parking fees, vehicle wear and travel time. The results showed the generalised cost elasticities are from -0.5 to -1.0 in the short-term, and from -1.0 to -2.0 in the long-term. In general, those studies illustrated that the generalised cost elasticities are different for different modes and range between -0.4 and -2.0. To simplify the analysis in this thesis focusing on passenger car, bus, motorcycle and new PT modes, it is assumed that the demand elasticity with respect to utility is equal to -1.0. This means that Equation (7-24) becomes as:

$$\frac{\Delta Q}{Q} = \frac{\Delta logsum}{logsum} \tag{7-25}$$

The logsums of general traffic in the before and after situations are shown as:

$$logsum\_before = \frac{1}{-b} \, Ln \, (e^{Ucar\_0} + e^{Umc\_0} + e^{Ubus\_0}) \tag{7-26}$$

$$logsum\_after = \frac{1}{-b} \, Ln \, (e^{Ucar\_1} + e^{Umc\_1} + e^{U_{PT\_1}}) \tag{7-27}$$

Hence, based on Equation (7-25), the 1/-b component is cancelled in both Equations (7-26) and (7-27) and the change in per cent in the total demand is therefore estimated as:

$$\frac{\Delta Q}{Q} = \frac{Ln\left(e^{Ucar_1}+e^{Umc_1}+e^{U_{PT_1}}\right) - Ln\,(e^{Ucar\_0}+e^{Umc\_0}+e^{Ubus\_0})}{Ln\,(e^{Ucar\_0}+e^{Umc\_0}+e^{Ubus\_0})} \tag{7-28}$$

where,

U_{car_0}, U_{mc_0}, U_{bus_0} are the utilities of car, motorcycle and bus in the before situation respectively;

U_{car_1}, U_{mc_1}, U_{PT_1} are the utilities of car, motorcycle and PT in the after situation correspondingly;

To estimate the endogenous growth in the total demand in the incremental elasticity analysis, the utility of each transport mode is required to be determined.

7.5 Case Study

There are distinct characteristics of the bus system in Hanoi and bus services running on the study corridor. Firstly, the bus system has been regulated in Hanoi (Hanoi Transport Management and Operation Centre, 2011). Secondly, there are four bus services running on the whole corridor and nine bus services running on segments of the corridor that are shown in Figure 6-1. For the existing situation, buses still shares the facilities with motorcycle and car. As a result, two main scenarios are considered in the thesis as follows:

Scenario 1: A new exclusive public transport mode (BRT, Metro or Monorail) is introduced to replace all bus services running on the partial and whole corridor. These bus routes can be relocated to not overlap with the new PT route. Therefore, they can either become feeder systems transport passengers to new PT stations/stops or serve neighbourhood areas of the new PT mode. This means that the new PT mode is run exclusively whilst car and motorcycle share the mixed environment. The incremental multinomial logit model is used for this case.

Scenario 2: A new exclusive public transport (BRT, Metro or Monorail) is introduced to replace the bus services running on the whole corridor. This means that the four bus services running on the whole corridor are adjusted to other corridors whilst the nine bus services running on partial segments of the corridor are still operated on the study corridor. The incremental nested logit model is used for this case.

For both Scenarios above, for the BRT option, median BRT lanes are considered, which leads to reduce the number of mixed traffic lanes by one lane per direction. Whilst, for the elevated Metro and Monorail, the number of mixed traffic lanes are unchanged.

The utility functions of different modes and traffic demand for the Hanoi case study are described below.

7.5.1 Utility functions

As discussed in subsection 3.2.1, Bray and Holyoak (2015) studied on travel behaviour in Hanoi by establishing a discrete choice modelling framework. The study focused on the discrete choice decision to use a motorcycle, car, motorcycle taxi, existing bus or proposed rapid transit modes (e.g. Urban Railway Transit or Bus Rapid Transit). In addition, subsection 5.5.5.4 discussed the value of time for the Hanoi case study. Based on the modal share data in the study of Japan International Cooperation Agency (2007) and the study of Bray and Holyoak (2015), coefficients of utilities for the Hanoi case study are estimated, which are shown in Table 7-1.

Table 7-1 Utility function parameters for the Hanoi case study, 2014 values

	MSC	Travel time	Walk time	Wait time	Fuel cost	PT fare
Motorcycle	1.6303476	-0.0100492			-0.0002116	
Car	1.3253908	-0.0045308			-0.0001628	
Bus	0.6655476	-0.0051492	-0.011216	-0.011216		-0.0146
New PT	0.9961844	-0.0044962	-0.011216	-0.011216		-0.0146
Motorcycle Taxi	0.0	-0.003636				-0.0079

Adapted from Japan International Cooperation Agency (2007) and Bray and Holyoak (2015)

Notes: The units of the time, fuel cost and PT fare in the utility functions are minute, VND/km and VND/1,000 respectively. The wait time coefficient is assumed to be the same as the walk time coefficient.

Table 7-1 shows that motorcycle has the highest MSC. The reason for that can be explained that the vast majority (92 per cent) of households do not own a car in the survey in the study of Bray and Holyoak (2015). Additionally, bus seems to be an unattractive mode compared to other modes. Bray and Holyoak (2015) showed that people are bothered more by some parts of a public transport trip than others. For example, the surveys indicate people are much more concerned by the time and bother of the walk to access public transport. Moreover, passengers are concerned about matters involving bus including safety and personal security, over-crowding, service reliability and air conditioning. Similarly, revealed preference mode choice surveys indicate that only people with the lowest income choose bus and/or bicycle for cost saving; the great number of people choose motorcycle for time saving and convenience; and the richest prefer car because of comfort and safety (Vu, 2015). The survey in that study was conducted in 2012 with 800 people including 300 motorcyclists, 200 bus users, 150 car users and 150 bicycle users. Those people were asked about their household size and income, as well as the reasons for choosing a transport mode such as time savings, convenience, comfort and safety.

To estimate the utility of each mode, the coefficients of utility functions shown in Table 7-1 are used, as well as the components of the utility functions must be calculated. These components, which include in-vehicle time, walking time, waiting time and fuel cost, are calculated from the social cost model and VISSIM simulation model. The fares of all public transport modes are assumed to be the same and be fixed. As this study focuses on the incremental framework, the PT fares element can be ignored.

7.5.2 Traffic demand

Generally, demand is the number of vehicles or other roadway users desiring to use a given system element during a specific time period, typically an hour or 15 minutes. Demand volume is the number of vehicles that arrive to use the facility. Under non-congested conditions, demand volume is equal to the observed volume (Transportation Research Board, 2010). Public transport demand is shown in three ways: annual numbers of passenger trips (one-way); annual passengers km; and annual passenger revenue (Balcombe *et al.*, 2004).

For the Hanoi case study, using traffic volume data at ten junctions and bus passenger data at all bus stops on the NT-TP-QT corridor, which were collected in two peak hours of between 16:30 and 18:30 (see Subsection 6.2), the demands for motorcycle, car and bus for the whole corridor are estimated below. In addition, as discussed in Chapter 6, the VISSIM simulation model for the peak period is developed for the segment (1.5 km) between the junctions J2 and J4 while the VISSIM simulation model for the off-peak period simulates the segment (0.9 km) between the junctions J2 and J3. Hence, the demands for these segments are also calculated. All values of existing demand are going to be used for the case study of the comparative economic assessment, which is illustrated in the next chapter.

7.5.2.1 Bus demand

Bus demand (passenger trips) of this corridor is estimated as the total number of boardings and alightings at all bus stops on the corridor minus the total number of bus trips of which origin and destination are bus stops on the corridor (named as O-D trips on the corridor). This ensures that the number of passengers is not counted twice. There are four bus services running on the whole corridor and nine bus services running on segments of the corridor which is less than 4 km. As a result, the number of O-D trips on the corridor is assumed as a factor of (4/13) multiplies by the number of boardings at all bus stops on the corridor. The results of the bus demand of the study corridor on 19 April 2018 are shown in Table 7-2.

Table 7-2 Existing bus demand of the study corridor for both directions from 16:30 to 18:30

	Simulated segment for off-peak period - Segment 1 (0.9 km)	Simulated segment for peak period - Segment 2 (1.5 km)	Whole corridor (7.0 km)
Bus demand (pax)	2,484	3,342	12,571
Bus demand for four replaced bus services (pax)	928	1,292	4,759
Bus demand for nine remaining bus services (pax)	1,556	2,050	7,812
Relative demand of a segment to the whole corridor for nine remaining bus services	19.9% (1,556/7,812)	26.2% (2,050/7,812)	

Table 7-2 shows the relative demand of Segment 1 to the whole corridor for only nine remaining bus services is around 19.9 % while that number for Segment 2 is about 26.2%. Hence, the daily bus demand, off-peak bus demand and peak bus demand are calculated and shown in Table 7-3.

Table 7-3 Existing daily bus demand, off-peak bus demand and peak bus demand

	Simulated segment for off-peak period - Segment 1 (0.9 km)	Simulated segment for peak period - Segment 2- (1.5 km)	Whole corridor (7.0 km)
Daily bus demand for remaining bus services (pax/direction/day)	4,442	5,848	22,320 = 7,812/17.5%/2
Mid-day off-peak remaining bus demand (pax/direction/hour)	289 = 22,320*6.5%*19.9%		
Peak remaining bus demand from 5:30pm-6:30pm (pax/direction/hour)		497 = 22,320*8.5%*26.2%	

Notes: Based on data in Table 5-7, demand for the period from 16:30 to 18:30 accounts for 17.5% of the daily demand while the number for the period from 17:30 to 18:30 is 8.5 %.

7.5.2.2 Private transport demand

Private transport demand (in passenger trips) of a segment from junction J1 to the junction J3 in Figure 7-3 is estimated as:

$$J1 - J3\ demand\ = Occupancy * (\ Maximum\ (J1\ Exit\ flow, J2\ Entry\ flow) - J2.2\ + Maximum\ (J2\ Exit\ flow, J3\ Entry\ flow)) \qquad \textbf{(7-29)}$$

Where,

Occupancy is 1.22 for motorcycle and 1.57 for car;

Maximum (J1 Exit flow, J2 Entry flow) represents the traffic volume of link 1 (vehicles). In reality, transport users can start or stop along with the link 1;

Maximum (J2 Exit flow, J3 Entry flow) represents the traffic volume of link 2 (vehicles);

J2.2 represents the straight flow passing the junction J2 (vehicles). This flow is counted once for the demand for link 1.

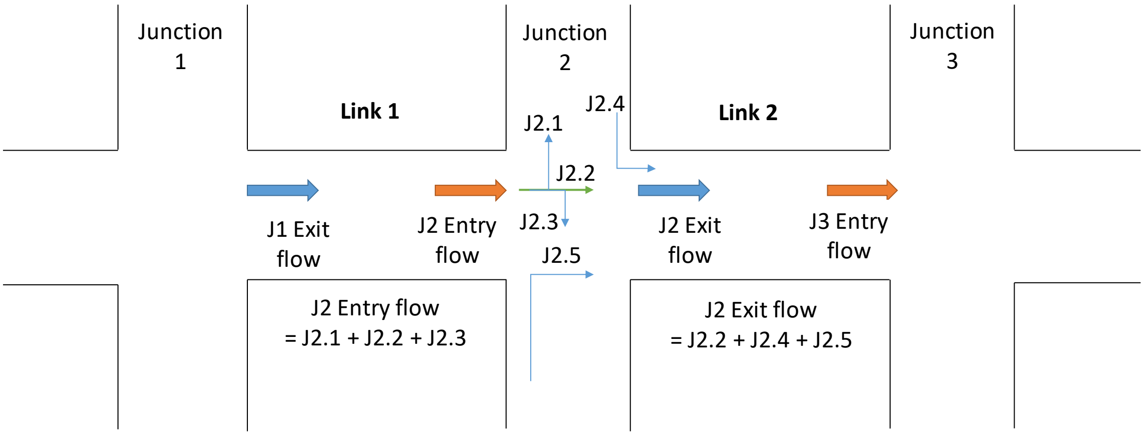


Figure 7-3 Estimating private transport demand of a segment from junction J1 to junction J3

The methodology to estimate private transport demand of the segment from junction J1 to the junction J3 is used for the NT-TP-QT corridor with 10 junctions. The total passenger trips for the corridor by motorcycle and car are calculated separately. Based on the collected data on 16 and 19 April 2018, existing demand levels of bus, motorcycle and car are shown in Table 7-4. The modal share of other modes, which are very minor, are therefore ignored in this study.

Table 7-4 Existing demand of the study corridor for both directions from 16:30 to 18:30

	Simulated segment for off-peak period - Segment 1 (0.9 km)	Simulated segment for peak period - Segment 2 (1.5 km)	Whole corridor (7.0 km)
Bus demand (pax)	2,484	3,342	12,571
Motorcycle demand (pax)	23,400	29,410	110,553
Car Demand (pax)	3,919	5,253	19,572
Total demand from 16:30-18:30 (pax)	29,803	38,005	142,697
Relative demand of a segment to the whole corridor	21% (29,803/142,697)	27% (38,005/142,697)	
Bus share (%)	8.33%	8.79%	8.81%
Motorcycle share (%)	78.52%	77.38%	77.47%
Car share (%)	13.15%	13.83%	13.72%

Firstly, Table 7-4 shows that modal shares for Segment 1, Segment 2 and the whole corridor are very similar for the period from 16:30 to 18:30. This can prove that the simulated segments for the peak period can be represented for the whole corridor. The total demand level from 16:30 to 18:30 for Segment 2 is equal to 27% of the total demand level for the whole corridor. This value can be used for estimating the total demand of the whole corridor after the demand level for Segment 2 is obtained from the VISSIM simulation model. This process is going to be outlined in the next chapter. Moreover, according to the passenger demand split into different times shown in Table 5-7, the daily passenger demand for this corridor is calculated as 407,700 pdd.

Secondly, demand data on the off-peak simulated segment from 12:00 to 13:00 on 19 March 2018 are obtained from video recordings provided by the Hanoi Police Department, which are shown Table 7-5. The results show that motorcycle and car demands are 8,855 and 1,664 pax correspondingly. The bus share for the whole corridor of 8.81% shown in Table 7-4 is used for estimating the bus demand for the off-peak period. Table 7-5 shows the existing demand for the off-peak simulated segment from 12:00 to 13:00 on 19 March 2018.

Table 7-5 shows that relative 16:30-18:30 demand (16 April 2018) to 12:00-13:00 demand (19 March 2018) is similar to the number for the national scale shown in Table 5-7. Additionally, the ratio of motorcycle demand to car demand for the off-peak period is estimated around 5.32 (8,855/1,664), which is close to the rate of (77.47%/13.72%) for the whole corridor for the peak period shown in Table 7-4. As a result, the simulated segments for the off peak period can be represented for the whole corridor. However, there is no available demand data of bus, car and motorcycle on the remaining corridor (junction J3 to J10) for the off-peak period. Hence, the ratio of the demand of Segment 1 to the whole corridor demand for the peak and off-peak periods are assumed to be the same, which is equal to 21%. After demand levels for Segment 1 are obtained from the VISSIM simulations, the total demand of the whole corridor is estimated by using this percentage. This process is mentioned in the next chapter.

Table 7-5 Existing demand for the off-peak simulated segment for both directions from 12:00 to 13:00 on 19/3/2018

	Simulated segment for off-peak period – Segment 1 (0.9 km)	Modal share (%)
Bus demand (pax)	1,016 (11,535 x 8.81%)	8.81%
Motorcycle demand (pax)	8,855	76.76%
Car Demand Motorcycle demand (pax)	1,664	14.43%
Total demand from 12:00-13:00 (pax)	11,535 = (8,855+1,664)/(1-8.81%)	100%
Relative 16:30-18:30 demand to 12:00-13:00 demand	2.58 (29,803/11,535)	
Relative 16:30-18:30 demand to 12:00-13:00 demand based on data for national scale	2.69 (17.5%/6.5%)	

7.6 Conclusion

When an existing mixed transport system changes, suitable incremental demand models need to be used to forecast changes in demand of each transport mode such as bus, car and motorcycle. If a new PT technology replaces all bus services running on the partial and whole corridor, the incremental multinomial logit model is used to estimate probabilities of choosing new PT, car and motorcycle. For a situation where a new PT mode replaces only bus services running on the whole corridor and the existing bus services running on segments of the corridor are still operated, the incremental nested logit model is used to estimate modal shares of new PT, bus, car and motorcycle. The next requirement is to identify absolute changes in demand for each transport mode. Hence, total demand is required to forecast. The incremental elasticity analysis estimates endogenous changes in the total demand by using the demand elasticity with respect to a logsum.

The main component of these incremental demand modal is the utility of each transport. Based on the study of Japan International Cooperation Agency (2007) and the study of Bray and Holyoak (2015), the utility functions of motorcycle, car, bus and new PT modes are developed for the Hanoi case study. Existing demand levels of each transport mode on the study corridor in Hanoi are calculated based on the collected data, which is shown in section 6.2. The results of the demand show that the VISSIM simulation models simulating Segments 1 and 2 can represent for the whole corridor. Calculation examples for the incremental demand models shown in this chapter are illustrated in the case study of the assessment, which are shown in Appendix C.2.

The components of the utility, which consist of in-vehicle time, walking time, waiting time and fuel cost, are estimated from the social cost model and VISSIM simulation model. Hence, the incremental elasticity analysis, incremental logit model, social cost model and VISSIM simulation model are integrated into a comprehensive comparative economic assessment to achieve the aims of this study. The next chapter is going to describe an application of this assessment to the Hanoi case study, which compares the existing mixed transport situation and proposed infrastructure options with an introduction of new PT technologies (Bus Rapid Transit, elevated Metro and Monorail) and a congestion charge scheme for PRV, in terms of ASC, total general demand and PT share.

Chapter 8 Comparative Economic Assessment Application

8.1 Introduction

The main aims of the comparative economic assessment are to analyse the feasibility of new public transport technologies in a mixed traffic environment with a dominance of motorcycles and identify the most cost-effective mixed transport system in terms of given criteria. Chapter 4 introduces the methodology of the assessment and Chapters 5-7 develop the social cost model, microscopic simulation model, incremental elasticity analysis and incremental logit model. This chapter demonstrates an application of the comparative economic assessment on the NT-TP-QT corridor in Hanoi, Vietnam. The assessment is applied to compare the existing mixed transport situation and proposed transport infrastructure options to find the best option in terms of ASC, total demand and PT share.

A new PT mode is introduced in the mixed transport environments to attract more private transport users to use PT. In conjunction with the new PT technology, a congestion charge scheme can be considered to achieve a larger shift from private transport. In most cities in the world, the congestion charge has been introduced with an expansion of public transport, for example London, Singapore and Stockholm (Santos, 2004). The congestion charge is included in the comparative assessment and its estimation for the Hanoi case study is illustrated in the next part of the chapter.

The third part of the chapter describes the detailed operating procedure of the comparative economic assessment application and illustrates twelve proposed options on the study corridor. The fourth part of the chapter indicates the comparative results of these proposed options on the corridor, as well as the best option.

As mentioned in Chapter 5, the sensitivity test with respect to the value of time is implemented in the social cost models to find the most cost-effective transport mode at a strategic planning level, in terms of ASC. The results show that the value of time seems to be sensitive to choosing the lowest ASC option at medium demand levels. Therefore, a sensitivity test with respect to the value of time is conducted with the completed assessment to evaluate the impacts of the value of time on the general results. The sensitivity test is illustrated in the fifth part of the chapter.

The sixth part of the chapter shows detailed results of the best option, compared to the existing situation.

8.2 Congestion Charge

In the private transport social cost model shown in Chapter 5, the total social costs (TSC) of each private transport mode (PRV) include total infrastructure operator costs (TOC), total vehicle user costs (TUC) and total external costs (TEC). The TOCs for PRV cover infrastructure costs, maintenance costs and parking costs. The TUCs for PRV consist of private vehicle capital costs, operating costs for users, travel time and congested-related delay costs. The congested-related delay costs are borne by the user themselves but not imposed on other travellers. The TECs cover noise pollution, air pollution, climate change and accident cost. Marginal environment costs and marginal accident costs are not considered as a basis for pricing in this thesis. The main reason is that the environment and accident costs in the private transport social cost model are estimated based on unit external costs of each mode in pence/passenger-distance. Moreover, the infrastructure and vehicle capital costs are also excluded because of the use of the short-run approach for estimating the marginal social cost. The long-run marginal costs of these components are issues for further work. Hence, the Marginal Congestion Cost (MCC), which is estimated in this study, relates to the change in travel time and operating costs for users. For one corridor, the MCC can be calculated as (Walters, 1961; Santos and Shaffer, 2004; Link *et al.*, 2016):

$$MCC = -E_S.\frac{V}{S} \qquad \textbf{(8-1)}$$

where,

MCC is the marginal congestion cost (£/vehicle-km);

E_S is the elasticity of speed with respect to traffic;

V is the value of time and additional operating costs (£/vehicle-hour);

S is the speed (km/hour).

8.2.1 Congestion charge estimation for the Hanoi case study

The marginal congestion costs are estimated for car and motorcycle separately. For each transport mode, the marginal congestion costs are calculated for the peak and off-peak periods individually as the VISSIM simulation models were developed for these two periods based on data collected on the study corridor in 2018. The development of the VISSIM simulations is shown in Chapter 6. The existing traffic demand for the peak and off-peak periods is described in Chapter 7 while the existing traffic volumes are summarised in Table 8-1.

Table 8-1 Existing car and motorcycle volumes of the simulated segments for both directions

	Simulated segment for the peak period between 17:30 and 18:30	Simulated segment for the off-peak period between 12:00 and 13:00
Motorcycle volume	12,054	7,258
Car volume	1,673	1,060

To identify the existing average motorcycle and car speeds, travel times of motorcycle and car between two given points are obtained from the VISSIM simulation models. The distance between the two points on the simulated segment for the peak period is 1.5 km while this length for the off-peak period is 0.9 km. In order to ensure the variability of the simulation results and to reduce the randomness, the VISSIM simulation has been run forty times with different random seeds. The travel time of each vehicle type for both directions between the two points on the corridor is estimated based on the average travel time of that vehicle type for each direction and number of vehicles observed for each direction in the VISSIM simulations. One calculation example of one VISSIM simulation run is shown in Table 8-2 while Table 8-3 shows the existing average motorcycle and car speeds based on 40 VISSIM simulation runs for the existing situation.

Table 8-2 Travel times for different modes in one VISSIM simulation run

	Number of Car	Number of Bus	Number of MC	Car travel time (s)	Bus travel time (s)	MC travel time (s)
Direction 1	124	41	825	122.16	182.57	121.96
Direction 2	180	39	1704	156.85	206.90	148.50
Both directions	304	80	2529			
Average travel time for both directions (second)				142.70 = ((124*122.16 + 180*156.85)/304)	194.43	139.84

Table 8-3 Existing average car and motorcycle speeds for the peak and off-peak periods

	Peak period (17:30-18:30)	Off-peak period (12:00-13:00)
Average car speed (km/h)	14.89	22.71
Average motorcycle speed (km/h)	16.09	23.17

In order to estimate the MCC for cars, the VISSIM simulations are developed for four scenarios with increases of 10% and 20%; and decreases of 10% and 20% in the total car volumes for the simulated segments, compared to the existing car volumes shown in Table 8-1. The motorcycle and bus volumes are unchanged in the VISSIM simulations. The VISSIM models simulate interactions between motorcycle, car and bus on the corridor, motorcycles and buses therefore impose congestion on cars. The average travel time and speed of cars are obtained from the VISSIM simulations and then compared to existing values to calculate elasticities of speed with respect to traffic. The average demand elasticities of speed, which is a mean of four values for the four scenarios, is used for calculations of the marginal congestion costs. Due to time limits of the study, the number of scenarios cannot be higher than four, as well as the estimated marginal congestion costs are not the optimal congestion charge.

Similarly, for the calculation of the MCC for motorcycles, the VISSIM simulations are developed for four scenarios with rises of 2% and 3%; and reductions of 2% and 3% in the total motorcycle volumes, compared to the existing motorcycle volumes shown in Table 8-1. The reason for the difference between the percentages of changes in the total car volumes and total motorcycle volumes is that the existing motorcycle volume is around seven times as high as the existing car volume. The car and bus volumes are unchanged in the VISSIM simulations, however, cars and buses still impose congestion on motorcycles.

Assumptions for input data in the VISSIM simulations

There is the following assumption for developing a VISSIM simulation for a scenario with the increase/decrease of *X*%, compared to the existing total car volume for the simulated segment. As mentioned above, *X*% are equal to 10% and 20%. The car volumes entering all junctions from all approaches (including the study corridor and intersected streets) rise/reduce by *X*%. These values are changed in the 'Vehicle Inputs' and 'Vehicle Compositions/Relative Flows' objects in the VISSIM simulations. The motorcycle and bus volumes are unchanged in the VISSIM simulations.

The same assumption is applied to the VISSIM simulations for estimating the MCC for motorcycles.

Value of time and additional operating costs

The value of time in PPP £/hour for the Hanoi case study is described in subsection 5.5.5.4. By taking into account the occupancies, the value of time in PPP £/vehicle-hour at 2015 prices for car and motorcycle are 1.76 and 2.34 correspondingly. Equations for estimating car and motorcycle operating costs are shown in subsection 5.3.1. After obtaining vehicle speeds from the VISSIM simulations, additional operating costs are estimated.

A calculation example

Table 8-4 shows the calculation for the scenario with an increase of 10% in the total car volume.

Table 8-4 The calculation of MCC for cars for the peak period, 2015 prices

Parameters	Values	Notes
Existing car speed (Km/h)	14.89	
New car speed (Km/h)	13.47	
Speed change (%)	-9.5%	(13.47-14.89)/14.89
Traffic change (%)	10%	For the scenario with increases of 10%
VoT (PPP £/car-hour)	1.76	

Parameters	Values	Notes
New fuel consumption (l/km)	0.1333	Use Equation (5-24) with the new car speed
Fuel price in Vietnam (VND/l)	19,000	In 2015 prices
Fuel price in Vietnam (PPP £/l)	1.73	A factor of (0.69/7,576.25) is used to convert the Vietnamese currency into the British currency (World Bank, 2015b)
New fuel cost (£/car-km)	0.2307	0.1333*1.73
Existing fuel cost (£/car-km)	0.2164	With respect to the existing car speed
Additional fuel cost (£/car-km)	0.0143	
MCC (£/car-km)	0.126	$MCC = -\frac{9.5\%}{10\%}.(\frac{1.76}{14.89}+0.0143)$

Results of marginal congestion cost

The results of the elasticity of speed with respect to traffic and MCC for cars for the peak and off-peak periods are shown in Figure 8-1 and Figure 8-2 respectively. Moreover, Figure 8-3 and Figure 8-4 illustrate the results of the elasticity of speed with respect to traffic and MCC for motorcycles for the peak and off-peak periods correspondingly.

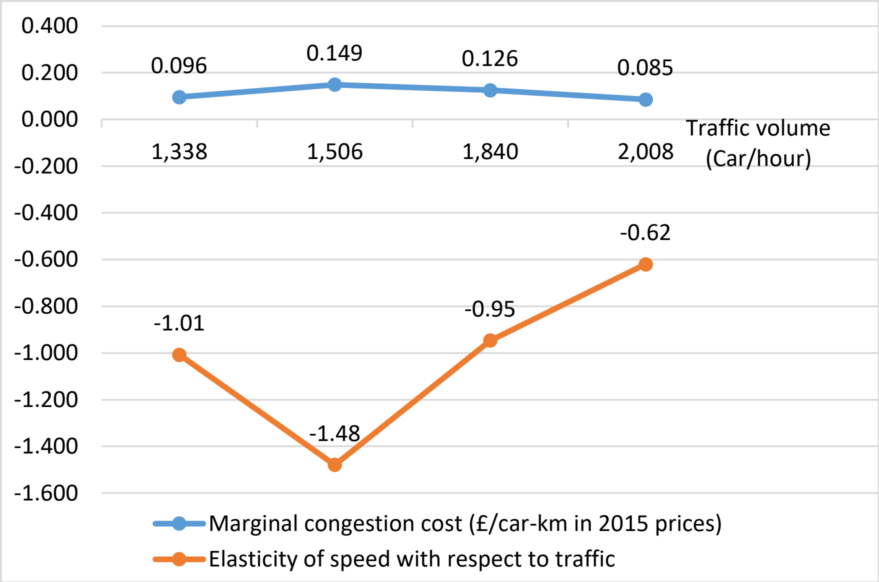


Figure 8-1 Relationship between elasticity of speed with respect to traffic, MCC and car traffic levels for the peak period

Notes: The existing car traffic level for both directions in the peak is 1,673 car/hour.

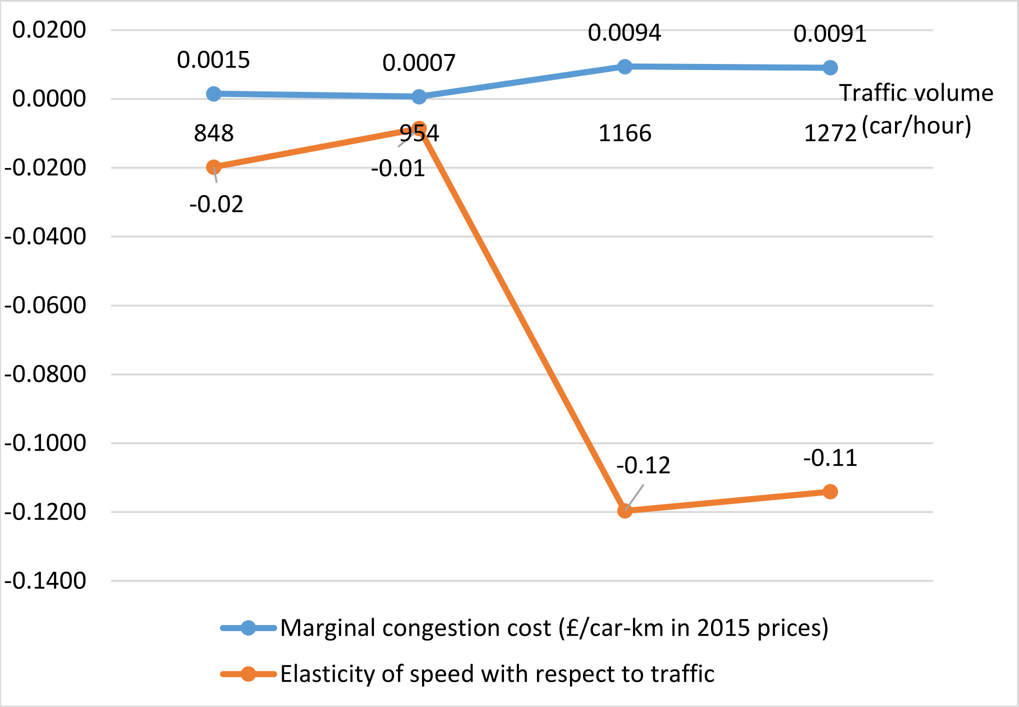


Figure 8-2 Relationship between elasticity of speed with respect to traffic, MCC and car traffic levels for the off-peak period

Notes: The existing car traffic level for both directions in the off-peak is 1,060 car/hour.

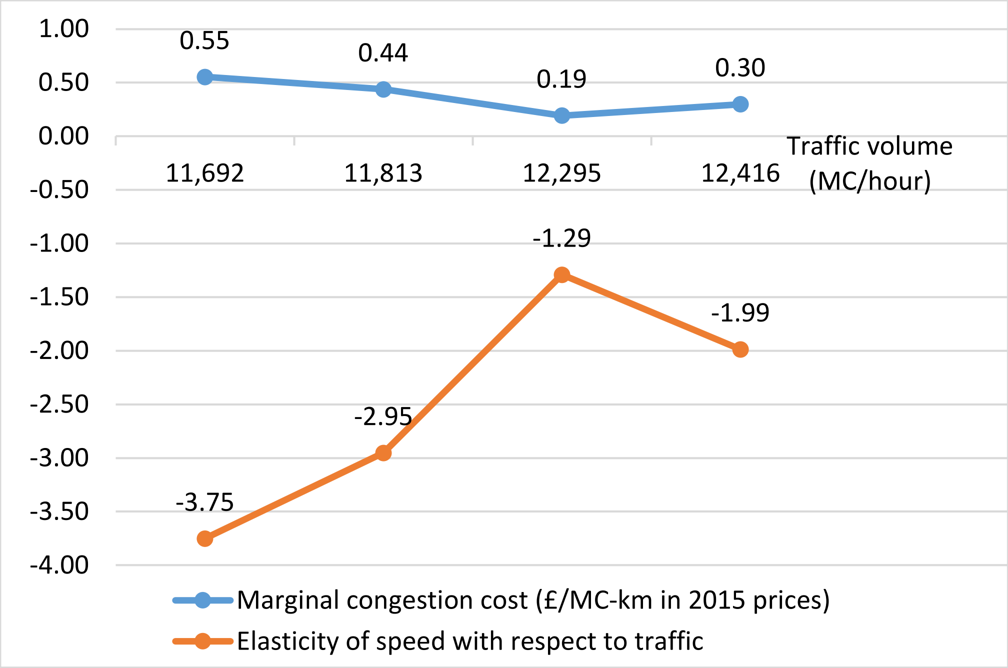


Figure 8-3 Relationship between elasticity of speed with respect to traffic, MCC and motorcycle traffic levels for the peak period

Notes: The existing motorcycle traffic level for both directions in the peak is 12,054 MC/hour.

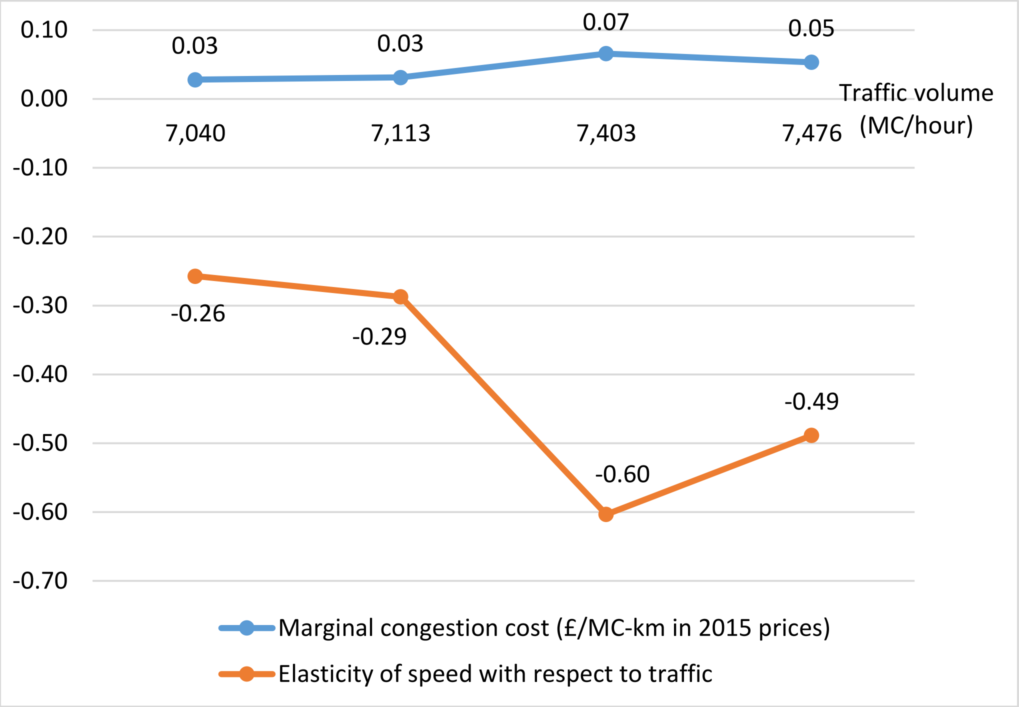


Figure 8-4 Relationship between elasticity of speed with respect to traffic, MCC and motorcycle traffic levels for the off-peak period

Notes: The existing motorcycle traffic level for both directions in the off-peak is 7,258 MC/hour.

Figure 8-1 and Figure 8-3 illustrate that the mean elasticity of speed with respect to traffic for both car and motorcycle in the peak period are -1.105 and -2.495 respectively. This implies that the speed of vehicles in the peak period is sensitive and motorcycle speeds are more sensitive to flow. In addition, the elasticity of speed with respect to traffic for both car and motorcycle are more sensitive when traffic reduces in the peak period. These can be explained that the existing speed and traffic in the peak period are critical in their relationship curve, which was produced in the study in Hanoi by Nguyen and Sano (2012). The relationship between mean speed and traffic flow for a four-lane (per direction) link in Hanoi s shown in Figure 8-5. The existing situation seems to be at a critical area, which is shown in a red circle in Figure 8-5. Hence, the mean speed appears to be very sensitive to changes in traffic.

As can be seen from Figure 8-1, Figure 8-2, Figure 8-3 and Figure 8-4, there are significant differences between the vehicles MCC in the peak and off-peak periods because the vehicle speeds and traffic volumes in these two periods are considerably different. Although the vehicles MCC for the off-peak period are minor, the different congestion charges should be implemented for both periods. If the congestion charge scheme is introduced for only the rush hours, private transport users can shift considerably from the peak period to the off-peak period while existing bus services and new PT mode are encouraged to use. This can relate set times for the start of work and school etc. Moreover, this suggestion seems to be consistent because a limitation of this thesis is that cross-effects between time periods are not considered.

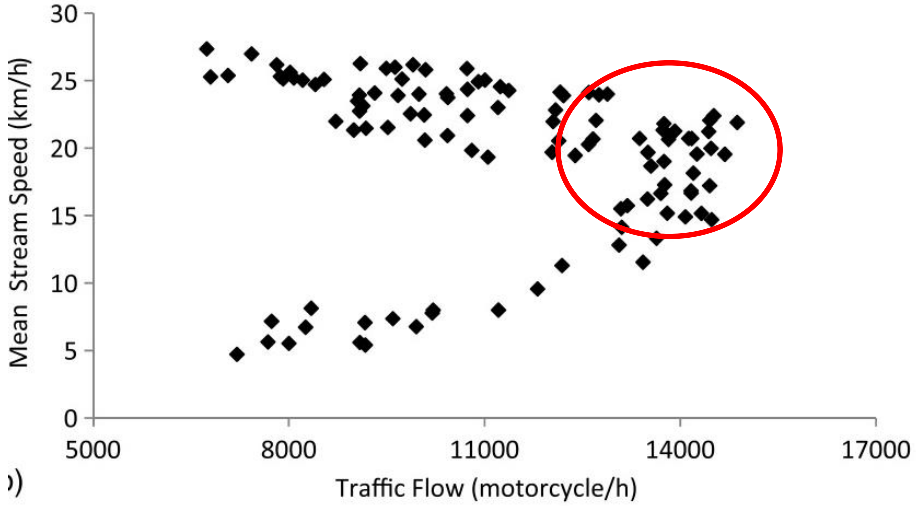


Figure 8-5 Relationship between mean speed and traffic flow for a four-lane (per direction) link in Hanoi

Source: Nguyen and Sano (2012)

Figure 8-1, Figure 8-2, Figure 8-3 and Figure 8-4 show that the MCCs for motorcycles are higher than those numbers for cars. The first reason is that the value of time for motorcycles is greater than for cars. Secondly, the motorcycle speed seems to be more sensitive than the car speed with respect to traffic as motorcycles are dominant in the existing mixed traffic situation. However, the congestion charge for cars can be suggested for both private transport modes for the Hanoi case study to ensure that the congestion charge cannot be a regressive tax on the middle-income and poor people. A regressive tax is defined as where a tax takes a higher share of the income of low-income people than of high-income people (Santos and Shaffer, 2004). Vu (2015) carried out a survey with 800 Hanoi citizens in 2012 about household vehicle ownership and mode choice preferences. The results of that study showed that the poorest mainly use bus and bicycle, the lower-middle-income and upper-middle-income people choose motorcycles while high-income individuals use cars.

If an average distance a vehicle travels is around 4 km in the peak period, the estimated MCC of £0.114/car-km suggests that the congestion charge should be £0.912 for one vehicle travelling a return trip on the corridor in the peak period. Table 5.4.4 in Data Book on WebTAG shows that the MCC in London for the PM peak is £0.827/car-km. In April 2015, the average wage of full-time employees in London citizens is £660 per week (Office for National Statistics, 2015). By contrast, this number of Hanoi citizens is PPP £96 per week (General Statistic Office of Vietnam, 2020). By taking into account comparable values of the MCC in London, the average wage in London and Hanoi, the estimated MCCs for the Hanoi case study might be acceptable. To conclude, the estimated MCCs of £0.114/vehicle-km and £0.005/vehicle-km are applied for the private transport users in the peak and off-peak period correspondingly. The peak periods are between 7-9 AM and 4-7 PM, which are shown in Table 5-7.

8.2.2 Congestion charge coefficients in the utility functions

The utility functions of motorcycle and car for the Hanoi case study, which are shown in subsection 7.5.1, includes only fuel cost in terms of cost. Hence, the congestion charge coefficients included in the utility functions need to be identified. The methods for estimating the congestion charge coefficients are used as: (i) development of equations of the elasticity of private transport demand with respect to fuel cost and congestion charge based on the logit model formulation and (ii) transferability of evidence from the London congestion charge scheme to the Hanoi case study. Using the PPP rate, the congestion charge for the off-peak and peak periods in the utility are estimated as 56.74 and 1,250.7 VND/ vehicle-km respectively. The results show that the congestion charge coefficients in car and motorcycle utilities are estimated as -0.000501 and -0.000393 respectively. The detailed calculations are shown in Appendix C.1. The congestion charge for car and motorcycle are only included in the utility function after the congestion charge scheme is introduced. In other words, this charge is not included in the utility function before the introduction of the charging scheme or in a situation where there is no congestion charge scheme. This charge affects demand in the incremental elasticity analysis and incremental logit models but it is not included in the total social cost calculation.

8.3 Procedure of Comparative Economic Assessment

In Chapter 1, Figure 1-2 shows the operating procedure of the comparative economic assessment. The operating procedure of the assessment application on the objective corridor in Hanoi is shown as a flow chart in Figure 8-6. The main steps in Figure 8-6 are shown in detail below.

8.3.1 Step 1

The first step is to set up the VISSIM simulation models that simulate an existing mixed transport corridor. These are the validated simulation models for the off-peak and peak periods, which are shown in Chapter 6. The VISSIM simulation model for the peak period simulates the segment (1.5 km) from the junction J2 to junction J4 while the VISSIM simulation model for the off-peak period represents the segment (0.9 km) from the junction J2 to junction J3. The completed assessment is run for the off-peak and peak periods separately.

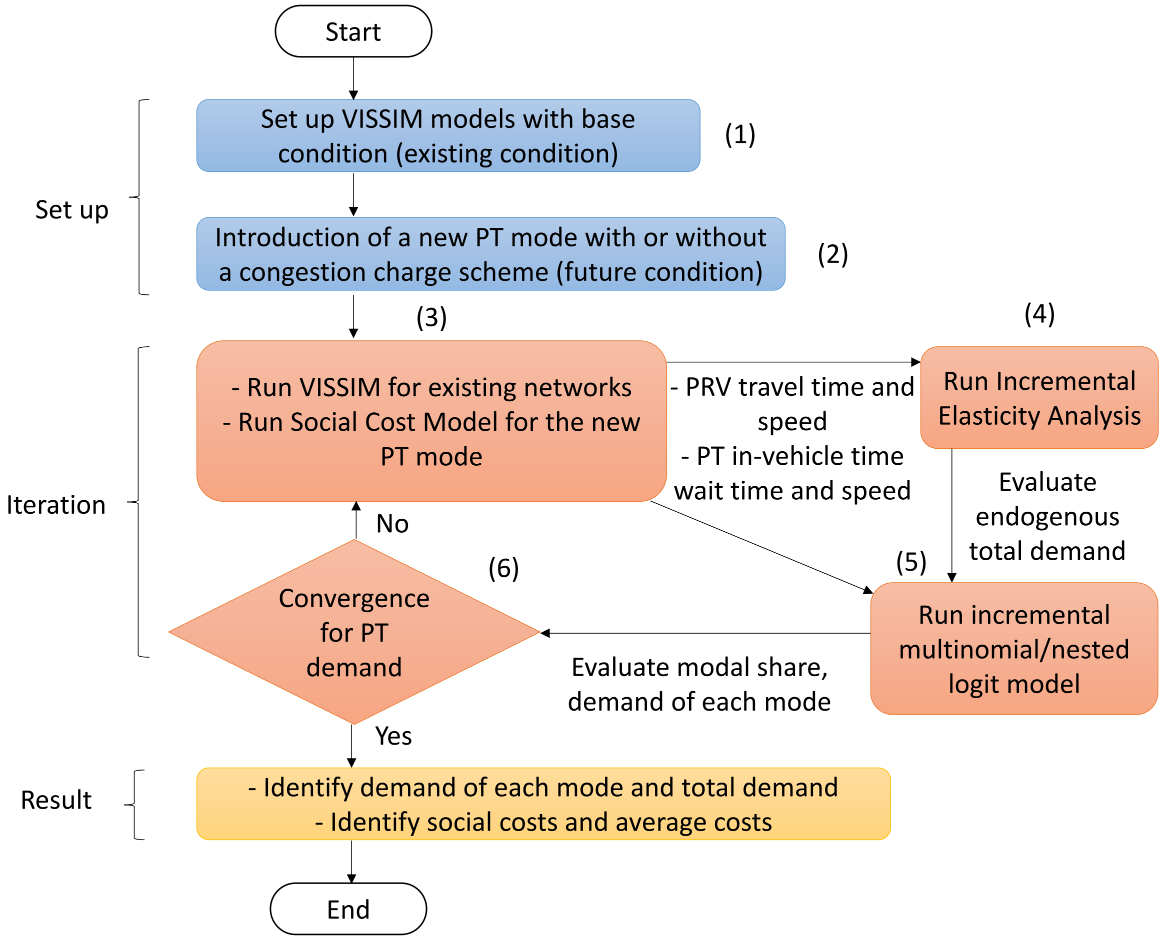


Figure 8-6 Model application procedure for each proposed option for each period time

8.3.2 Step 2

A new PT mode is introduced on the study corridor with or without a congestion charge scheme. Three new PT modes, BRT, Monorail or Elevated Metro, are considered in the assessment. As mentioned in subsection 7.5, two scenarios are suggested as follows: (i) **Scenario 1**: The new exclusive public transport replaces all bus services running on the partial and whole corridor. The incremental multinomial logit model is used for Scenario 1; and (ii) **Scenario 2**: The new exclusive public transport replaces the bus services running on the whole corridor whilst nine bus services running on segments of the corridor are still operated on the study corridor. The incremental nested logit model is used for Scenario 2. To conclude, twelve options are proposed on the study corridor in Hanoi to improve the performance of the existing situation, which are shown in Table 8-5. Each option is run in the next steps of the completed assessment.

Table 8-5 Twelve proposed options on the study corridor in Hanoi

No	Proposed options	Incremental multinomial logit model	Incremental nested logit model	Introduction of a congestion charge scheme
1	BRT - Scenario 1 without congestion charge	x		
2	Monorail - Scenario 1 without congestion charge	x		
3	Metro - Scenario 1 without congestion charge	x		
4	BRT - Scenario 2 without congestion charge		x	
5	Monorail - Scenario 2 without congestion charge		x	
6	Metro - Scenario 2 without congestion charge		x	
7	BRT - Scenario 1 with congestion charge	x		x
8	Monorail - Scenario 1 with congestion charge	x		x
9	Metro - Scenario 1 with congestion charge	x		x
10	BRT - Scenario 2 with congestion charge		x	x
11	Monorail - Scenario 2 with congestion charge		x	x
12	Metro - Scenario 2 with congestion charge		x	x

Figure 5-5 in Chapter 5 shows the results of the ASCs of PT, PRV and Taxi/Uber modes for 1-lane (per direction) corridor in the Hanoi case study. Figure 5-5 shows BRT shows great potential when demand ranges from 107,000 to 220,000 pax/direction/day (pdd). However, the BRT infrastructure capacity is 240 vehicle/direction/hour that the BRT system can supply around 109,000 pdd. Similarly, the Monorail and Elevated Metro infrastructure capacities are 138 and 156 vehicle/direction/hour correspondingly. These systems can supply approximately 255,000 and 512,000 pdd respectively. Hence, 109,000 pdd, 255,000 pdd and 512,000 pdd are set for introducing a BRT, Monorail or elevated Metro line correspondingly. New PT frequencies for the off-peak and peak periods are estimated based on these demand levels above, which are assumed to be fixed. Therefore, travel time and waiting time of new PT users are calculated in the social cost model with respect to these frequencies.

8.3.3 Step 3

Firstly, the VISSIM simulation models representing the existing networks are run to obtain travel time and speed of motorcycle, car and bus. To reduce the randomness, forty random seeded runs are made to achieve the average travel time of each vehicle. Secondly, the social cost model evaluates operating speed, in-vehicle time and waiting time of new exclusive PT users, as well as waiting time of the existing bus.

8.3.4 Step 4

Based on the traffic data obtained in Step 3, the incremental elasticity analysis is run to estimate new endogenous general traffic with respect to a logsum. The utility of each transport mode is estimated by using data on time and cost in Step 3, the logsum of general traffic is then calculated. Coefficients in utility functions for BRT, Monorail and Elevated Metro are assumed to be the same in this thesis. The reason is that the utilities of transport modes are estimated based on the study by Bray and Holyoak (2015). The surveys of that study considered motorcycle, car, bus and proposed rapid public transport (BRT and Mass Rapid Transit). However, the proposed public transport was made generic because neither exists at that time and people therefore has limited precise understanding of the service characteristics that Metro and BRT will provide. Only one BRT line has been operated in Vietnam since 2017 whilst Metro or Monorail have not yet operated in Vietnam.

8.3.5 Step 5

Input data for the incremental multinomial/nested logit models include: (i) In-vehicle time data and vehicle speed for each existing mode obtained from the VISSIM simulation model in Step 3, (ii) Data on in-vehicle time, waiting time and operating speed for the new PT mode achieved from the social cost model in Step 3, as well as waiting time of bus users and (iii) New endogenous total demand from the incremental elasticity analysis in Step 4. The incremental multinomial/nested logit models are run to obtain modal share and new demand for each transport mode.

8.3.6 Step 6

The changes in PT demand are estimated. After step 6, the first iteration of the assessment is finished. New demand for each transport mode obtained from Step 5 of the first iteration is used as inputs for the second iteration. Implement the next iterations (Steps 3-6) until convergence - the difference between the previous PT passenger demand and current PT passenger demand is less than 1%.

After the convergence is achieved, the final demand levels of each transport mode for the simulated segments are obtained. As discussed in Chapter 7, the demands of each transport mode for the simulated segments for the off-peak and peak periods are equal to 21% and 27% of the demand level for the whole corridor respectively. As a result, for each Option in Table 8-5, the demands for each transport mode for the whole corridor are calculated for the off-peak and peak periods by using these ratios. The daily demand for each transport mode is the sum of the demand for the off-peak and peak periods. These demand levels are inserted in the mixed transport social cost model to obtain the total social cost and ASC for each Option. A description of new daily demand for one option is shown in Appendix C.3. Moreover, the congestion charge is an additional component of the ASC of motorcycle and car for the options with the congestion charge scheme in Table 8-5.

8.3.7 VISSIM models from the second iteration

There are the following assumptions in the VISSIM simulation models from the second iteration in Figure 8-6.

- For the BRT option, a median lane is converted to be a dedicated BRT lane per direction. This means that three lanes per direction are shared by car, motorcycle and bus. Turn-left lanes are allocated to lanes next to the median lanes at junctions. Traffic signal cycles at two junctions are assumed to be unchanged. These changes are adjusted in the input data settings in the VISSIM simulation. Hence, the VISSIM model simulates the mixed traffic including motorcycle, car and bus while the PT social cost model is run for BRT. This means that BRT is given a priority at junctions when travel time of BRT is estimated in the social cost model. However, this is a limitation because interactions between BRT vehicles and private transport vehicles at junctions are not simulated.

- Assume that private vehicle volumes entering all junctions from all approaches (including the study corridor and intersected streets) are changed proportionally to changes in the total private transport demand for the simulated segment. These values are changed in the 'Vehicle Inputs' object in the VISSIM simulation.

- For each private vehicle type, the proportion of vehicles going straight, turning right and turning left from one approach to each junction are assumed to be identical to the existing situation.

For the proposed options with Scenario 1 in Table 8-5, all existing bus lines are removed in the VISSIM model, only motorcycle and car share mixed lanes.

For the proposed options with Scenario 2 in Table 8-5, there are the following assumptions in the VISSIM simulation models.

- Nine existing bus services running on segments of the corridor are still operated. Assume that departure times and frequency of buses are fixed and identical to the existing situation.

- Assume that boarding passengers and bus occupancy at all bus stops are proportional to total bus demand for the whole corridor whilst alighting rates at all bus stops are unchanged. For example, the ratio of new bus demand to the existing bus demand is equal to 0.87. The value of 0.87 is used to calculate boarding passengers and occupancy for the nine remaining bus services at all bus stops, compared to values for the existing situation.

8.3.8 Procedure in Python

The comparative economic assessment is integrated from the social cost model, microscopic simulation model, incremental elasticity analysis and incremental multinomial/nested logit model. The social cost model is developed in Microsoft Excel and MATLAB by using a range of equations. The incremental demand models are run based on a number of equations. The microscopic simulation models for the off-peak and peak period are built in the VISSIM package. However, there may be several iterations of the completed assessment to achieve the convergence. Moreover, there are twelve proposed options are considered for this study. Therefore, Python program is chosen to run the completed assessment because of four main reasons: (i) The Python program can access and control the VISSIM simulations externally and automatically, and (ii) The Python program can run all equations for the social cost model and incremental demand models, (iii) There is a loop function in Python and (iv) All performance indicators can be shown in outputs of the Python program.

8.4 Comparative Results of Twelve Proposed Options

The comparative economic assessment is run for each option and each period. Normally, the process requires from two to eight iterations to achieve the convergence. The existing situation is compared with all options in terms of ASC, modal share of PT and total demand to analyse the feasibility of each option and choose the best option. These comparative results are shown below. The calculation example for the completed assessment is shown in Appendix C.2.

8.4.1 Modal shares

This subsection covers the comparisons of modal shares and shifts for the options with and without the congestion charge while comparisons of the total demands for all options are shown in the next subsection. Figure 8-7 and Figure 8-8 describe the modal shares for the Metro options.

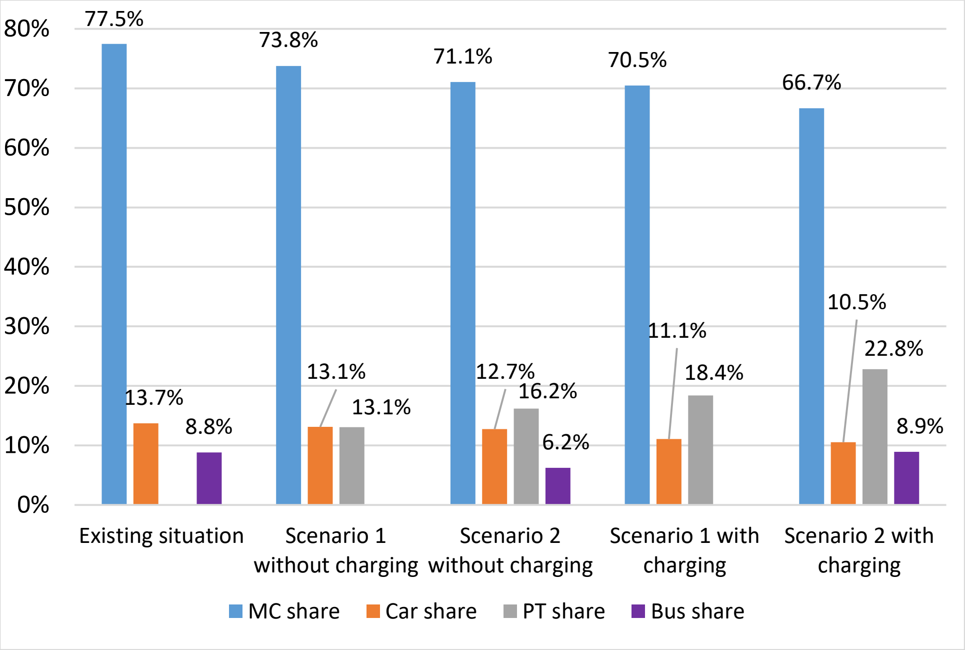


Figure 8-7 Modal shares in the peak period for the Metro options for both Scenarios with and without the congestion charge scheme

Figure 8-7 shows that significant shifts from private transport to public transport occur in both scenarios with the congestion charge where PT shares increase more than twice in the peak period. For example, the PT share for the Metro option for Scenario 2 with charging rises from 8.8% to 22.8%. This can prove the attractiveness of the new PT mode due to its better performance and the congestion charge scheme, compared to the existing conventional bus. These shifts are mainly from motorcyclists because of the following reasons: (i) the existing motorcycle is dominant, which is around 77% of the total demand and (ii) differences between changes in motorcycle and car utilities are small because car and motorcycle travel times are very similar in the mixed traffic environment. The similar trend of modal share for the BRT and Monorail options are shown in Appendix C.4.

For both scenarios without the congestion charge, there is a modest shift from private transport to public transport with increases in PT share by 4 - 8 percentage points. Although these numbers are smaller than those values for the options with charging, this might still prove that the introduction of the new PT attracts more passengers compared to the existing situation.

Compared to the Metro options with Scenario 1, the PT shares for the options with Scenario 2 are higher because both the Metro service and the remaining bus service are competitive with private transport including motorcycle and car. However, the interchange between bus and Metro cannot be determined in this thesis because of the main following reason. Nine existing bus services running on the partial corridor are still operated while four existing bus services running on the whole corridor are replaced by the Metro service. It seems to be difficult to determine existing bus users of the four replaced bus services will still use buses or shift to use Metro.

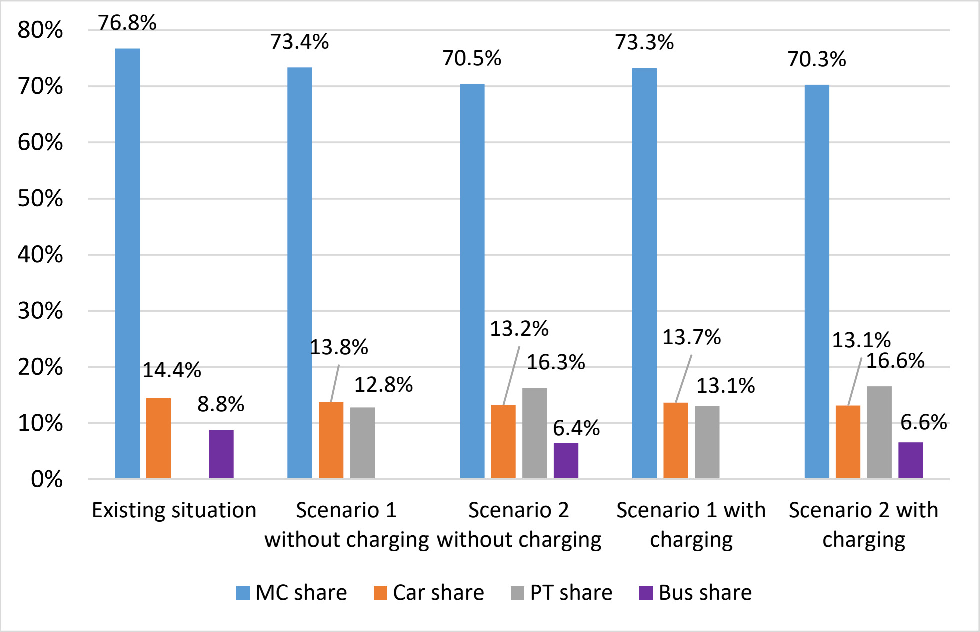


Figure 8-8 Modal shares in the off-peak period for the Metro options for both Scenarios with and without the congestion charge scheme

As can be seen from Figure 8-8, there is a modest shift from private transport to public transport for both scenarios with and without the congestion charge scheme. The increases in the PT share range between 4 per cent and 8 per cent. In addition, the modal shares for the options with and without the congestion charge scheme are very similar for the off-peak period because the congestion charge for private transport in the off-peak period is very minor compared with the charge in the peak period.

8.4.2 Analysis of feasible and best options

In order to analyse the feasibility of new PT technologies and identify the most cost-effective mixed transport system, the ASC, total daily demand and PT share of all infrastructure options are produced and then shown in Figure 8-9.

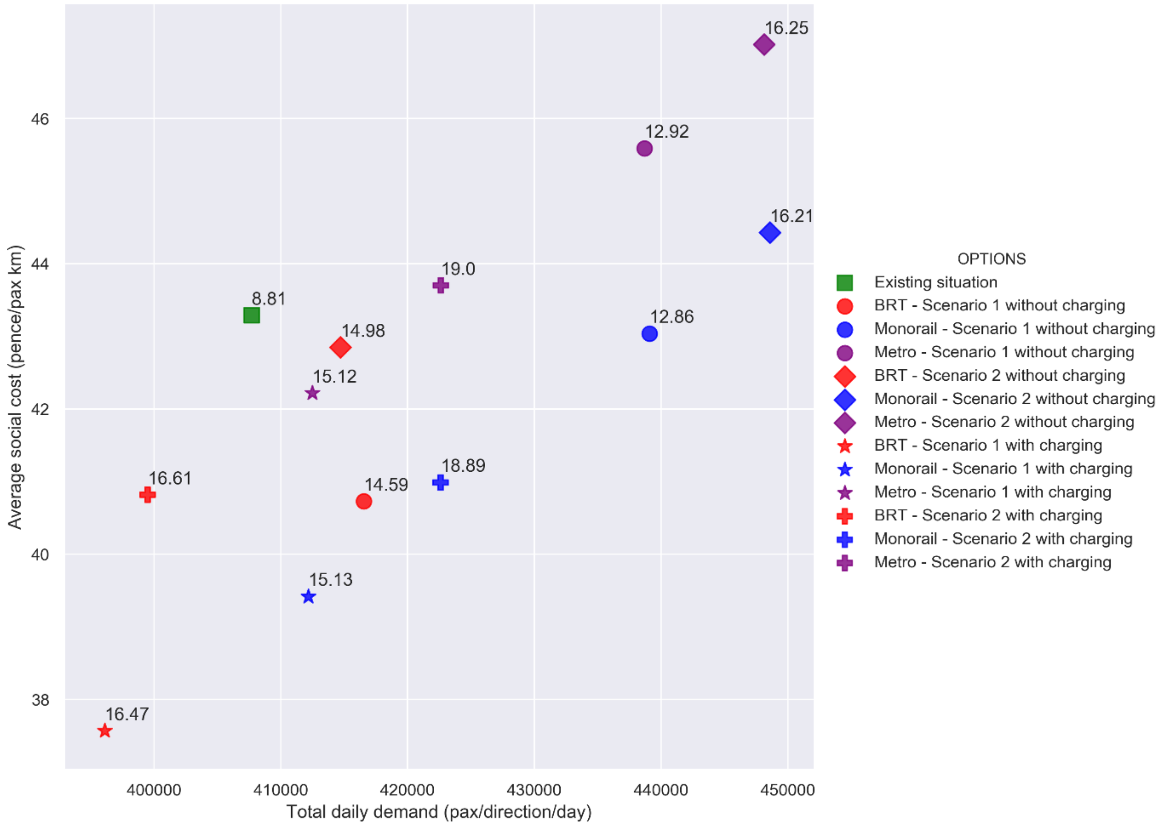


Figure 8-9 ASCs, total daily demand and PT share of twelve infrastructure options, a discount rate of 12%, 2015 prices

Notes for Figure 8-9:

- One marker presenting for one option is plotted based on the total daily demand and the ASC of the option while a label number above the marker shows the PT share for this option.
- The BRT, Monorail and Metro options are shown in red, blue and purple markers respectively.
- Circle markers show options of Scenario 1 without the congestion charge scheme.
- Diamond markers show options of Scenario 2 without the congestion charge scheme.
- Star markers show options of Scenario 1 with the congestion charge scheme.
- Plus markers show options of Scenario 2 with the congestion charge scheme.

As can be seen from Figure 8-9, there are the following findings.

- Two comparisons among the options of the three new PT modes are shown below. Firstly, the ASCs of the BRT options are the smallest whilst the elevated Metro options have the greatest ASCs. This can be explained that the introduction of Monorail or elevated Metro attracts approximately between 45,000 pdd and 70,000 pdd respectively, which are much lower than their infrastructure capacity of around 255,000 for Monorail and 512,000 pdd for Metro. Therefore, the ASCs of the Metro and Monorail options are still great, especially the Metro options with the highest operator costs. By contrast, the daily BRT demands for all options are around half of the BRT capacity, which is 109,000 pdd. Secondly, the total demands of the corridor after the introduction of Monorail or elevated Metro are similar but higher than those numbers for the BRT options. The main reason is that a median mixed traffic lane is converted to be a dedicated BRT lane per direction while private transport users have more spaces in the same current number of mixed traffic lanes when the existing bus is partially or completely replaced by Metro or Monorail. To summary, the Monorail or elevated Metro demands are considerably lower than their infrastructure capacity although the frequency of the new PT mode reaches the infrastructure capacity. Hence, a sensitivity test with respect to the Alternative Specific Constant of all transport modes must be conducted for further work because the ASCs of new PT modes are smaller than those numbers for private transport. The reason is that the utility functions are adapted from the surveys in the study by Bray and Holyoak (2015) that were carried out in 2014 when the performance of only PT mode (bus) seemed to be quite poor. Furthermore, a crowding function can be included in further work in order to evaluate the attractiveness of Metro. Another limitation is that external factors (e.g. land-use changes) are not considered in this thesis.

- Two comparisons between Scenario 1 with circle and star markers and Scenario 2 with diamond and plus markers are drawn. First, the ASCs of the options with Scenario 2 are higher than those numbers of the options with Scenario 1. Compared to the options with Scenario 1, the PT shares for the options with Scenario 2 are higher but the new PT demand is smaller because the partial existing bus services still share the facility with private transport. The smaller new PT mode demand can cause the higher ASCs due to the high operator costs of the new PT mode. Second, the total demands for the corridor for Scenario 2 are greater than those numbers for Scenario 1. The exception is the BRT option without the congestion charge scheme. This can prove that operating both new segregated PT mode and existing bus service can be more competitive and attractive than private transport.

- Both the total demand for the corridor and the ASCs of the options with the congestion charge scheme are smaller than those values for the options without the congestion charge scheme. For the comparison of the total demand, the congestion charges lead to dramatic decreases in car and motorcycle demand, as well as significant shifts from private transport to public transport. For example, the PT share for the Monorail option with the congestion charge is around 18.9%, compared to 8.8% for the existing situation. Compared to the options without the congestion charge scheme, the higher PT demand and the smaller private transport demand for the options with the congestion charge scheme result in the lower ASCs. To summary, the congestion charge scheme leads to lower ASCs and higher PT share for all options. This charging scheme also causes the higher demand for the Monorail and Metro options. As a result, the transport planners and decision makers should consider the congestion charge scheme for the local conditions to meet specific objectives such as a reduction in ASCs and an increase in modal share of PT. Moreover, those people might introduce internalised environment costs as well as the congestion charge to attract more Metro or Monorail passengers to avoid wasteful investments.

- When decision makers set the ASC, total demand and PT share as the multi-criteria for analysing the feasibility of each option, one feasible option has smaller ASC, higher total demand and higher PT share compared to the existing situation. Therefore, six options including the Monorail options for Scenario 1 with and without charging, the Monorail option for Scenario 2 with charging, the BRT options without charging for Scenario 1 and Scenario 2, the Metro option for Scenario 1 with charging are feasible. Among these six options, decision makers can select the Monorail option for Scenario 2 with charging because this option has always two advantages in three criteria compared to the other options.

- To compare with the existing situation in terms of ASC, eight options including the Monorail options for Scenario 1 with and without charging, the Monorail option for Scenario 2 with charging, the Metro option for Scenario 1 with charging and all four BRT options are better. Interestingly, five of six options with charging are feasible except the Metro option for Scenario 2 with charging. Among these eight feasible options, the BRT option for Scenario 1 with charging has the smallest ASC of 37.57 pence/pax-km. However, the total demand for this option decreases by around 12,000 pdd, compared to the existing situation. This decrease is caused by the congestion charging scheme. To conclude, the BRT option for Scenario 1 with charging is the best of the options considered in the comparative economic assessment of this study. The detailed results of comparisons between this option and the existing situation are shown in section 8.6.

8.5 Sensitivity Test with respect to Value of Time of PT Users

A sensitivity test with respect to the value of in-vehicle time for new PT technologies is implemented because of the following reasons. Firstly, the user costs account for a main portion of the total social cost. This is also discussed in subsection 5.5.5.4 shown in Chapter 5. Secondly, the VoT can impact on results of the incremental demand models due to change in the utility. Thirdly, the VoT for the Hanoi case study is adapted from the study by Bray and Holyoak (2015). The surveys in that study were carried out at the time when no new PT mode was operated. Fourthly, after the introduction of a new PT technology, this new mode can provide better comfort, safety and service reliability etc. This will be reflected in lower IVT parameter in the utility functions. Hence, the reduced VoT should only be in the after situation whilst the increased VoT is not considered. The baseline estimate of the value of in-vehicle time for new PT (in 2015 prices) is shown in Table 5-8 and alternative value is equal to 50% of the baseline value. The alternative value for PT users is therefore smaller than the VoT for cars. That is why a factor of 25%, which is suggested by the Department for Transport (2017b), is not used for this study. It is assumed that PT fares are unchanged, the coefficients of travel time in the PT utility functions decrease by 50%. Furthermore, the coefficients in the utilities for car and motorcycle remained unchanged but the values of car and motorcycle utilities still vary due to changes in travel time and fuel cost. Figure 8-10 and Figure 8-11 show changes in the mean PT utilities and probabilities for twelve options after conducting this sensitivity test for the off-peak and peak periods respectively. In general, the changes in mean PT utilities and probabilities are similar. Additionally, these two parameters appear to slightly sensitive respect to the value of time for new PT users.

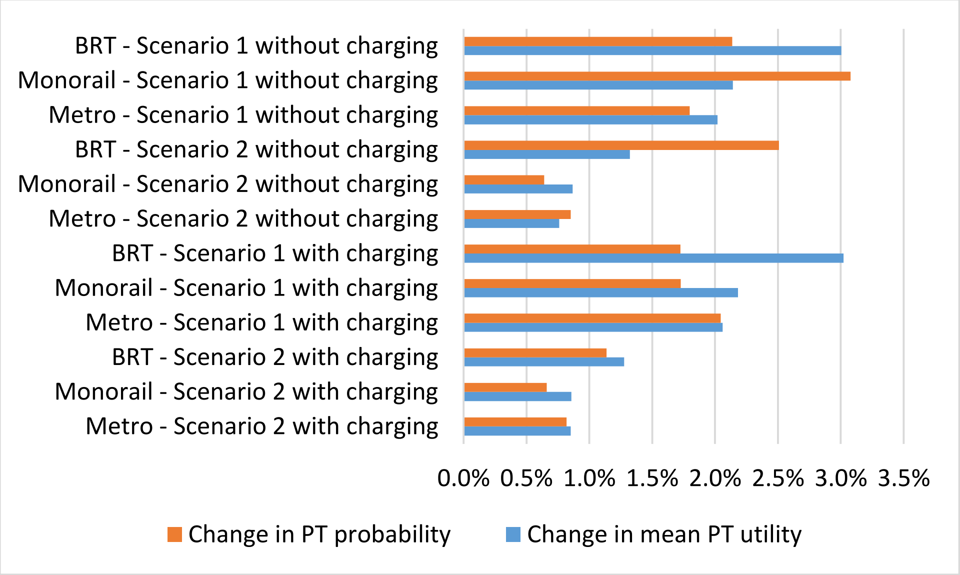


Figure 8-10 Changes in mean PT utilities and probabilities for different options for the peak period after the sensitivity test

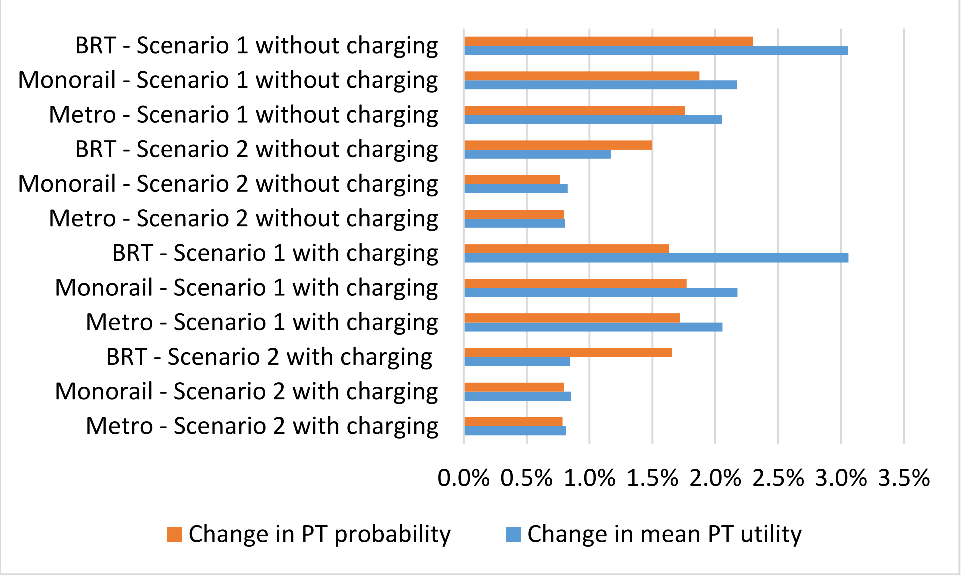


Figure 8-11 Changes in mean PT utilities and probabilities for different options for the off-peak period after the sensitivity test

Figure 8-12 shows changes in the total daily demand and PT share for different options when the value of time for new PT users reduced by 50%, compared to the base values. Figure 8-13 illustrates changes in the ASC for all options.

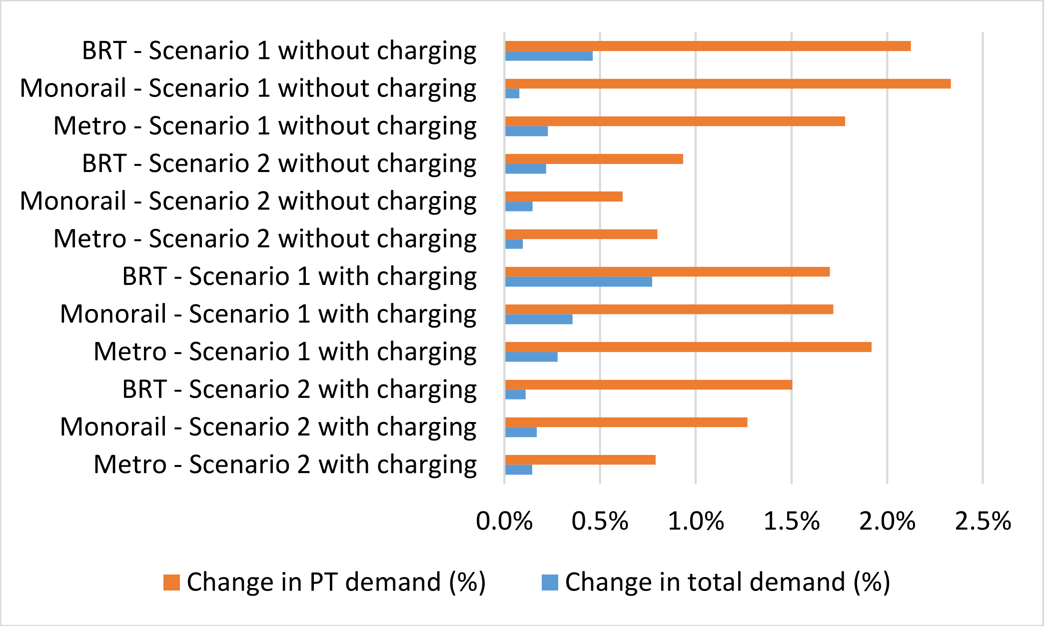


Figure 8-12 Changes in total demand and PT share for different options when the value of time for new PT users reduced by 50%, compared to those values with the base VoT

As can be seen from Figure 8-12, the total demand of all modes and PT share seem to be insensitive with respect to the value of time for new PT users. The increases in the total demand for all twelve options are very small ranging from 0.1% to 0.8% while the changes in PT share ranges between 0.7% and 2.4%.

Figure 8-13 shows that the ASCs of twelve options appear to be slightly sensitive with respect to the value of time for new PT users because the decreases in the ASC of twelve options range from 2% to 5% when the new PT users’ value of time declined by 50%. Compared to the changes in the total demand and PT share, the changes in the ASC of the twelve options are higher. The reason can be that the total new PT user costs account for between around 30% and 50% of the total new PT social costs at forecasted demand after the introduction of the new PT mode. Additionally, at forecasted demands, the IVT costs for Monorail and Metro account for around 20% of the total user costs while this number for BRT is about 30%. However, the new PT share of between approximately 12% and 17% for all options cannot make the ASC be sensitive with respect to the value of time for new PT users.

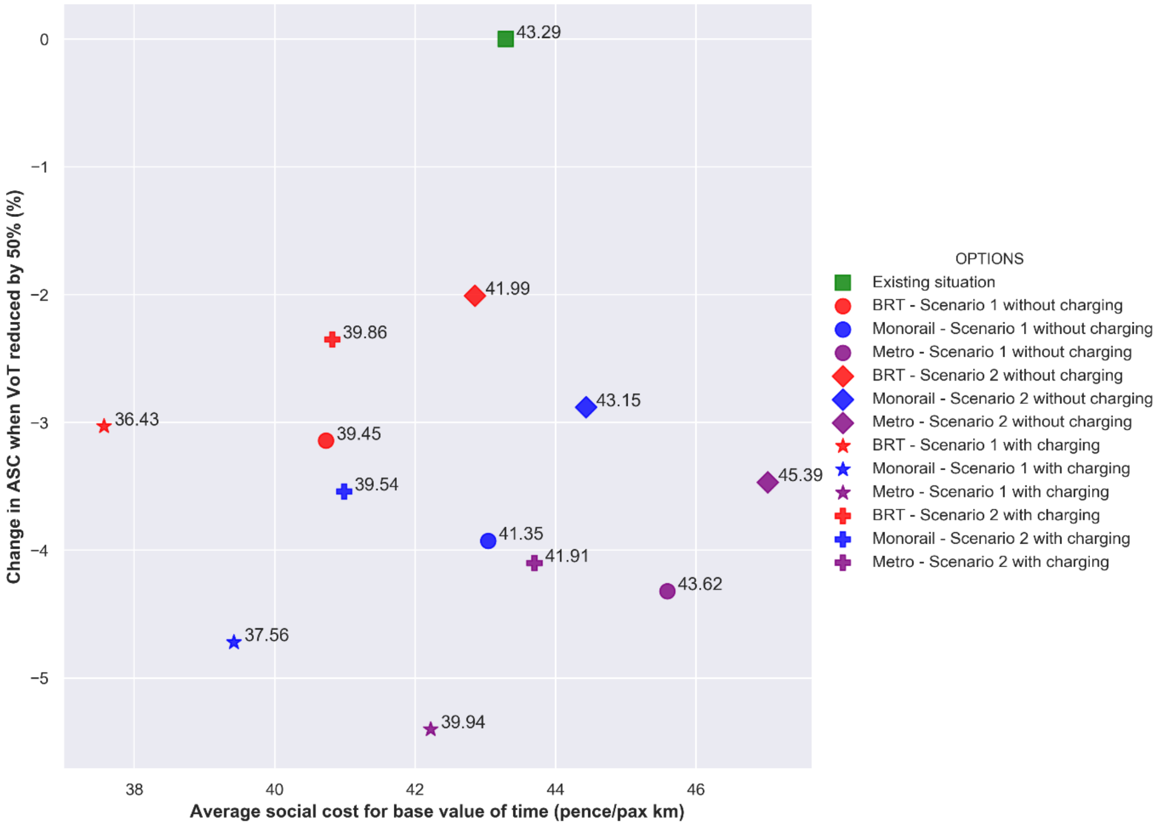


Figure 8-13 Changes in the average social cost for different options when the value of time for new PT users reduced by 50%, compared to the ASCs with the base VoT

Notes:

- One marker presenting for one option is plotted based on the change in the ASC when the VoT reduced by 50% and the ASC of this option with the base VoT while a label number above the marker shows the ASC of this option when the VoT reduced by 50%.
- The BRT, Monorail and Metro options are shown in red, blue and purple markers respectively.
- Circle markers show options of Scenario 1 without the congestion charge scheme.
- Diamond markers show options of Scenario 2 without the congestion charge scheme.
- Star markers show options of Scenario 1 with the congestion charge scheme.
- Plus markers show options of Scenario 2 with the congestion charge scheme.

However, the comparison of the ASC between one proposed option and the existing situation might be sensitive with respect to the value of time for new PT users. Two of four options, of which their ASCs are higher than the ASC of the existing situation, become to have smaller ASCs when the new PT users' value of time reduced by 50%. In other words, these two options, which are the Monorail for Scenario 2 without the congestion charge scheme and the Metro for Scenario 2 with the congestion charge scheme, are feasible in terms of ASC. In addition, the BRT option for Scenario 1 with the congestion charge scheme is still the best option when the new PT users' value of time reduced by 50%. To summary, for an analysis of the feasibility of one option on a given corridor, the sensitivity test with respect to new PT users' value of time should be taken into account.

8.6 Detailed Results of the Best Option

This section describes the results of comparisons between the best option and the existing situation. The best option mentioned in section 8.4 is the BRT option for Scenario 1 with the congestion charge scheme. For this option, all existing bus services running on the study corridor are replaced by the BRT service and one existing mixed traffic lane is converted into an exclusive BRT lane per direction.

8.6.1 Performance indicators

The performance indicators of the existing situation are obtained from the mixed transport social cost models. After running the comparative economic assessment, the performance indicators of the best option are achieved from the social cost model and incremental demand models. Table 8-6 shows the performance indicators of the best option and the existing situation.

Table 8-6 Results for performance indicators

Performance indicators	Existing situation	The best option	Change (%)
Total daily demand (pdd)	407,700	396,115	-2.84%
Motorcycle demand (pdd)	315,846	281,562	-10.85%
Car demand (pdd)	55,936	49,312	-11.84%
Bus demand (pdd)	35,918		81.64%
BRT demand (pdd)		65,241	
Modal share of PT (%)	8.81	16.47	86.95%
Average speed of car and motorcycle in the peak period, 5-6 PM (km/h)	9.69	12.55	29.51%
Average speed of car and motorcycle in off peak period, 7-8 PM (km/h)	23.47	23.79	1.36%
Average operating speed of bus in peak period, 5-6 PM (km/h)	8.24		306.31%
Average operating speed of BRT in peak period, 5-6 PM (km/h)		33.48	
Average operating speed of bus in off-peak period, 7-8 PM (km/h)	16.58		101.93%
Average operating speed of BRT in off-peak period, 7-8 PM (km/h)		33.48	

Notes: Speeds are obtained from the social cost models. Speeds of car and motorcycle in mixed traffic are assumed to be the same.

Compared to the existing situation, the total daily demand of the best option decreases by 2.84% while the demand for private transport reduces by around 11%. The reductions are caused by the congestion charging and a shift from private transport to public transport. On the contrary, there is a significant rise of about 82% in PT demand. Moreover, the speeds of all private transport vehicles increase considerably in the peak period due to reductions in private transport demand and the replacement of existing bus services. In addition, the speed of BRT is around four times greater than the speed of the existing bus because the BRT vehicles run on the exclusive lane while existing bus vehicles share facilities with motorcycles and cars. Therefore, the BRT system attracts more existing bus users and private transport users - mainly motorcyclists to reach 65,241 pdd, over half of the BRT capacity. The BRT demand could be higher if the attractions of BRT are taken into account in the VISSIM models. For example, motorcycles and cars are not affected by the priority of BRT at intersections in the VISSIM models in this research.

8.6.2 Costs

Table 8-7 describes the results of cost indicators for both the best option and the existing situation.

Table 8-7 Results of cost indicator, 2015 prices

Cost indicators, 2015 prices	Existing situation	The best option	Change (%)
Total social costs (£/year)	368,507,631	310,718,882	-15.68%
Average social cost (p/pax-km)	43.29	37.57	-13.21%
Average generalised time cost for motorcycle (p/pax-km)	20.03	18.78	-6.24%
Average generalised time cost for car (p/pax-km)	11.69	10.96	-6.24%
Average generalised time cost for bus (p/pax-km)	37.38		-56.71%
Average generalised time cost for BRT (p/pax-km)		16.18	

Notes: Generalised time costs for PT include in-vehicle time, walk time and wait time while those costs for PRV include only travel time.

Compared to the existing situation, the total social costs and average social cost per passenger-km of the best option decrease modestly by about 16% and 13% respectively. The main reasons can be explained as (i) the BRT services attract more existing bus users and private transport users to reach over half of the BRT capacity; (ii) compared to the current situation, the speeds of mixed traffic and BRT increases in the best option, particularly a significant rise in the speed of BRT in the peak period, and (iii) one existing mixed traffic lane is converted into one exclusive BRT lane per direction, therefore infrastructure costs of the BRT option are not high, especially much lower than those costs of the Monorail and elevated Metro options. These mean that the approximate doubling of bus demand leads to a dramatic decrease in the ASCs of PT users while the ASCs of private transport users reduce slightly. Moreover, the changes in speed imply that the average generalised time cost for PT users decreases dramatically whilst there are minor reductions in the average generalised time cost for car and motorcycle users.

8.6.3 Summary

When the BRT service is introduced on the Nguyen Trai – Tran Phu – Quang Trung corridor to replace all existing bus services, in conjunction with charging for private transport, there are several significant improvements in performance and cost. The total social costs and average social cost decrease by approximately 16% and 13% respectively while the total daily demand reduces from 407,700 pdd to 396,115 pdd. In particular, the daily PT demand nearly doubles from 35,918 to 65,241 passengers. Additionally, the average generalised time cost for private transport users reduces by around 6% whilst there is a great decline of about 57% in the average generalised time cost for PT users. These enhancements might be improved if the BRT service provides better comfort, safety and service reliability etc. This will be reflected in a lower value of in-vehicle time and/or a higher alternative specific constant (or preference) in the utility function of BRT. In addition, the Mode Specific Factor, which represents these attributes, can be expressed in minutes of equivalent in-vehicle travel time (Currie, 2005). In other words, these attributes can be estimated as equivalent to an in-vehicle travel time reduction.

8.7 Conclusion

In conjunction with an introduction of a new PT mode on an urban corridor, a congestion charge scheme for private transport is suggested. The congestion charges for car and motorcycle are estimated based on collected data on the study corridor and the VISSIM simulation models. Due to the higher value of time and dominance in mixed traffic, the estimated MCCs for motorcycles are higher than those numbers for cars. However, the congestion charge for cars can be suggested for both private transport modes for the Hanoi case study to ensure that the congestion charge cannot be a regressive tax on middle- and low-income people, because these people are a majority of the population and mostly use motorcycles in Hanoi. Furthermore, although the MCC for the off-peak period, which is minor, should be implemented to encourage people to use PT and avoid private transport users shifting considerably from the peak period to the off-peak period. Hence, the MCCs of £0.114/vehicle-km and £0.005/vehicle-km are suggested for charging private transport users in the peak and off-peak periods correspondingly.

The three new PT modes including BRT, Monorail and Elevated Metro are considered in the comparative economic assessment, as well as a congestion charge scheme. Replacing all or partial existing bus services with a new PT technology are defined as two alternatives. Hence, twelve options shown in Table 8-5 are proposed on the study corridor in Hanoi to improve the performance of the existing situation. All options are compared in terms of ASC, modal share of PT and total daily demand. The results imply following general findings.

For the comparisons between new PT modes, the ASCs of the BRT options are smallest whilst the elevated Metro options have the greatest ASCs due to high operator costs. The demands for Monorail or elevated Metro reach between around 15% - 25% of their infrastructure capacity. On the contrary, the number of BRT passengers is about half of the BRT capacity. In addition, the capital infrastructure costs of BRT is much lower than those costs of Monorail or Metro because one existing mixed traffic lane is converted to one exclusive BRT lane per direction. If Monorail or Metro are invested in an urban corridor, these technologies need to attract a large number of passengers to reduce the ASCs. Transport planners and decision makers should suggest transport policies in conjunction with the introduction of the new PT. This is implied by the results of options with the congestion charge scheme because this scheme leads to lower ASCs and higher PT share for all options.

Compared to the options replacing all existing bus services, the options replacing the partial existing bus services have higher total daily demand and higher PT share but higher ASCs. However, replacing the whole or partial existing bus service must be considered based on the local bus regulation or deregulation. Additionally, it is necessary to take into account the whole transport networks and bus networks because the replaced bus services should become feeder systems transport passengers to new PT stations/stops.

A sensitivity test with respect to the value of in-vehicle time for new PT technologies is conducted in a situation where the alternative value is equal to 50% of the baseline value. The total demand of all modes and PT share seem to be insensitive with respect to the value of time for new PT users while the ASCs of twelve options appear to be slightly sensitive because changes in ASCs range between 2% and 5%. In addition, the comparison of the ASCs between one proposed option and the existing situation might be sensitive with respect to the value of time for new PT users because two of four options are reversed to become smaller ASCs when the new PT users' value of time reduced by 50%. Hence, it is recommended to conduct the sensitivity test with respect to the value of time for new PT modes for analysing the feasibility of proposed infrastructure options. However, the BRT option for Scenario 1 with the congestion charge scheme is still the best option in terms of ASC when the new PT users' value of time reduced by 50%.

The detailed results of the best option show several significant improvements in performance and cost when the BRT service is operated on the Nguyen Trai – Tran Phu – Quang Trung corridor to replace all existing bus services and the charging scheme is introduced. Compared to the existing situation, the total social cost and average social costs decrease by 16% and 13% respectively while PT demand nearly doubles. In addition, there are a modest reduction of 6% in the average generalised time cost for private transport users while the average generalised time cost for PT users decreases by 57%. However, the total daily demand reduces from 407,700 pdd to 396,115 pdd due to reductions in private transport users caused by the charging.

Chapter 9 Conclusion

9.1 Overview

Currently, several PT projects (e.g. BRT, Metro and Monorail) have been invested in urban mixed traffic environments in low- and middle-income countries in which motorcycles are dominant. The following two questions need to be addressed. Firstly, does improving PT lead to improvements in system efficiency given motorcycle dominance? Secondly, how is the best PT technology found among several feasible options in terms of given criteria such as average cost per passenger, modal share of public transport or increases in total general demand? However, there seems to be very little evidence on evaluation methods to answer these questions. CBA is one of the most popular approaches for assessing transport projects in LMICs (Asian Development Bank, 2017). However, CBA cannot be suitable in a mixed traffic situation where several new PT technologies modes are introduced because the analysis needs to cover a range of modes such as bus, car, motorcycle, BRT, Monorail and Metro. Moreover, the 'rule of half' in CBA might not be appropriate for modal shifts among these transport modes (Asian Development Bank, 2013). Hence, this study develops a methodology of a comprehensive comparative economic assessment to fill these research gaps. The comparative economic assessment is integrated from four models: the social cost model, the incremental elasticity analysis, the incremental multinomial/nested logit model and the microscopic simulation model, which is shown in Figure 1-2.

The next part of this chapter summarises the main activities compared with the aims and objectives of this study, which was set in the first chapter. Moreover, the findings of this research are drawn. The third part of the chapter explains the contribution of the study. The final part notes the limitations of this research and then illustrates the potential future work.

9.2 Research Summary

To answer the research questions above, the main aims of the comparative economic assessment are to (i) Analyse the feasibility of new public transport technologies in the mixed traffic environment with an abundance of motorcycles and (ii) Identify the most cost-effective mixed transport system where transport modes share infrastructure facilities in terms of given criteria. The main activities of this research have been reported in Chapter 2 - Chapter 8. The literature review of transport supply and demand are shown in Chapter 2 and Chapter 3 respectively. Chapter 4 describes the methodological framework of this study. The social cost model is developed in Chapter 5. Chapter 6 illustrates the traffic microscopic simulation model based on the VISSIM package. The incremental demand model is demonstrated in Chapter 7. The comparative economic assessment is applied to the Hanoi case study, which is shown in Chapter 8.

9.2.1 Research tasks

To determine the main achievements of this study, the research objectives, which were set in Chapter 1, are evaluated with the tasks completed during this research.

9.2.1.1 Research objective 1

Assess social costs including operator costs, user costs and external costs of the fixed-line PT technologies, private transport, DRT and mixed transport for different user demand levels.

1) The social cost models are developed for an urban corridor for fixed daily passenger demand ranging from 1,000 pdd to 700,000 pdd. The total social costs include the total operator costs (or infrastructure operator costs for PRV), total user costs (or vehicle user costs for PRV) and total external costs. For all modes, the total external costs include accident cost, noise pollution cost, air pollution cost and climate change cost. Elements of total operator costs and total user costs are different for dissimilar modes. Firstly, the operator costs of the PT service, which include both operating cost and capital investment cost, are assigned to variables in the Fully Allocated Costs model. These variables cover Vehicle-Hours, Vehicle-Distance and Peak Vehicle, Track/Lane Distance, number of Stops/Stations and number of Depots. The PT user costs cover walking time, waiting time and in-vehicle time. Secondly, the infrastructure operator costs for PRV cover infrastructure costs, maintenance costs and parking costs. The vehicle user costs for PRV consists of operating costs for users, private vehicle capital costs, travel time and congested-related delay costs. Thirdly, the Taxi/Uber operator costs cover capital cost; non-fuel operating cost; fuel cost; administrative cost; infrastructure costs and highway maintenance cost; and driver earnings. The Taxi/Uber user costs cover in-vehicle time and waiting time.

2) The public transport, private transport and demand responsive transit social cost models are considered in a situation where only one transport mode uses infrastructure facility. To calculate the costs in these models, the intermediate outputs are estimated in the first place. For the PT social cost model, these intermediate outputs are operating speed, Vehicle-Kilometres, Peak Vehicle Requirement, Vehicle-Hours, Track/Lane Distance, number of Stations/Stops, number of Depots, Passenger-Kilometres. For the PRV and Taxi/Uber social cost models, the key intermediate output is operating speed.

3) The mixed transport social cost model is developed in a situation where several modes share facilities in mixed transport systems with a dominance of motorcycles. The total social costs for

mixed transport include the total social costs for PT, PRV and Taxi/Uber, except the infrastructure costs. The infrastructure costs consist of the infrastructure costs of an exclusive PT mode (e.g. Metro and Monorail) and the infrastructure costs of mixed lane facilities. The infrastructure costs of mixed lane facilities are allocated to modes sharing infrastructure facilities based on the study by Sansom *et al.* (2001). Furthermore, the flow-speed relationship is improved by using the Lambert W function to determine the average speed of mixed traffic corresponding to a given traffic flow.

4) The four social cost models are applied to the Nguyen Trai – Tran Phu – Quang Trung corridor in Hanoi by using all basic parameters and unit costs. These models identify the most cost-effective transport mode with respect to different passenger demand levels at a strategic planning level, in terms of ASC.

9.2.1.2 Research objective 2

Develop traffic simulation models of mixed transport with a dominance of motorcycles to present their interactions and congestion effects in an existing mixed traffic environment. These models can evaluate the performance of each transport mode such as vehicle travel time.

1) Microscopic Simulation Models were developed to represent an existing mixed traffic environment, and therefore evaluate the performance of each transport mode. Among several microscopic traffic simulation, the VISSIM package is chosen to simulate a mixed transport network with a dominance of motorcycles. As the comparative economic assessment is applied to the NT-TP-QT corridor, all required data were collected on this corridor. The required data include traffic volume data at junctions, data on bus, data on signals at junctions, infrastructure geometry, motorcycle acceleration and vehicle travel time. As a result, the VISSIM simulation models were built for the off-peak and peak periods separately. The local acceleration of motorcycle was analysed and inserted directly in VISSIM because the default value of acceleration is for typical motorcycles used in Europe.

2) Model calibration and validation were implemented to prove that VISSIM simulation model results are sufficiently reliable to represent the real mixed traffic network. The nine-step procedure by Park and Schneeberger (2003) is used for the calibration and validation process with a different set of data. The travel time of motorcycle, car and bus are selected as key performance indicators for this process. The independent two-tailed Student's t-test and the Kolmogorov-Smirnov are performed to test the reliability of the VISSIM simulation model. The first test examines means of vehicle travel times while the second one tests distributions of vehicle travel times.

3) Traffic volumes might increase or decrease according to any change to the existing transport condition such as an introduction of a new PT mode and/or a transport policy. By inputting new

traffic volumes in the VISSIM transport network, the simulation model can evaluate the new performance of each transport mode in the network. This helps the VISSIM simulation model to integrate the incremental demand models in the comparative economic assessment.

9.2.1.3 Research objective 3

Develop transport demand models to evaluate changes in total demand for each transport mode and all transport modes after the introduction of a new PT mode and/or a transport policy in an existing mixed traffic environment. These models can find out how the performance of the PT system and the transport policy might affect level of service of each transport modes, and therefore the total user demand levels.

1) When a new PT mode and/or a transport policy are introduced on an existing mixed traffic corridor, incremental demand models are developed to predict changes in demand of each transport mode such as bus, car and motorcycle. The incremental logit models were developed to estimate probabilities of choosing a new PT and each existing mode while the incremental elasticity analysis forecasted endogenous changes in the total demand by using the demand elasticity with respect to a logsum. If the new PT technology replaces all bus services running on the partial and whole corridor, the incremental multinomial logit model is used. When the new PT mode replaces only bus services running on the whole corridor and the existing bus services running on segments of the corridor are still operated, the incremental nested logit model is used.

2) These incremental demand models are applied to the Hanoi case study. As the main component of these models, the utilities of motorcycle, car, bus and new PT modes were determined. The coefficients in the utility functions were calculated based on the study of Bray and Holyoak (2015). The components of the utility, which consist of in-vehicle time, walking time, waiting time and fuel cost, are estimated from the social cost models and VISSIM simulation models.

9.2.1.4 Research objective 4

Integrate the social cost model, microscopic simulation model and demand models into the comparative economic assessment. Apply this assessment to a case study in Hanoi, Vietnam where a new PT mode and/or a transport policy are introduced. This application might demonstrate the usefulness of the comparative economic assessment in analysing the feasibility of a new PT technology and determining the most cost-effective mixed transport system.

1) After developing the social cost model, the VISSIM simulation model, incremental elasticity analysis and incremental logit model, these models are integrated into the comparative economic assessment. In-vehicle time, wait time and speed of the PT mode obtained from the social cost

model and travel time and speed of motorcycle, car and bus achieved from the VISSIM simulation models are inputs for the incremental elasticity analysis and incremental logit models. The new demand for each transport mode obtained from the incremental demand models is input for the social cost model and VISSIM simulation model.

2) The comparative economic assessment was applied on the chosen corridor in Hanoi to compare the existing mixed transport situation and twelve transport infrastructure options with an introduction of new PT technologies (Bus Rapid Transit, elevated Metro and Monorail) replacing the whole or partial existing bus services; and with or without a congestion charge scheme for PRV, in terms of ASC, total general demand and PT share.

3) Comparative results of the assessment were given to analyse the feasibility of each option and identify the best option in terms of ASC. Eight of twelve options are feasible and the BRT option with a congestion charge scheme, where all existing bus services are replaced by BRT, is the best alternative for the Hanoi case study. This proves the usefulness of the completed assessment. The framework of the assessment, which includes the social cost model, incremental logit models, incremental elasticity analysis and traffic simulation model, might be transferred to other cities. The defaults parameters in these models can be able to be modified to suit other local conditions while data on traffic volumes, infrastructure and signalised control in the traffic simulation need to be updated for those contexts.

4) An alternative to the methodology of this study is to run a four-stage transport model and a CBA, which is one popular approach for assessing transport projects in developing countries funded by the World Bank and Asian Development Bank (World Bank, 2015a; Asian Development Bank, 2017). Compared to this macro-level working procedure, the comparative economic assessment of this thesis has the following advantages. Firstly, since the four-stage transport model is used to forecast transport demand for the whole network if a new PT mode is introduced, a huge amount of traffic data for the whole network is required to be collected for this model, whilst only traffic data on the study corridor is required in the comparative economic assessment. Secondly, a main issue of the four-stage model is the consistent use of variables affecting demand such as travel time. For example, at the end of the traffic assignment stage, the new traffic volumes are produced and new travel times will be obtained. These might be different from travel times assumed when the distribution and mode choice models were run. Hence, the distribution and modal-split models need to be re-run based now on the new travel times, and can therefore lead to an unstable set of distribution, modal split and assignment models with consistent travel times (Ortuzar and Willumsen, 2011). This problem is overcome in the assessment of the current study because the comparative economic assessment integrating from the social cost model, microscopic simulation

model, incremental elasticity analysis and incremental multinomial/nested logit model is run automatically in Python to achieve a convergence of PT demand after several iterations. Thirdly, as there are several PT modes such as conventional bus, BRT, Monorail and Metro, as well as PRV including car and motorcycle, it seems to be difficult for estimating modal shifts between these modes in the four-stage model whilst the assessment can forecast modal shifts between PT and PRV. However, the assessment has drawbacks that are outlined in subsection 9.4.

9.2.2 Key findings

9.2.2.1 Social cost models for strategic assessment

For homogeneous traffic environments

The PT, PRV and Taxi/Uber social cost models are for use in a strategic assessment of transport modes in a homogeneous traffic environment. Through comparing the ASCs of four PT technologies (bus, BRT, Monorail and elevated Metro); two PRV modes (car and motorcycle); and two DRT modes (Taxi and Uber) for an urban corridor in the Hanoi case study, this study identifies the most cost-effective transport mode with respect to different passenger demand levels at a strategic planning level. Transport planners and decision makers in LMICs can draw the following from the Hanoi case study depending on demand levels.

First, car cannot be the best social option at any demand levels due to the higher ASC. With service quality advantages and great support by technology companies, Uber and Taxi are still expensive and, therefore might not be chosen. The main drawback of these modes is the low occupancy of around 1.57 passengers (Department for Transport, 2017b). To some extent, this supports the policy adopted by some cities to promote car sharing and UberPool to increase the occupancy. “Three-in-one” policy in Jakarta, Indonesia is an example. All private cars on two major roads were required to carry at least three passengers during peak hours in Jakarta. This policy was abandoned in April 2016. However, Hanna, Kreindler and Olken (2017) proved that this policy may improve traffic conditions by showing increases in delays in the peak hours after ending the policy.

Second, motorcycle is cheapest at low demand levels due to small size and flexibility advantages and hence low travel time. This may prove that motorcycle dominates and may be sufficient in many small and medium cities in LMICs. However, conventional bus seems to be an alternative because the ASC of conventional bus is only slightly higher than the ASC of motorcycle. It should be noted that demand is assumed to be fixed. In reality, all other things being equal, we might still expect different modes to have dissimilar level of usage due to different individual preferences and capabilities - in particular not everyone can ride a motorcycle. When demand levels increase, and especially when the capacity of motorcycle infrastructure is exceeded, this mode does not have advantages any more due to a dramatic decrease in speed. Expanding one more motorcycle lane per direction is not as competitive as dedicated bus-based technologies. Conventional bus or BRT are the best modes for a daily demand range of between 35,000 and 220,000 pdd.

Third, for big cities where demand levels are greater, expanding one more exclusive bus lane per direction and rail-based technologies could be compared to choose the cost-effective mode. For example, when the daily demand level is greater than 220,000, bus option with expansion of ROW and Monorail can be two competitive alternatives. For the Hanoi case study, the two bus lanes per direction option might be better. However, at the highest demand level (above around 315,000 pdd), elevated Metro seems the best option, given its high person capacity.

For mixed traffic environments

The mixed transport social cost model is applied for a four-lane (per direction) divided corridor in Hanoi where modal shares of motorcycle, car and bus are 77.47%, 13.72% and 8.81% respectively. By assuming that the new PT mode (BRT, Monorail and elevated Metro) replaces all existing bus and attracts 20% of the existing demand (407,700 pdd), all three options have ASCs than the existing situation. To improve the performance of the existing mixed transport conditions, these potential new PT modes might be considered for analysing their feasibility in a more detailed assessment. However, the assumption that the PT share increases from 8.81% to 20% needs to be considered sensibly by transport planners and decision makers, based on local conditions and their objectives of an investment in a new PT technology.

9.2.2.2 Comparative economic assessment for more detailed assessment

The comparative economic assessment, which is integrated from the social cost model, VISSIM simulation model, incremental elasticity analysis and incremental logit model, can be used for more detailed evaluations of urban transport infrastructure options. This completed assessment is applied to the Nguyen Trai - Tran Phu - Quang Trung corridor in Hanoi, Vietnam. The key findings are listed below. Firstly, a congestion charge scheme, which is introduced in conjunction with a new PT technology, leads to lower ASC and higher modal share of PT share. Secondly, compared to the options replacing all existing bus services, the options replacing partial existing bus services have advantages in terms of total daily demand and PT share but have higher ASCs. Thirdly, for the study corridor with the dominance of motorcycle, the ASCs of the BRT options are the smallest whilst the elevated Metro options have the greatest ASCs due to high operator costs. Lastly, the BRT option with a charging scheme replacing all existing bus service, which is the best option, has several significant improvements in performance and cost, compared to the existing situation. These include smaller total social cost, lower ASC and lower generalised time cost for all users as well as a significant increase in PT demand.

9.3 Contributions

This research not only suggests the key findings but also makes contributions. This study and its results imply the following contributions, especially for LMICs where motorcycles are dominant in mixed transport environments.

9.3.1 Evaluation of urban transport infrastructure options at a strategic planning level

This thesis introduced the social cost models for motorcycle and DRT including Uber and Taxi as well as developed the cost models for car and PT technologies based on the previous studies. Furthermore, the mixed transport social cost model is developed in a situation where several modes share facilities. With optional inputs and the flexibility of the cost function, the social cost models are able to be modified to suit other local conditions where there are conventional bus, car and motorcycle sharing facilities, as well as innovative PT modes. For homogeneous traffic environments, the PT, PRV and Taxi/Uber social cost models can determine the most cost-effective transport mode with respect to different passenger demand levels at a strategic planning level, in terms of ASC. For an existing mixed traffic corridor, potential public transport modes can be suggested to analyse their feasibility in a more detailed assessment by using the mixed transport social cost model. Policy makers might apply the total social cost models to strategically assess urban transport infrastructure options.

9.3.2 More detailed evaluation of urban transport infrastructure options

The VISSIM models are developed to simulate a mixed transport network where small and medium-sized motorcycles are dominant compared with cars and buses. The desired acceleration default value in VISSIM, which is for typical motorcycles used in Europe, should be replaced by local acceleration of motorcycle. Four calibrated parameters in VISSIM were validated on the Hanoi case study. The methodology for developing a microscopic traffic simulation and model calibration and validation can be modified to suit other local mixed traffic conditions with a dominance of small and medium-sized motorcycles.

Overall, the main contribution of this study is to develop the comprehensive methodology of the comparative economic assessment to analyse the feasibility of a new PT mode and/or a congestion charge scheme and identify the best mixed transport system with an abundance of motorcycles, in terms of ASC, modal share of PT and total general traffic. The comparative economic assessment is integrated from the social cost model, VISSIM simulation model, incremental elasticity analysis and incremental logit models. Firstly, the comparative economic assessment evaluates the social costs, including the operator, user and external costs for both private transport and public transport, as well as mixed transport. Secondly, this assessment simulates the interactions between all vehicles in a mixed traffic environment by using the VISSIM simulation models. Thirdly, this assessment forecasts the endogenous growth of the total demand for the corridor and the changes in demand for each transport mode when the existing conditions change. Forth, the assessment is run through the interface between VISSIM and Python. The methodology of the comparative economic assessment can be applied and modified to various mixed transport networks with a dominance of motorcycles to analyse the feasibility of a new PT mode and best infrastructure options, and therefore to provide evidence for decision makers.

9.4 Limitations and Future Work

Despite some contributions mentioned in the previous section, it is necessary to note the limitations of this study and then illustrate the future work.

Firstly, as the social cost models are run to obtain in-vehicle time of new PT modes including BRT, Monorail and elevated Metro, interactions between BRT vehicles and private transport vehicles at junctions are not taken into account. Hence, the VISSIM simulation models need to simulate BRT and other modes running on the transport network to obtain vehicle travel time and speed. The priority of BRT at intersections in the VISSIM models should be simulated.

Secondly, the utilities of transport modes in the incremental demand models are estimated based on the study by Bray and Holyoak (2015). Those surveys in the study by Bray and Holyoak (2015) were carried out in 2014 when only PT mode (bus) was operated in Vietnam. In addition, the incremental modelling approach in this research is driven by the low initial PT share of 8.81% and the increase in PT share seems to be modest. Many factors affecting the attractions of a new PT mode are not taken into account in the current research. Hence, future research should consider the role of non-time factors such as comfort, safety, convenience and service reliability etc. Moreover, the value of time for all mode users should be studied because the non-time factors above can change and the average income of Hanoi citizens might increase over time. Variation of the value of time seems to imply error ranges of ASCs of each option.

Thirdly, for the options with Monorail and elevated Metro, the demands for these modes are considerably lower than their infrastructure capacity at which the frequency reaches. Hence, a sensitivity test with respect to the MSCs of all transport modes must be conducted for further work because the MSCs of new PT modes are the same and smaller than those numbers for PRV in this study. Ben-Akiva and Morikawa (2002) estimated the relative attraction of bus and rail relative to the car modes, which is measured by the coefficients of the dummy variables representing the mode specific constants. Those authors concluded that the Metro service in the Washington DC area attracts more ridership than a bus service with comparable travel times and costs. In addition, a high quality express bus service with exclusive right-of-way may be equally attractive as the Metro service. Furthermore, Scherer (2010) used cognitive approaches to understand the preferences of light rail to bus transit. Four main factors for higher ridership attraction for light rail included capacity of light rail vehicles (load factor); qualitative factors of reliability and comfort; individual perception about transit (modern vehicles, special design, visibility of route and media presence). These factors need to be included in demand models through the MSCs. Hensher and Rose (2007) showed that the MSCs of PT modes are higher than those for cars. Those authors introduced state-of-the-art stated choice designs to parameterise modal choice models for commuting and non-commuting travel futures in the introduction of new public transport infrastructure in the north-west section of metropolitan Sydney such as new heavy rail, light rail and segregated busway systems. A two-level nested logit model with a competition between car and all PT modes is run for both work trip and non-work trip segments. Furthermore, a crowding function can be included in further work in order to evaluate the attractiveness of Metro. Another limitation is that external factors (e.g. land-use changes) are not considered in this research.

Fourthly, this study shows that the introduction of both a congestion charge scheme and a new PT mode leads to an increase in the modal share of public transport. Hence, considering air pollution and climate change charge for private transport is a potential additional work to evaluate impacts of these charges. These environmental charges can be a solution to attract more existing private transport users to use PT.

Fifthly, after the comparative economic assessment is run for the off-peak and peak periods separately, the daily demand is the sum of the demands for the off-peak and peak periods. This means that demand shift between different periods of the day is not considered. Hence, the additional work needs to consider that the utility of peak travel may be affected by the time and costs of off-peak travel and vice versa. Moreover, the interchange between a new PT mode and remaining bus services running on an urban corridor needs to be assessed in the assessment for further work. This might evaluate how existing bus passengers would shift to the new PT mode or still use the remaining bus services.

Sixthly, because transport projects seem to be sensitive to capital costs and forecasted demand (Asian Development Bank, 2013), future research might conduct sensitivity tests with respect to infrastructure costs and demand elasticity with respect to a composite cost. Additionally, wider economic and social benefits should be included because these factors can change the results of ASC of each option.

Seventhly, it is recommended that further development work on the completed assessment should focus on developing a comprehensive, usable, automated and integrated tool based on Python and VISSIM. This can be the tool in a web-based platform. Because Python is easy to interface with other software or packages such as Microsoft Excel, VISSIM and spatial data software. Moreover, Python creates basic modules to interface and recall other software or program. First, the tool needs to store a substantial database covering the information and characteristic of existing transport modes in the world, in particular public transport technologies. Second, a spreadsheet cost model for each transport mode must be designed as a basic package, which can interface with Python. Third, another kind of basic package in Python is created for each incremental demand form. Fourth, VISSIM simulations should be developed for typical transport networks in terms of length, the number of lanes per direction, the number of junctions, types of junctions, types of transport modes. Python packages need to be built to interface and control externally with these VISSIM networks to update input data with respect to different local conditions. Fifth, the core package in Python, which interfaces with all basic packages and the VISSIM simulations, will produce the outputs. The users can change easily input data in the packages of the integrated tool to suit the local conditions because characteristics, parameters, costs etc. differ from locations. Note that the users should update their own VISSIM simulations representing the local transport networks in one of two following ways: (i) This process can be done based on this integrated tool, and (ii) the users can develop independently their VISSIM transport networks and then link them to the tool. The outcomes of the core package in Python should be performance indicators such as average social cost, total social cost, total demand, modal share etc.

Eighthly, an equal marginal utility of income is assumed in the assessment. This means that the effect of different incomes on demand of is neglected although dissimilar incomes might impact on VoT, mode specific constants and congestion charges in reality. Hicks (1946) suggested that income effect needs to be included for market demand that has almost exactly the same properties as individual demand. The actual change in individual demand is based on the income effect and the substitution effect and the change in the demand of a group is the sum of changes in individual demands. Additionally, the results of the TSCs and ASCs of infrastructure options can be changed if different incomes of dissimilar groups are taken into account. To overcome these issues, further work might consider income and socio-demographics segmentation in variable demand models (Department for Transport, 2017d) and the total social cost models.

Finally, the social cost models in this study do not include other transport modes in urban areas such as bicycle, electric bicycle, electric motorcycle or taxi-motorcycle. Moreover, Taxi and Uber are included in the social cost models but not considered in the comparative economic assessment due to time limits. As a result, those transport modes must be considered for future work. The incremental logit model needs to expand more levels and nests or a cross-nested logit model should be considered. The microscopic simulation models need to be developed to simulate more transport modes in mixed traffic networks.

Appendix A Transport Social Cost Model

A.1 Unit PT Operator Cost

Table A-1 Calculation of fully allocated costs for conventional bus route 08 in Hanoi (2015)

No	Expense object / Allocation variables	Vehicle Hours	Vehicle Distance	Peak Vehicle	Track /lane Distance	Number of stations / stops	Number of depots	% compo-nents
1	Crew, Admin	1,417,661						45.53%
2	Fuel, oil, tyres, third party inssurance		1,020,415					32.77%
3	Vehicle depreciation			310,663				9.98%
4	Vehicle maintenance	239,487						7.69%
5	Building/workshop			27,801				0.89%
6	Annual track/lane infrastructure cost				457,233			14.69%
7	Annual station/stop infrastructure cost					12,071		0.39%
8	Annual depot infrastructure cost						60,964	1.96%
9	Allocated costs	1,657,148	1,020,415	338,463	24,386	12,071	60,964	
10	Allocated costs percentage	53.23%	32.77%	10.87%	0.78%	0.39%	1.96%	
11	Value of allocation variables	78,393.47	1,838,868.75	22	18.75	66	1	
12	**Unit cost (£), 2015 prices**	**21.14**	**0.55**	**15,384.70**	**1,300.57**	**182.89**	**60,964.43**	
13	**Total operater cost (£), 2015 prices**	**3,113,447.46**						

Table A-2 Calculation of fully allocated costs for BRT line 1 in Hanoi (2015)

No	Expense object / Allocation variables	Vehicle Hours	Vehicle Distance	Peak Vehicle	Track /lane Distance	Number of stations / stops	Number of depots	% compo-nents
1	Crew, Admin	1,419,077						17.08%
2	Fuel, oil, tyres, third party inssurance		1,021,433					12.30%
3	Vehicle depreciation			1,219,289				14.68%
4	Vehicle maintenance	239,726						2.89%
5	Building/workshop			27,828				0.34%
6	Annual track/lane infrastructure cost				1,789,428			21.54%
7	Annual station/stop infrastructure cost					2,528,805		30.44%
8	Annual depot infrastructure cost						60,964	0.73%
9	Allocated costs	1,658,803	1,021,433	1,247,117	1,789,428	2,528,805	60,964	
10	Allocated costs percentage							
11	Value of allocation variables	93,913.50	1,840,704.60	20	15	23	1	
12	**Unit cost (£), 2015 prices**	**17.66**	**0.55**	**62,355.85**	**121,729.80**	**109,948.03**	**60,964.43**	
13	**Total operater cost (£), 2015 prices**	**8,306,550.17**						

Table A-3 Calculation of fully allocated costs for Elevated Metro in Hanoi (2015)

No	Expense object / Allocation variables	Vehicle Hours	Vehicle Distance	Peak Vehicle	Track /lane Distance	Number of stations / stops	Number of depots	% compo-nents
1	Crew, Admin	4,297,531						5.57%
2	Electricity supply		5,625,898					7.30%
3	Vehicle depreciation			5,086,356				6.60%
4	Maintenance (rolling stock, track…)	5,400,049						7.00%
5	Building			223,678				0.29%
6	Annual track/lane infrastructure cost				24,063,982			31.21%
7	Annual station/stop infrastructure cost					26,923,146		34.92%
8	Annual depot infrastructure cost						5,483,418	7.11%
9	Allocated costs (AlC)	9,697,581	5,625,898	5,310,034	24,063,982	26,923,146	5,483,418	
10	Allocated cost percentage (AlC/OC)	12.58%	7.30%	6.89%	31.21%	34.92%	7.11%	
11	Value of allocation variables	21,820.80	714,631.20	12.00	13.10	12.00	1.00	
12	**Unit cost (£), 2015 prices**	**444.42**	**7.87**	**442,502.85**	**1,836,945.18**	**2,243,595.49**	**5,483,418.43**	
13	**Total operater cost (£), 2015 prices**	**77,104,059.26**						

A.2 Equation of Speed in Mixed Traffic

The application and validation of the speed-volume equation in the mixed transport social cost model are shown below. For an urban corridor with four lanes per each direction, speed (*v*)-flow (*q*) relationship is expressed as:

*q =5,852*v*exp(-v/11.3)*

Hence, the speed is expressed as a function of the flow:

*v = -11.3*W(-q/66,127.6)*

The *lambertW(-1,x)* function can be used in the MATLAB program. The validation process includes the following steps:

- *Step 1*: Values of traffic flow ranged from 1 to 24,335 in 24,335 cells of the first column in one Excel file named as ‘test.xlsx’.

- *Step 2*: Import data on traffic flow in ‘test.xlsx’ into the MATLAB program and create a matrix named ‘flow’ in the MATLAB program. This matrix has 24,335 rows (from 1 to 24,335) and only 1 column.

- *Step 3*: The following commands are run in the MATLAB program:

```
speed=-11.3*lambertw(-1,-flow(:,1)/66127.6);

filename='speed.xlsx'

xlswrite(filename,speed(:,1))
```

- *Step 4*: The results of speed are shown in an Excel file named ‘speed.xlsx’. In this Excel file, the revised flow is calculated from the values of estimated speed by using the equation *q =5,852*v*exp(-v/11.3)*. Consequently, the values of the revised flow are compared with the values of the original flow in the ‘test.xlsx’ file. The results show that difference between the revised flow and the original flow ranges from -0.033% to $4*10^{-17}$%. The difference is -0.033% at the maximum flow of 24,335. Because those numbers are very minor, the application of the speed equation can be acceptable.

A.3 Examples for Calculating Average Social Cost

Table A-4 One motorcycle (MC) lane per direction corridor with a demand of 10,000 pdd

Cost elements	Key parameters / short description	Values (round numbers up)	Notes
	Total demand, D	10,000	Unit is pax/direction/day.
	Journey length, JL (km)	4	
	Annualisation factor, a (day)	261	
	Annual Passenger-km for both directions, PKM	20,880,000	$PKM = 2 * D * JL * a$
	Demand for Morning/Afternoon peak hour (Period 1), $D1$	1,000	$D1 = 10\% * D$ (see Table 5-7). Unit is pax/direction/hour.
	Corridor length, L (km)	7	
	MC occupancy, MC_O	1.22	
	Annual MC-km	17,114,754	Annual MC.km = PKM / MC_O
	MC flow in Period 1, $Q1$ (MC/h)	820	$Q1 = D1 / MC\_O$
	MC speed on links in Period 1, $V1$ (km/h)	38.92	As $Q1 < C$, $V1$ is calculated as V_{Nocap}, which is shown in Equation (5-29).
	Travel time per one trip in Period 1, $TT1$ (hour)	0.136	$TT1 = JL / V1 + 0.033$. Assume that travel time at intersections is 0.033 hours.
	Total travel times per direction per day, $TTPD$ (hour)	1,110	Travel time per trip is calculated in different periods showing in Table 5-7. Then, $TTPD$ is the sum of travel times of all periods of a day.
	Value of time for MC in Hanoi, MC_VOT (£/hour in 2015 prices)	1.54	
1. Annual travel time costs	These are variable costs.	890,184 (£/year)	Annual travel time costs for both directions are equal to $2*a*MC\_VOT*TTPD$. These costs are related to speed.
2. Annual delay costs	The congested-related delay costs are variable costs.	88,386 (£/year)	Based on methods to estimate reliability from the Department for Transport (2017b). These costs are related to speed.
3. Annual vehicle capital costs	These are variable costs, which are products of MC capital cost per MC-km and Annual MC-km.	658,978 (£/year)	Average annual distance one motorcyclist travels is adapted from the study of Transport Engineering Design Incorporated (2013). Then MC capital cost is estimated as 0.0385 (£/MC-km).
4. Annual operating costs	These are semi variable costs. Operating cost for 1 motorcycle in Period 1 is calculated as 0.059 (PPP £/km).	254,927 (£/year)	Based on the relationship between MC operating costs and speed from the study of Sugiyanto *et al.* (2011). These costs, which are related to speed, are estimated for all periods of a day, then for the whole day.
5. Annual maintenance costs	These are variable costs, which are products of maintenance cost per MC-km and Annual MC-km.	36,515 (£/year)	The total maintenance costs for Hanoi entire road networks are allocated into motorcycle, car and bus based on total kilometre travelled by modes. Then the MC maintenance cost is estimated as 0.213 (p/MC-km).
6. Annual parking costs	These are fixed costs, which are products of average parking cost per MC-km and Annual MC-km.	179,705 (£/year)	The average parking cost is estimated as 1.05 (p/MC-km).
7. Annual infrastructure costs	These are fixed costs, which are the product of annual infrastructure cost per km and L.	8,434,363 (£/year)	CRF=r*(1+r)m/((1+r)m-1). r is DR, 12%. m is the life expectancy of infrastructure, 20 years. Annual infrastructure cost per km is the product of infrastructure cost per km and CRF.
TUC	TUC = (1) + (2) + (3) + (4)	1,892,475	Unit cost is £/year.
TOC	TOC = (5) + (6) + (7)	8,650,583	Unit cost is £/year.
TEC	These are variable costs, which are products of external unit costs and annual Passenger-km.	465,207	Unit cost is £/year. These costs include air pollution, noise pollution, climate change and accidents costs.
TSC	TSC = TUC + TOC + TEC	11,008,265	Unit cost is £/year, in 2015 prices.
ASC	ASC = TSC*100 / PKM	52.72	Unit cost is p/pax-km, in 2015 prices.

Table A-5 Elevated Metro option with a demand of 100,000 pdd

Cost elements	**Key parameters / short description**	**Values** (round numbers up)	**Notes**
	Total demand, D	100,000	Unit is pax/direction/day.
	Journey length, JL (km)	4	
	Annualisation factor, a (day)	261	
	Annual Passenger-km, PKM	208,800,000	$PKM = 2 * D * JL * a$. This is for both directions.
	Demand for Morning/Afternoon peak hour (Period 1), $D1$	10,000	$D1 = 10\% * D$ (see Table 5-7). Unit is pax/direction/hour.
	Corridor length, L (km)	7	
	Average distance between station/stop, D_{Stop} (km)	1.1	
	Person capacity, PC (pax)	820	
	Infrastructure capacity, C (veh/h)	138	This is the maximum possible vehicle numbers per track, which is based on safety headway.
	Max speed, V_{Max} (km/h)	80	
	Operating speed, V_{Nocap} (km/h)	30.53	$V_{Nocap}=(V_{Max}*A*D_{Stop}*1000)/((V_{Max}/3.6)^2+A*(D_{Stop}*1000+T_{Dwell}*V_{Max}/3.6))$ (Brand and Preston, 2003). A is acceleration/deceleration, 1.12 m/s^2. T_{Dwell} is average vehicle dwell time per station, 60.36 s.
	α	1.1	A factor to allow for seasonal fluctuations.
	γ	50%	This is the maximum relative load factor at which level a new vehicle is required.
	Required service frequency in Period 1, $F1$ (veh/h)	27	$F1 = (\alpha*D1) / (PC*\gamma)$ (Brand and Preston, 2003). This is also a Metro volume, $Q1$.
	Speed in Period 1, $V1$ (km/h)	30.53	As $Q1 < C$, $V1 = V_{Nocap}$
	In vehicle time (IVT) per one trip in Period 1, $IVT1$ (hour)	0.13101	$IVT1 = JL / V1$
	IVT per direction per day, $IVTPD$ (hour)	13,101	IVT per trip is calculated in different periods showing in Table 5-7. Then, $IVTPD$ is sum of travel times of all periods of day.
	Walking time (WKT) per passenger, WKT (hour). This is the same value for all passengers.	0.109	Based on the average distance between stations, the service coverage of 0.65 km and the pedestrian speed of 4 km/h.
	WKT per direction per day, $WKTPD$ (hour)	21,800	$WKTPD = 2*D*WKT$. A factor of 2 is considered to take into account for both accessing the stops and getting to the destination.
	Waiting time (WTT) per passenger for Period 1, $WTT1$ (hour).	0.027	$WTT1= 1/(2*F1)+ T_{Dwell}/(2*3600)$
	WTT per direction per day, $WTTPD$ (hour)	3,624	WTT per trip is calculated in different periods showing in Table 5-7. Then, $WTTPD$ is the sum of travel times of all periods of a day.
	Value of IVT for Metro in Hanoi, $Metro\_VOT$ (£/hour, 2015 prices)	0.54	Values of walking and waiting time are twice the value of in-vehicle time.
1. Annual user costs	These costs include IVT, WKT and WTT. These are variable costs.	17,989,676 (£/year)	$TUC = 2*a*Metro\_VOT*(IVTPD+2*WKTPD+2*WTTPD)$. These costs are related to speed.
	Annual Vehicle Hours, VH	32,226	Based on required service frequency (F), speed (V) and L. F and V are calculated for all periods of day. Time-related operating costs are variable costs.
	Annual Vehicle Distance, VD	983,941	Based on F and L. Distance-related operating costs are semi variable costs.
	Peak Vehicle Requirement, PVR. This is calculated for Period 1, that requires the maximum number of vehicles.	14	$PVR=CEILING(F1*2*L/V1*(1+\delta))$. CEILING() is a function to round up to integer values. δ is a factor allowing for spare vehicles, 10%. Vehicle-related operating costs are semi variable costs.
	Track Distance, TD	7	Track Distance costs are fixed costs.
	Number of Station, NoS	7	$NoS=CEILING(L/D_{Stop})$. This value is double for the bus option. Station costs are fixed costs.
	Number of Depots, NoD	1	Depot costs are fixed costs.
2. Annual operator costs	The operator costs include vehicle operating and maintenance costs; and capital investment costs.	62,310,195 (£/year)	$TOC = \sum (VH*unit\ cost\_VH+VD*unit\ cost\_VD+PVR*unit\ cost\_PVR+TD*unit\ cost\_TD+NoS*unit\ cost\_NoS+NoD*unit\ cost\_NoD)$. Using default unit operator costs in Table 5-6.
3. Annual external costs	These are variable costs, which are products of external unit costs and annual Passenger-km.	6,245 (£/year)	These costs include air pollution, noise pollution, climate change and accidents costs. Using default unit external costs in Table 5-9.
TSC	$TSC = TUC + TOC + TEC$	80,306,116	Unit cost is £/year, in 2015 prices
ASC	$ASC = TSC*100 /PKM$	38.46	Unit cost is p/pax-km, in 2015 prices

Appendix B Traffic Microscopic Simulation Model

B.1 General Traffic Volumes

B.1.1 General traffic difference between the peak and off-peak periods

Figure B-1 shows a screenshot of the junction J3 from video recordings provided by the HPD. Based on these video recordings, the general traffic volumes are counted in-house. Figure B-2 shows the traffic volumes in an interval of five minutes at the junction J3 on 22 March 2018.

Figure B-1 Screenshot of the junction J3 from video recordings provided by the HPD

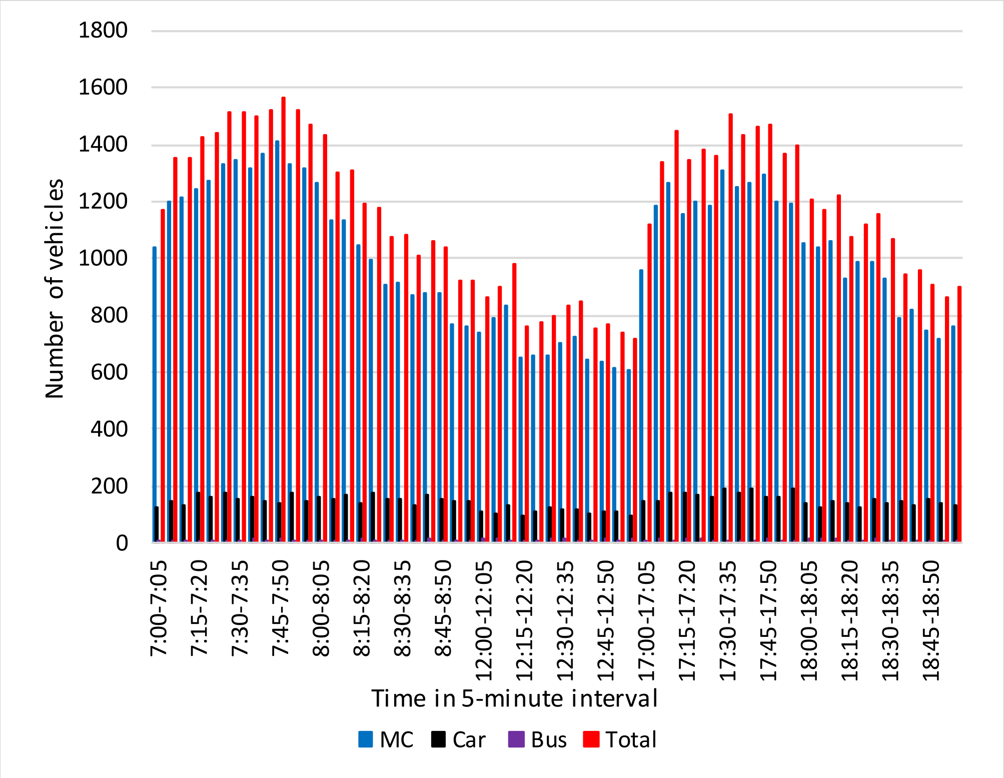


Figure B-2 Traffic volumes at the junction J3 on 22nd March 2018

As can be seen from Figure B-2, there are significant differences in the traffic volumes of the junction J3 between the peak period and the mid-day period. In addition, the traffic volumes between the morning peak period and the afternoon peak period are similar.

B.1.2 Peak period

Figure B-3 and Figure B-4 show the general traffic volumes at the junction J2 and J4 for the period between 17:30 and 18:30.

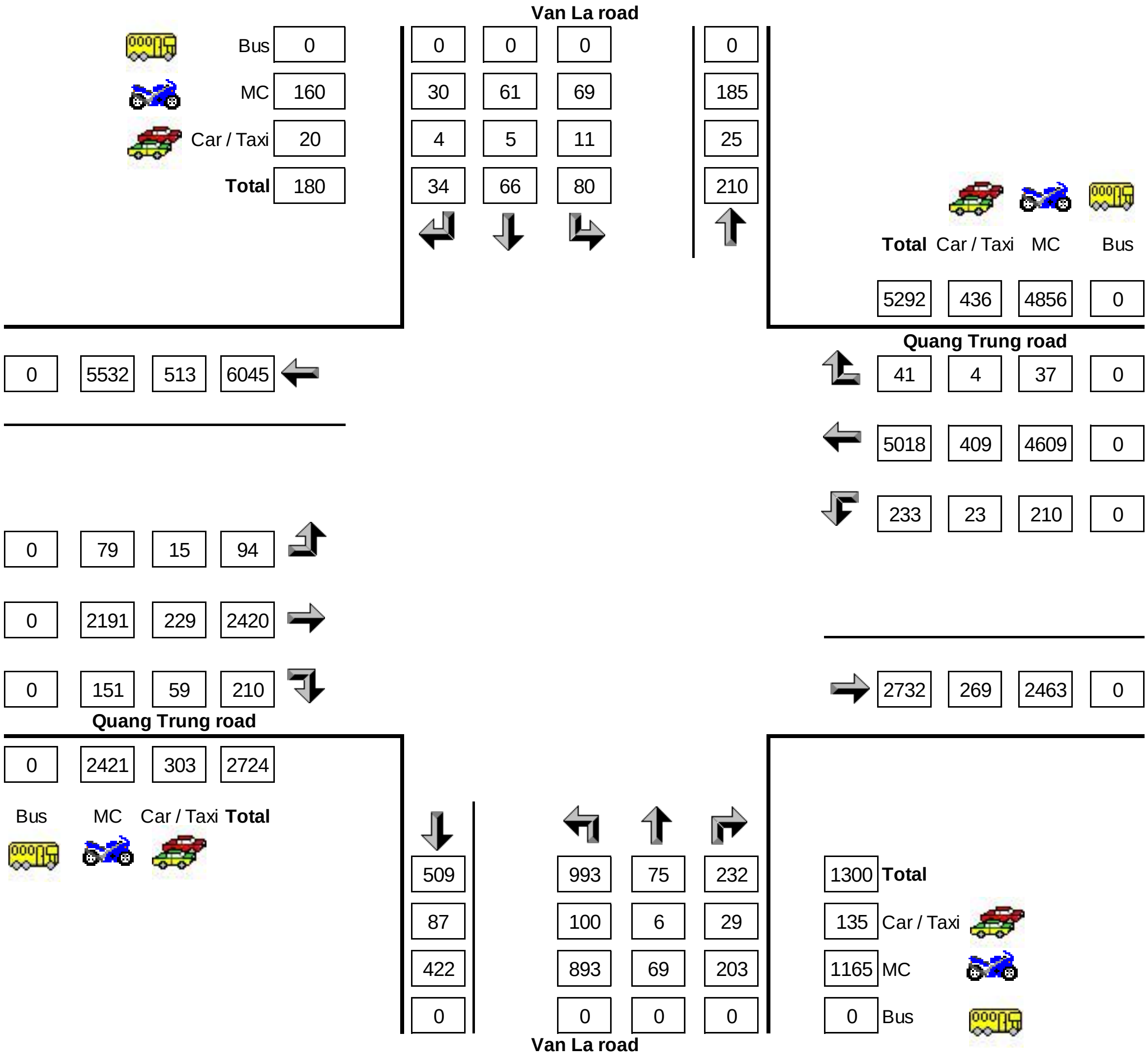


Figure B-3 Volumes of car and motorcycle at the junction J2 from 17:30 to 18:30 on 16 April 2018

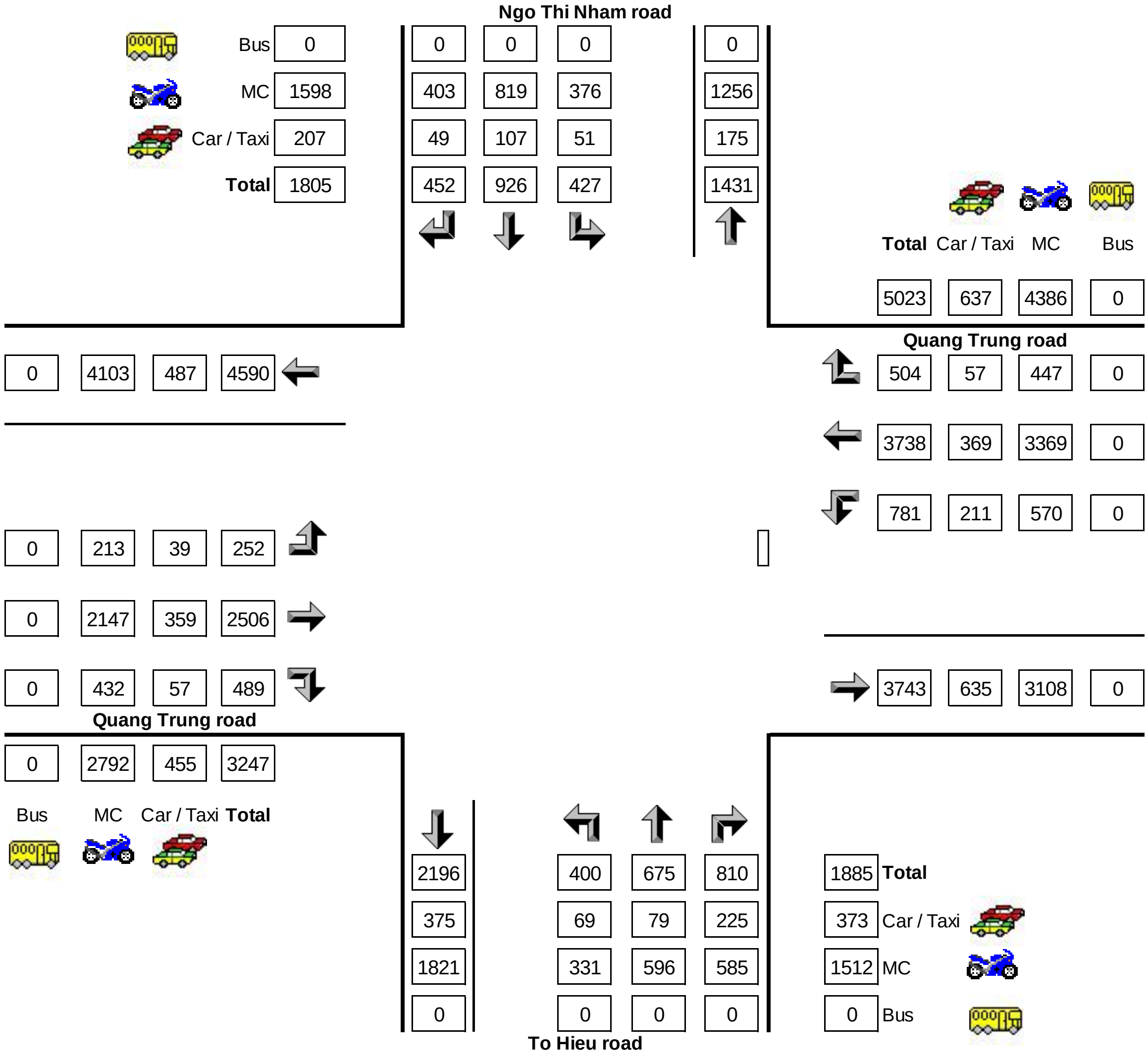


Figure B-4 Volumes of car and motorcycle at the junction J4 from 17:30 to 18:30 on 16 April 2018

B.1.3 Off-peak period

Figure B-5 and Figure B-6 show the general traffic volumes at the junction J2 and J3 for the period between 12:00 and 13:00.

Appendix B

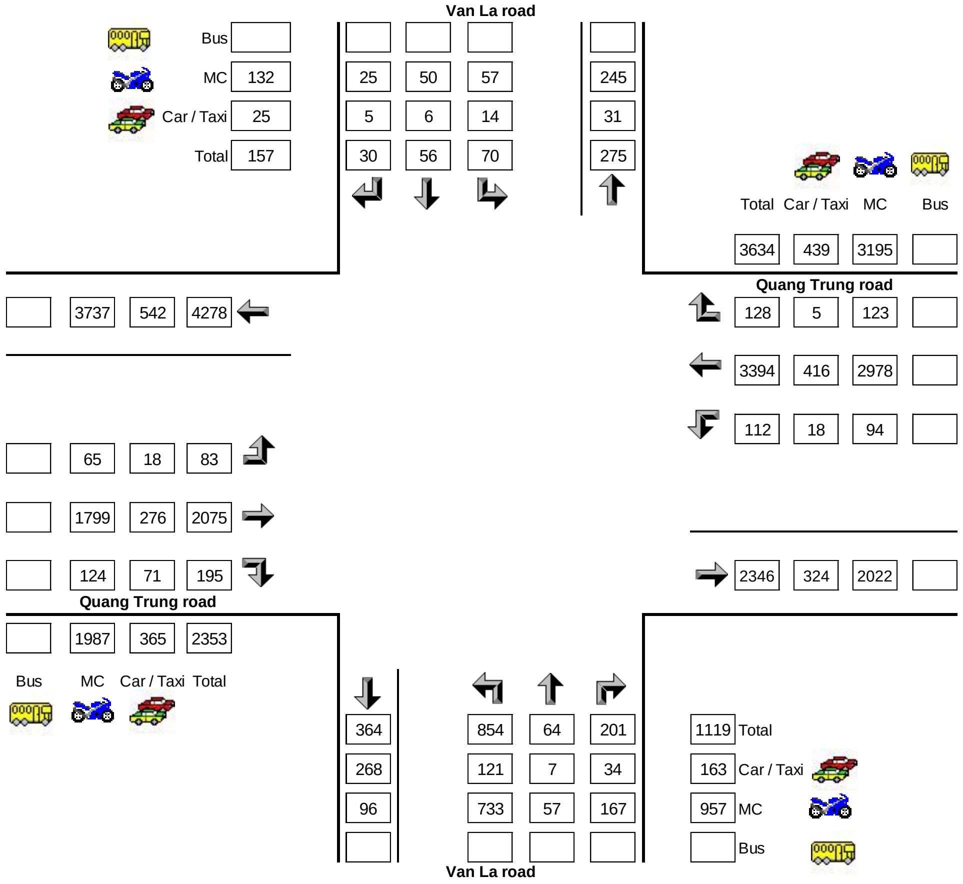


Figure B-5 Volumes of car and motorcycle at the junction J2 from 12:00 - 13:00 on 22 March 2018

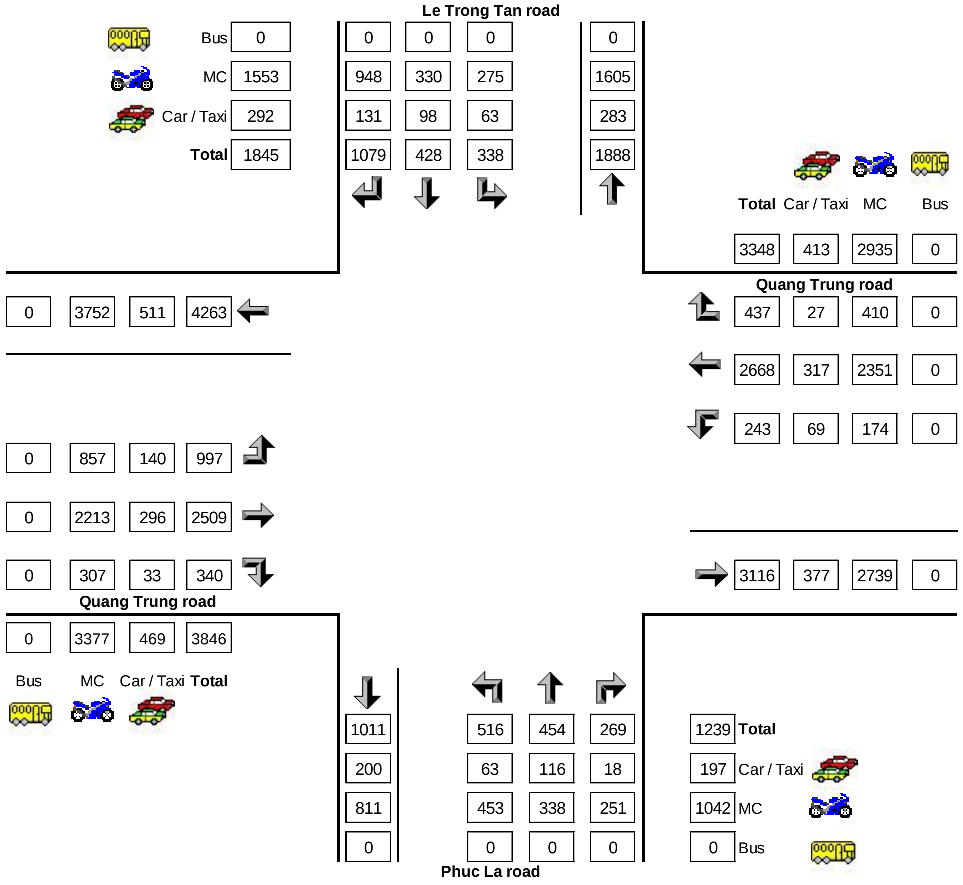


Figure B-6 Volumes of car and motorcycle at the junction J3 from 12:00 - 13:00 on 22 March 2018

B.2 Data on Bus

Table B-1 shows an example of results for the 267 Quang Trung stop.

Table B-1 Results for 267 Quang Trung stop

No	Bus route	Bus plate number	Arrival time (hh:mm:ss)	Stopping time (second)	Number of boardings	Number of alightings
1	02	30T-4731	16:30:01	16	13	0
2	02	30T-4664	16:32:34	12	7	0
3	01	30Z-5154	16:35:02	23	25	2
4	21a	29B-06747	16:36:56	14	7	0
5	27	29B-16550	16:39:12	6	1	0
6	02	30T-4789	16:39:29	8	5	1
7	57	29B-04919	16:40:23	11	3	2
8	89	29B-09994	16:42:12	9	7	0
9	33	29B-15461	16:42:39	13	5	0
10	01	30Z-5979	16:43:13	6	3	2
11	02	29B-00379	16:44:23	7	1	0
12	21A	29B-06654	16:45:13	8	1	0
13	27	29B-16734	16:45:34	7	0	0
14	02	30T-4911	16:45:59	14	0	0
15	57	29B-04931	16:47:13	8	1	0
16	02	30T-4893	16:47:35	7	2	0
17	27	29B-16339	16:52:02	8	4	0
18	01	30Z-5494	16:52:56	8	1	0
19	78	30B-04924	16:54:12	6	2	0
20	02	30T-4924	16:55:23	10	2	0
21	33	29B-15468	16:57:02	8	0	0
22	21A	29B-06771	16:57:34	8	0	1
23	27	29B-10729	16:59:04	7	2	1
24	02	30T-4926	16:59:49	10	5	1
25	01	30Z-5065	17:00:34	7	0	0
26	57	29B-04934	17:02:04	8	1	1
27	89	29B-02871	17:02:23	6	3	0
28	21A	29B-06780	17:02:45	9	2	0
29	02	30T-4976	17:02:56	7	1	1
30	27	29B-16630	17:04:03	9	4	1
31	33	29B-15464	17:04:46	6	0	0
32	02	30T-04005	17:06:01	12	1	1
33	01	30Z-5544	17:08:24	7	0	1
34	02	29B-02084	17:09:34	8	1	0
35	21A	29B-05775	17:11:12	9	4	0
36	27	29B-16837	17:11:56	6	0	0
37	02	30T-4045	17:13:01	7	0	1
38	57	29B-02842	17:15:24	10	1	0

No	Bus route	Bus plate number	Arrival time (hh:mm:ss)	Stopping time (second)	Number of boardings	Number of alightings
39	02	30T-4174	17:16:02	9	2	1
40	33	29B-15447	17:18:19	8	2	0
41	89	30T-2852	17:18:35	9	0	0
42	01	30T-4190	17:18:57	6	3	0
43	27	29-16779	17:20:18	7	1	0
44	01	30Z-5054	17:21:02	14	0	0
45	21A	29B-06754	17:22:23	9	2	2
46	57	29B-04865	17:22:56	7	1	0
47	02	30T-4215	17:23:45	8	3	1
48	27	29B -16703	17:23:02	13	4	0
49	02	30T-4758	17:23:09	12	4	0
50	21A	29B-09298	17:25:14	7	0	0
51	51	30Z-5961	17:26:45	8	1	1
52	27	29B-16828	17:28:12	9	2	1
53	02	30Z-4865	17:28:25	10	2	0
54	33	29B-15453	17:30:13	10	3	0
55	01	30U-0919	17:30:47	7	0	0
56	78	29B-05531	17:33:12	6	0	0
57	57	29B-4651	17:33:49	8	1	1
58	27	29B-16797	17:34:02	13	8	0
59	21A	29B-06786	17:35:09	14	5	0
60	02	30T-4240	17:35:37	11	4	3
61	33	29B-15438	17:40:16	10	4	2
62	89	29B-02861	17:40:36	7	0	0
63	78	29B-01497	17:40:49	9	3	0
64	02	30T-4254	17:42:15	11	6	1
65	21A	29B-06748	17:42:34	6	0	0
66	27	29B-16795	17:42:56	7	0	0
67	01	30Z-5566	17:43:02	7	1	0
68	02	30T-4337	17:47:02	9	2	0
69	57	29B-04612	17:49:37	10	1	5
70	27	29B-10783	17:50:13	10	6	0
71	02	30T-4565	17:50:45	9	3	1
72	02	30T-4426	17:51:13	6	0	0
73	01	30Z-5882	18:14:34	7	0	0
74	21A	29B-06683	18:17:01	5	0	0
75	89	29B-02937	18:17:01	7	0	0
76	33	29B-15466	18:17:23	9	2	2
77	27	29B-10698	18:21:24	8	2	2
78	01	30U-0720	18:23:04	10	3	1
79	57	29B-04613	18:23:23	8	2	0
80	21A	29B-088464	18:25:02	6	0	0
81	78	29B-01449	18:26:04	9	2	2
82	02	30T-4526	18:29:03	9	1	0

Based on the collected data on travel time in the field, average bus travel times in intervals of ten minutes are calculated to analyse differences of bus travel time between time periods and both directions. Figure B-7 and Figure B-8 show results for the eastbound and westbound directions respectively.

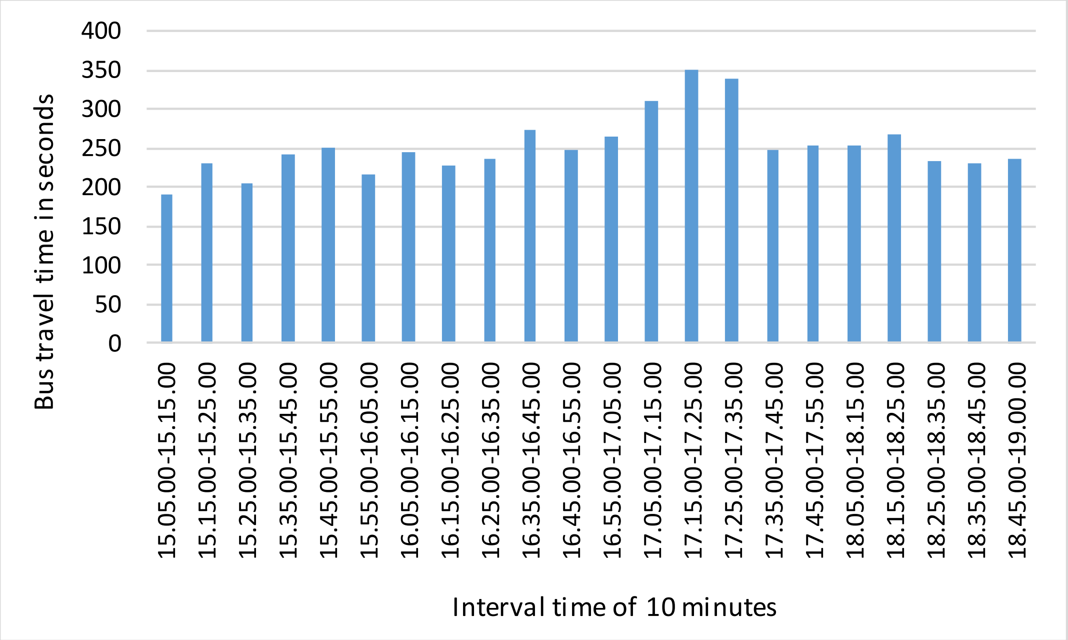


Figure B-7 Average bus travel time from 182 Quang Trung stop to 418 Quang Trung stop on the westbound corridor on 17th May 2018

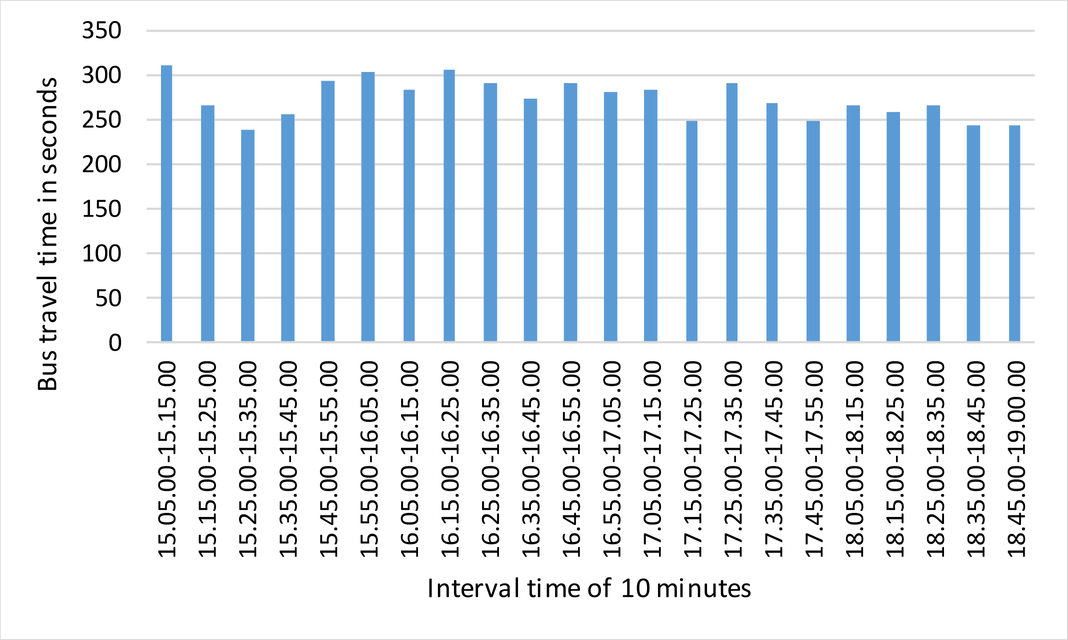


Figure B-8 Average bus travel time from 705 Quang Trung stop to 267 Quang Trung stop on the eastbound corridor on 17th May 2018

Figure B-7 shows that the average bus travel time in the peak period between 17:05 and 17:35 is higher than that number in the off-peak period. The reason for that can be that the traffic volume of westbound direction is significantly high during afternoon peak hours, compared to the morning peak hours and the mid-day period because most people in central areas return home from work during the afternoon peak period.

Figure B-8 illustrates that the average bus travel times on the eastbound corridor are similar from 15:00 to 19:00. The reason can be that the eastbound direction is towards the central areas, hence the traffic volumes in this direction are similar in the afternoon period. Moreover, the signal phases of these junctions are fixed without bus priority.

B.3 Data Analysis Process for Motorcycle Acceleration

There are six steps for estimating motorcycle acceleration as follows:

First step: For each speed band of 5 km/h, observed motorcycles, which accelerated within this speed band, are chosen for the next steps.

Second step: After chasing vehicles on-site, raw data were stored in the speed gun Stalker ATS, which is linked with software. For example, Figure B-9 shows an example of raw data from the Stalker ATS 5.0 representing the speed-time relationship of an objective motorcycle. The speed gun chased the motorcycle in around 12.5 seconds. The range of the motorcycle speed is between 2 km/h and 50 km/h. However, some biased points can occur if there are other vehicles nearby the objective vehicle. Hence, these biased points need to be eliminated. For instance, all points in the red box are eliminated in the Stalker ATS 5.0 software. This motorcycle is chosen for estimating acceleration for several speed bands ranging from 10 km/h to 40 km/h.

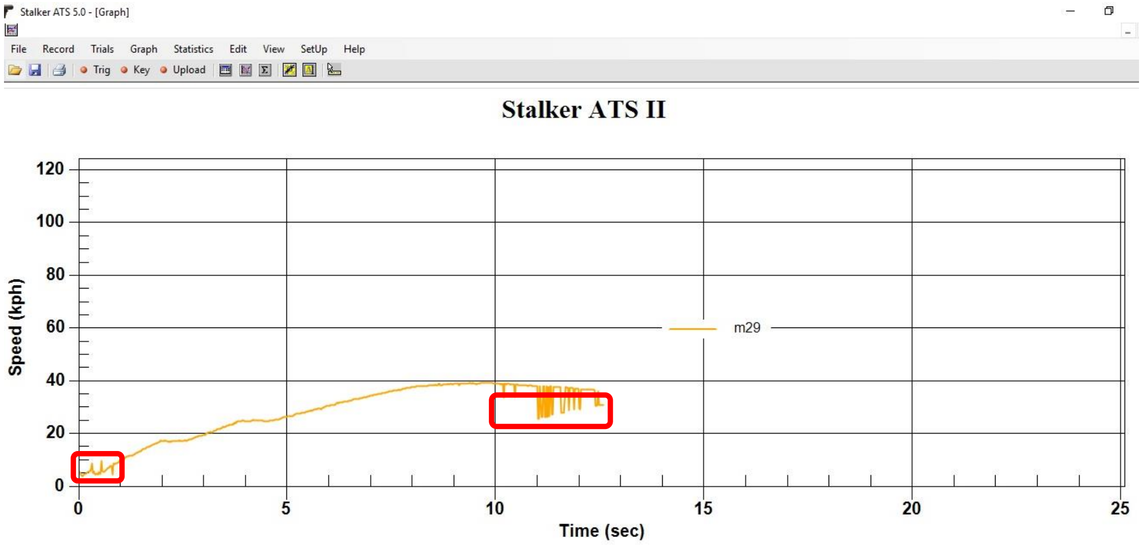


Figure B-9 An example of raw data from Stalker ATS 5.0

Third step: speed-time values for each vehicle from Stalker ATS 5.0 are exported to an Excel file. Table B-2 shows an example of an Excel file for one motorcycle. Values of time in second and speed in km/h are used for the next step. For each speed band of 5-km/h, values of time and speed are grouped separately as well as speed unit in km/h is converted into in m/s. For example, Table B-2 shows samples from 16 to 54 were used for estimating acceleration for the band speed from 2.5 km/h to 7.5 km/h.

Fourth step: for each speed band of 5-km/h, a linear function is made for speed-time relationship for each observed motorcycle. A correlation coefficient and equation of the fitted line are determined for this motorcycle for each speed band. The strength of a linear relation is measured by the square of the sample correlation coefficient, which represents the proportion of the *y* variability explained by the linear relation (Johnson and Bhattacharyya, 2014). Figure B-10 presents the time-speed relationship of the motorcycle ‘m12’ in the speed band between 2.5 and 7.5 km/h.

Table B-2 An example of an Excel file exported from Stalker ATS 5.0

STALKER	Version	5.02	Using	ATS	II
TRIAL	NAME	:	m12		
05/26/2018	08:28:13	(mm/dd/yyyy)			
SAMPLE	RATE	:	46.875		
SAMPLES	:	738			
DATA	TYPE	:	0	:	Acceleration
UNITS	:	2	:	METRIC	
Speed	Units	:	Kph		
Acceleration	Units	:	G		
Distance	Units	:	Meters		
	Sample	**Time**	**Speed**	Accel	Dist
	0	0	0.04		0
	1	0.02	0.18		0
	2	0.04	0.33		0.01
	…	…	…		…
	15	0.02	2.39		0.11
	16	0.34	2.55		0.13
	17	0.36	2.71		0.14
	18	0.38	2.87		0.16
	…	…	…		…
	54	1.15	7.44		1.3
	55	1.17	7.54		1.35
	…	…	…		…

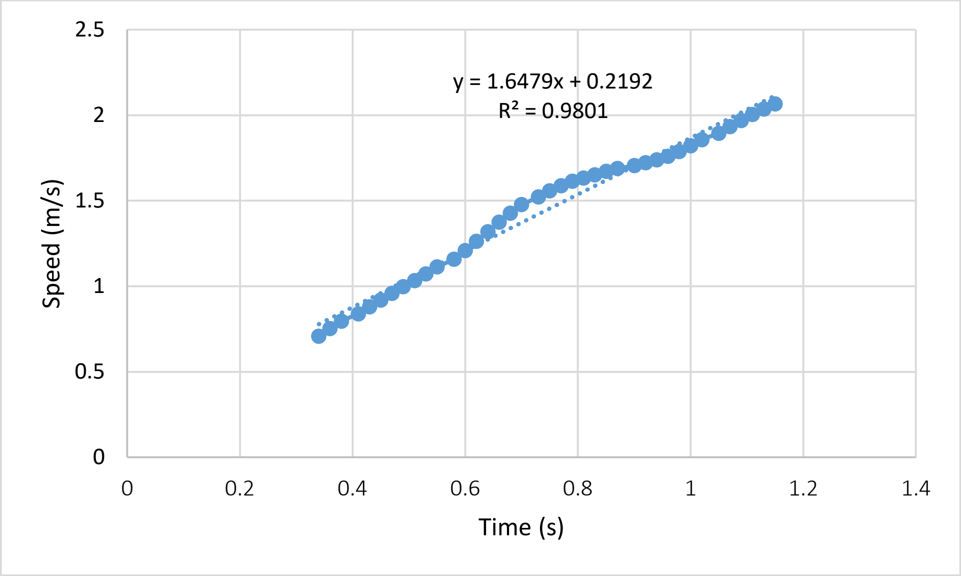


Figure B-10 Speed-time relationship of an observed motorcycle ‘m12’, speed of between 2.5-7.5 km/h

For the speed band of 2.5-7.5 km/h, outputs from the speed gun Stalker ATS show 39 paired values of speed and time, which are shown by 39 points in the scatter chart in Figure B-10. As can be seen from Figure B-10, the equation of the fitted line is expressed as $y = 1.6479 x + 0.2192$ while the sample correlation coefficient is as 0.9801. Therefore, the acceleration of the motorcycle 'm12' for the speed band of 2.5-7.5 km/h is estimated as 1.6479, which is the slope of the fitted line.

Fifth step: If the speed-time linear model appears to be consistent, the acceleration of each observed vehicle is calculated from the slope of the fitted line. Then, all acceleration values are sorted from smallest to largest. For example, Table B-3 demonstrates the results of 43 observed motorcycles for the speed band of 2.5-7.5 km/h. The results show that 41 out of 43 sample correlation coefficient are higher 0.90, 2 out of 43 sample correction coefficient are between 0.85 and 0.90. Therefore, for 5-km/h speed increments the speed-time linear model seems satisfactory.

Sixth step: To minimize affected by outliers, an approach is to use a 5 per cent trimmed median, where the 5 per cent of observations in each tail of the distribution are removed from the sample. For the speed band of 2.5-7.5km, values of 95th percentile, 5th percentile and trimmed median are 3.66, 1.12 and 2.13 m/s^2 respectively. These three values are shown as upper bound, lower bound and median of desired acceleration of motorcycle at 5 km/h. Then, values of 95th percentile, 5th percentile and trimmed median for different 5-km/h speed increments (from zero to 50 km/h) are produced. Based on these values, Figure 6-4 is plotted.

Table B-3 Results from a linear model for 43 observed motorcycles (2.5-7.5 km/h)

No	Observed motorcycle ID Number	Speed (y) - time (x) linear relation	Sample correlation coefficient: r-square	Estimated Acceleration (m/s^2)
1	m50	y = 4.0343x + 0.0099	0.9992	4.0343
2	m62	y = 3.8101x - 0.0796	0.9968	3.8101
3	mt9	y = 3.6769x + 0.1143	0.9976	3.6769
4	m1	y = 3.5281x + 0.205	0.9867	3.5281
5	m45	y = 3.3672x + 0.6204	0.8293	3.3672
6	m38	y = 3.3056x - 2.9581	0.935	3.3056
7	m82	y = 3.0231x - 0.2166	0.9844	3.0231
8	mt5	y = 3.0097x - 0.014	0.9996	3.0097
9	mt3	y = 3.0089x + 1.2013	0.9788	3.0089
10	m22	y = 2.9327x - 0.0094	0.9996	2.9327
11	mt4	y = 2.865x + 1.2666	0.9744	2.8650
12	m92	y = 2.7014x - 18.532	0.9945	2.7014
13	m96	y = 2.5692x + 0.068	0.9916	2.5692
14	m14	y = 2.4406x - 1.3739	0.9946	2.4406
15	m66	y = 2.3943x - 2.4516	0.9799	2.3943
16	m98	y = 2.3924x - 0.4461	0.9859	2.3924
17	mt2	y = 2.3098x + 0.6723	0.9602	2.3098
18	m34	y = 2.2284x + 0.0012	0.9997	2.2284
19	m89	y = 2.2258x - 0.7278	0.9975	2.2258
20	m32	y = 2.1925x - 0.0385	0.9966	2.1925
21	m76	y = 2.167x + 0.0452	0.9979	2.1670
22	m20	y = 2.133x + 0.1674	0.9554	2.1330

Appendix B

No	Observed motorcycle ID Number	Speed (y) - time (x) linear relation	Sample correlation coefficient: r-square	Estimated Acceleration (m/s^2)
23	m68	y = 2.0433x - 0.6732	0.8732	2.0433
24	m84	y = 2.0423x + 4E-05	0.9998	2.0423
25	m74	y = 1.8989x + 0.0124	0.9955	1.8989
26	m10	y = 1.8124x + 1.3914	0.9677	1.8124
27	m64	y = 1.8097x - 2.0014	0.8757	1.8097
28	mt8	y = 1.6706x - 1.9965	0.9885	1.6706
29	m12	y = 1.6479x + 0.2192	0.9801	1.6479
30	m24	y = 1.5908x + 0.6549	0.9218	1.5908
31	m70	y = 1.5849x + 0.0904	0.9759	1.5849
32	m18	y = 1.5747x + 0.6121	0.9658	1.5747
33	m94	y = 1.5447x - 0.2133	0.9896	1.5447
34	m53	y = 1.5293x - 0.107	0.9965	1.5293
35	m56	y = 1.5215x - 0.0984	0.9963	1.5215
36	m43	y = 1.4695x + 0.0223	0.9806	1.4695
37	m19	y = 1.4306x + 0.0016	0.9999	1.4306
38	m55	y = 1.346x - 0.3459	0.8539	1.3460
39	m78	y = 1.3024x + 0.3984	0.9856	1.3024
40	m58	y = 1.1397x + 0.3821	0.9559	1.1397
41	mt7	y = 1.1133x + 0.0002	0.9999	1.1133
42	m60	y = 1.1045x + 0.5848	0.9425	1.1045
43	m72	y = 1.2605x - 0.3697	0.9733	0.2605

B.4 Vissim Simulation Model

B.4.1 Infrastructure

Figure B-11 shows the detailed layout of the junction J3, which was produced based on the collected data on geometry on-site.

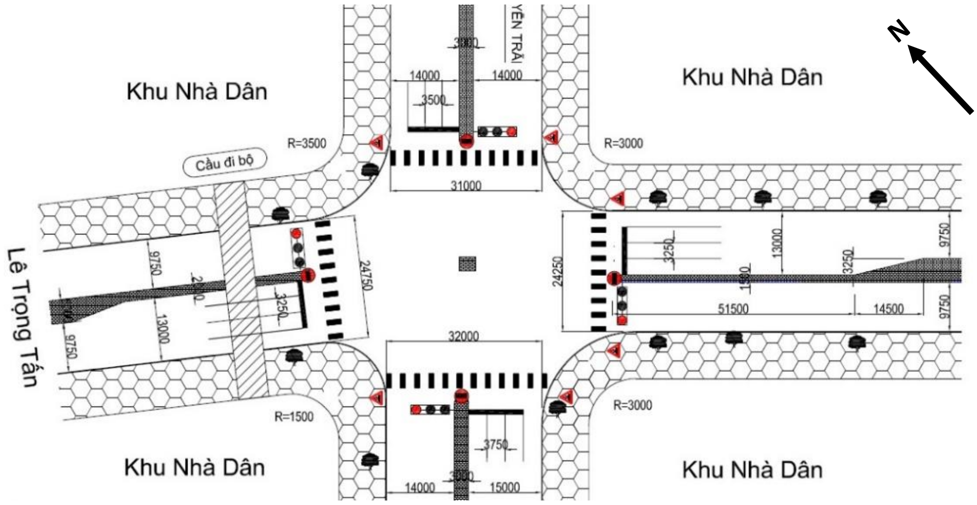
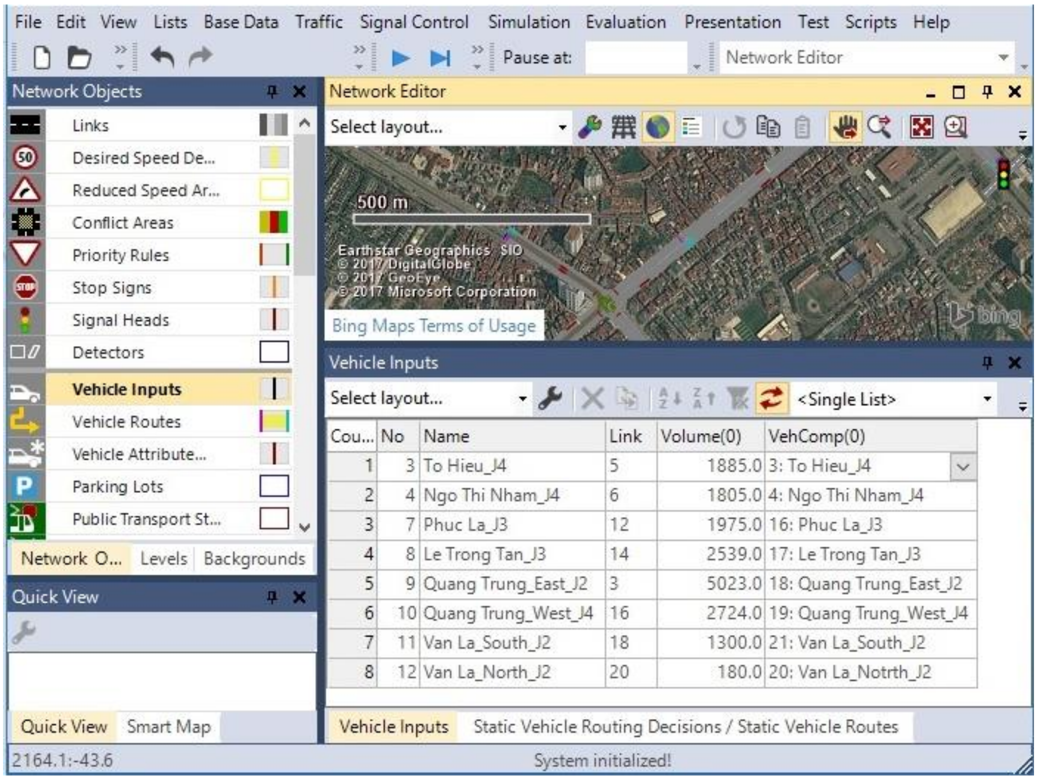


Figure B-11 Detailed layout of the junction J3

B.4.2 General traffic input

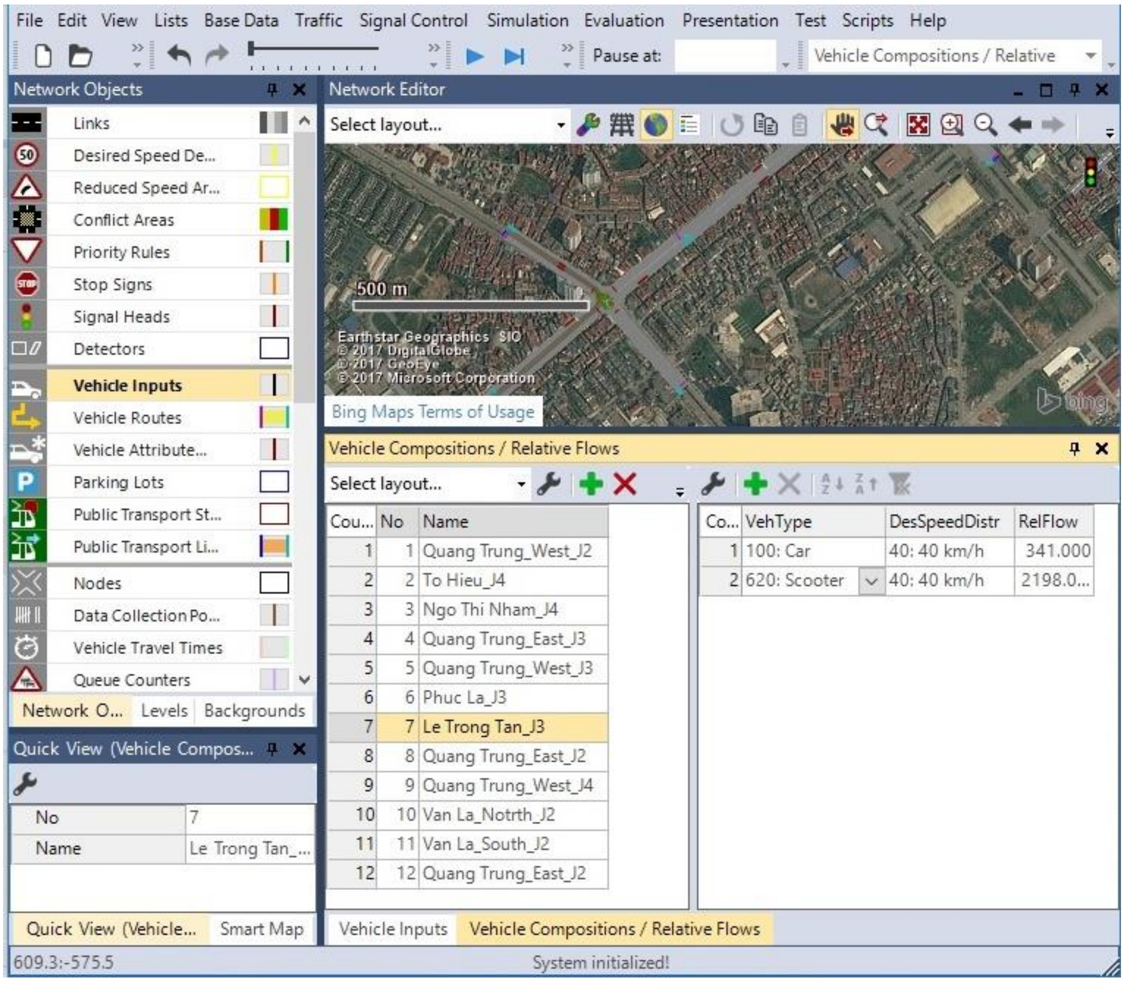
Figure B-12, Figure B-13 and Figure B-14 show the process of general traffic input in VISSIM.



Cou...	No	Name	Link	Volume(0)	VehComp(0)
1	3	To Hieu_J4	5	1885.0	3: To Hieu_J4
2	4	Ngo Thi Nham_J4	6	1805.0	4: Ngo Thi Nham_J4
3	7	Phuc La_J3	12	1975.0	16: Phuc La_J3
4	8	Le Trong Tan_J3	14	2539.0	17: Le Trong Tan_J3
5	9	Quang Trung_East_J2	3	5023.0	18: Quang Trung_East_J2
6	10	Quang Trung_West_J4	16	2724.0	19: Quang Trung_West_J4
7	11	Van La_South_J2	18	1300.0	21: Van La_South_J2
8	12	Van La_North_J2	20	180.0	20: Van La_Notrth_J2

Figure B-12 Vehicles Input user interface in VISSIM

Total volumes of motorcycle and car for each approach at a junction are inserted through the ‘Volume’ function in VISSIM. For example, 2,539 vehicles per hour is the total volume from the Le Trong Tan approach to the junction J3.



Cou...	No	Name
1	1	Quang Trung_West_J2
2	2	To Hieu_J4
3	3	Ngo Thi Nham_J4
4	4	Quang Trung_East_J3
5	5	Quang Trung_West_J3
6	6	Phuc La_J3
7	7	Le Trong Tan_J3
8	8	Quang Trung_East_J2
9	9	Quang Trung_West_J4
10	10	Van La_Notrth_J2
11	11	Van La_South_J2
12	12	Quang Trung_East_J2

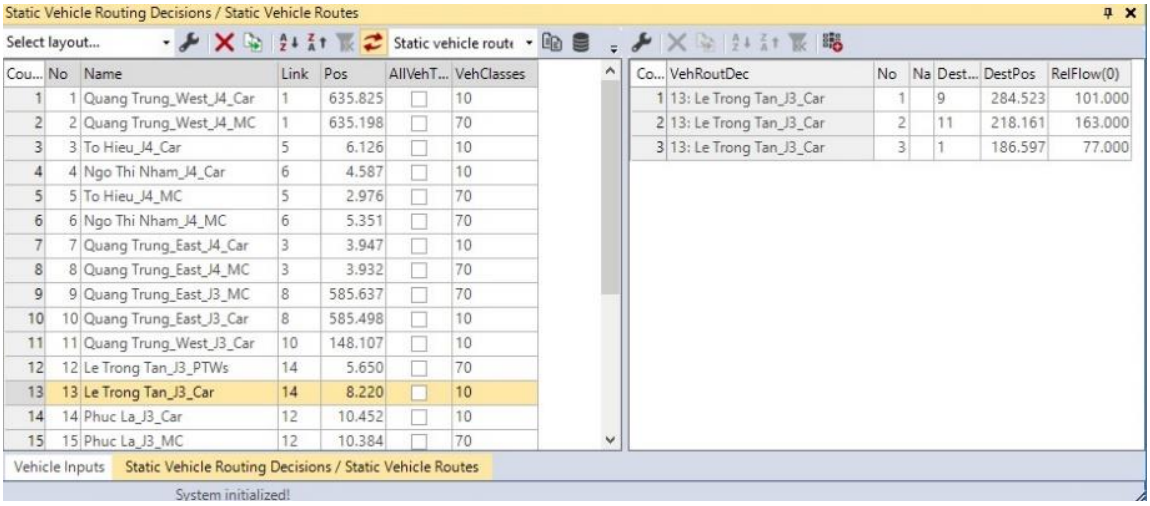
Co...	VehType	DesSpeedDistr	RelFlow
1	100: Car	40: 40 km/h	341.000
2	620: Scooter	40: 40 km/h	2198.0...

No	7
Name	Le Trong Tan_...

Figure B-13 Vehicle Compositions settings in Vissim

Firstly, for each approach to a junction, volumes of car and motorcycle should be inserted in the ‘relative flow’ attribute. For example, in Figure B-13, 341 and 2198 are inputs for car and motorcycle volumes of ‘Le Trong Tan’ approach at the junction J3. These values are shown in Figure 6-3.

Movements of motorcycle or car are determined by using Static Vehicle Routing Decisions in VISSIM. Going straight, turning left and turning right are three movements of a vehicle at a crossroads. The origin of the movement is placed at each approach at a junction while the destination of the movement is placed at an exit. After setting the movements of each vehicle type, the proportions of these movements are inserted through the ‘Relative Flow’ attribute in VISSIM. For instance, from the Le Trong Tan approach at the junction J3, the numbers of cars turning right, going straight and turning left are 101, 163 and 77 respectively. These input data for car and motorcycle are imported separately in Figure B-14.



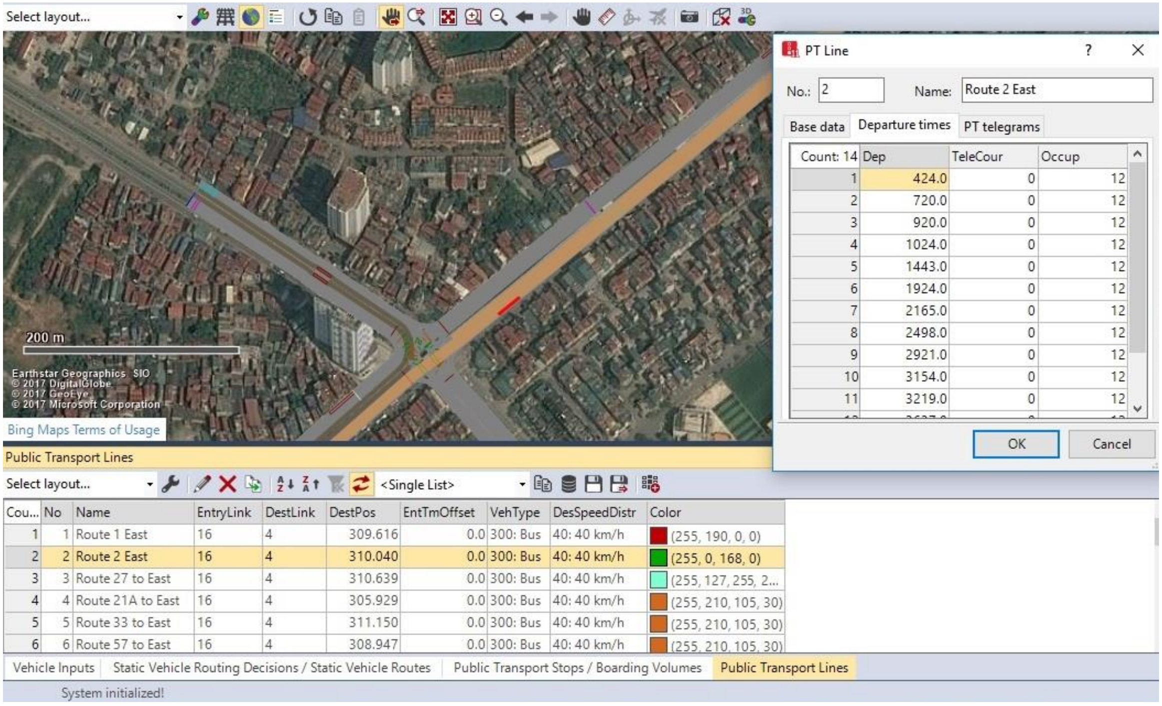
Cou...	No	Name	Link	Pos	AllVehT...	VehClasses
1	1	Quang Trung_West_J4_Car	1	635.825	☐	10
2	2	Quang Trung_West_J4_MC	1	635.198	☐	70
3	3	To Hieu_J4_Car	5	6.126	☐	10
4	4	Ngo Thi Nham_J4_Car	6	4.587	☐	10
5	5	To Hieu_J4_MC	5	2.976	☐	70
6	6	Ngo Thi Nham_J4_MC	6	5.351	☐	70
7	7	Quang Trung_East_J4_Car	3	3.947	☐	10
8	8	Quang Trung_East_J4_MC	3	3.932	☐	70
9	9	Quang Trung_East_J3_MC	8	585.637	☐	70
10	10	Quang Trung_East_J3_Car	8	585.498	☐	10
11	11	Quang Trung_West_J3_Car	10	148.107	☐	10
12	12	Le Trong Tan_J3_PTWs	14	5.650	☐	70
13	13	Le Trong Tan_J3_Car	14	8.220	☐	10
14	14	Phuc La_J3_Car	12	10.452	☐	10
15	15	Phuc La_J3_MC	12	10.384	☐	70

Co...	VehRoutDec	No	Na	Dest...	DestPos	RelFlow(0)
1	13: Le Trong Tan_J3_Car	1		9	284.523	101.000
2	13: Le Trong Tan_J3_Car	2		11	218.161	163.000
3	13: Le Trong Tan_J3_Car	3		1	186.597	77.000

Figure B-14 Static Vehicle Routing Decisions settings in VISSIM

B.4.3 Public transport input data

Figure B-15, Figure B-16 and Figure B-17 show an example of the process of public transport input in VISSIM.



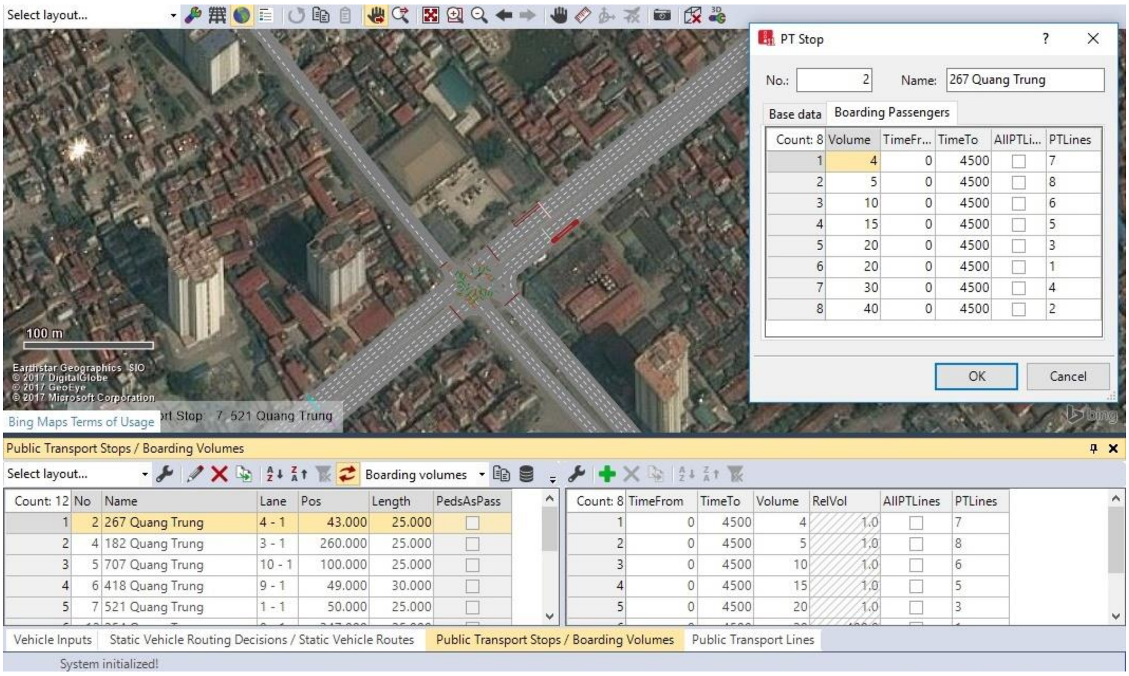
No.: 2
Name: Route 2 East

Count: 14	Dep	TeleCour	Occup
1	424.0	0	12
2	720.0	0	12
3	920.0	0	12
4	1024.0	0	12
5	1443.0	0	12
6	1924.0	0	12
7	2165.0	0	12
8	2498.0	0	12
9	2921.0	0	12
10	3154.0	0	12
11	3219.0	0	12

Cou...	No	Name	EntryLink	DestLink	DestPos	EntTmOffset	VehType	DesSpeedDistr	Color
1	1	Route 1 East	16	4	309.616	0.0	300: Bus	40: 40 km/h	🟥 (255, 190, 0, 0)
2	2	Route 2 East	16	4	310.040	0.0	300: Bus	40: 40 km/h	🟩 (255, 0, 168, 0)
3	3	Route 27 to East	16	4	310.639	0.0	300: Bus	40: 40 km/h	🟦 (255, 127, 255, 2...
4	4	Route 21A to East	16	4	305.929	0.0	300: Bus	40: 40 km/h	🟧 (255, 210, 105, 30)
5	5	Route 33 to East	16	4	311.150	0.0	300: Bus	40: 40 km/h	🟧 (255, 210, 105, 30)
6	6	Route 57 to East	16	4	308.947	0.0	300: Bus	40: 40 km/h	🟧 (255, 210, 105, 30)

Figure B-15 Public Transport Lines setting in VISSIM

Figure B-15 shows an example of inserting data for the bus route 2 in the eastbound direction. The desired speed distribution is 40 km/h. The first bus vehicle of the bus route 2 enters the VISSIM network at 424 seconds (7 minutes and 4 seconds) after starting running the VISSIM simulation. In other words, if the VISSIM model starts to run at 16:30:00, the first bus vehicle of the bus route 2 enters the network at 16:37:04. The occupancy of each vehicle of the bus route 2 at the first bus stop on the eastbound direction is 13 passengers.



PT Stop

No.: 2 Name: 267 Quang Trung

Base data | Boarding Passengers

Count: 8	Volume	TimeFr...	TimeTo	AllPTLi...	PTLines
1	4	0	4500	☐	7
2	5	0	4500	☐	8
3	10	0	4500	☐	6
4	15	0	4500	☐	5
5	20	0	4500	☐	3
6	20	0	4500	☐	1
7	30	0	4500	☐	4
8	40	0	4500	☐	2

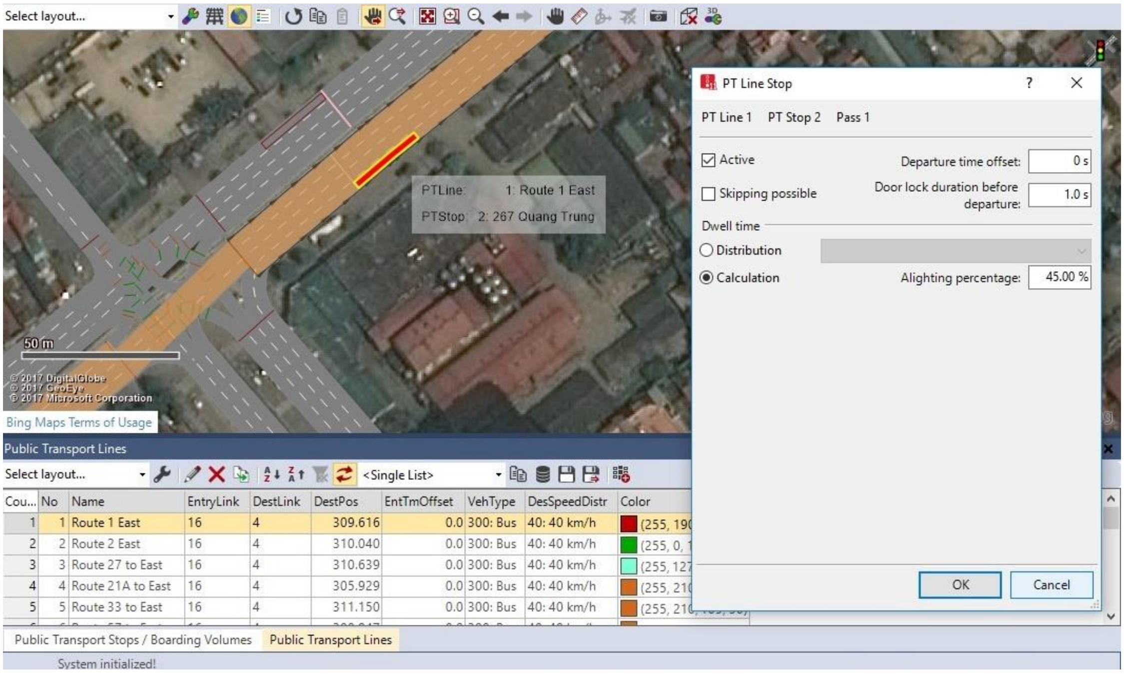
Public Transport Stops / Boarding Volumes

Count: 12	No	Name	Lane	Pos	Length	PedsAsPass
1	2	267 Quang Trung	4 - 1	43.000	25.000	☐
2	4	182 Quang Trung	3 - 1	260.000	25.000	☐
3	5	707 Quang Trung	10 - 1	100.000	25.000	☐
4	6	418 Quang Trung	9 - 1	49.000	30.000	☐
5	7	521 Quang Trung	1 - 1	50.000	25.000	☐

Count: 8	TimeFrom	TimeTo	Volume	RelVol	AllPTLines	PTLines
1	0	4500	4	1.0	☐	7
2	0	4500	5	1.0	☐	8
3	0	4500	10	1.0	☐	6
4	0	4500	15	1.0	☐	5
5	0	4500	20	1.0	☐	3

Figure B-16 Public Transport Stops settings in VISSIM

Figure B-16 shows an example of inserting data for the 267 Quang Trung bus stop on the eastbound direction. The location of this stop is at 43 metres from the beginning of the lane '4-1'. The length of the stop is 25 metres. The boarding passengers of the bus line 7 at this stop is four passengers per hour.



PTLine: 1: Route 1 East
PTStop: 2: 267 Quang Trung

PT Line Stop

PT Line 1 PT Stop 2 Pass 1

☑ Active

Departure time offset: 0 s

☐ Skipping possible

Door lock duration before departure: 1.0 s

Dwell time

○ Distribution

● Calculation

Alighting percentage: 45.00 %

Public Transport Lines

Cou...	No	Name	EntryLink	DestLink	DestPos	EntTmOffset	VehType	DesSpeedDistr	Color
1	1	Route 1 East	16	4	309.616	0.0	300: Bus	40: 40 km/h	🟥 (255, 19
2	2	Route 2 East	16	4	310.040	0.0	300: Bus	40: 40 km/h	🟩 (255, 0,
3	3	Route 27 to East	16	4	310.639	0.0	300: Bus	40: 40 km/h	🟦 (255, 127
4	4	Route 21A to East	16	4	305.929	0.0	300: Bus	40: 40 km/h	🟧 (255, 21
5	5	Route 33 to East	16	4	311.150	0.0	300: Bus	40: 40 km/h	🟧 (255, 21

Figure B-17 Alighting percentage input through 'PT Line Stop' attribute in the Public Transport Lines setting

The alighting rate of each bus route at each bus stop is inserted through the 'PT Line Stop' attribute, which is shown in Figure B-17.

B.5 Model Calibration and Validation for the Off-peak Period

This appendix shows the detailed calibration and validation process of the simulation model for the off-peak period. The first five steps of the process for the off-peak period are the same as the peak period, which are shown in section 6.4.1. The last four steps are described below.

B.5.1 Surface function development

A surface function was created to estimate the relationships between the bus travel times obtained from the simulation model and the calibration parameters. A linear regression model was developed in SPSS with the four calibration parameters as the independent variables and the bus travel time as the dependent variable (Park and Schneeberger, 2003; Li, 2015).

a) Bus travel time on the eastbound direction

Bus travel time is a criterion (or dependent variable). Motorcycle desired speed distribution (MCSpeed), desired speed distribution of car and bus (BusCarSpeed), minimum lateral distance driving (LateralDistance), average standstill distance (AvgStandstillDistance) are the predictors (or independent variables). Table B-4 shows the outputs in SPSS for the bus travel time in the eastbound direction.

Table B-4 Results of a linear regression model for bus travel time on the eastbound direction (to centre)

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.926[a]	.858	.850	1.56703
a. Predictors: (Constant), MCSpeed, BusCarSpeed, LateralDistance, AvgStandstillDistance				

Coefficients[a]						
		Unstandardized Coefficients		Standardized Coefficients		
Model		B	Std. Error	Beta	t	Sig.
1	(Constant)	74.430	1.652		45.060	.000
	AvgStandstillDistance	5.778	.279	.895	20.696	.000
	LateralDistance	.104	1.066	.004	.098	.922
	BusCarSpeed	-.110	.021	-.223	-5.158	.000
	MCSpeed	-.043	.021	-.087	-2.006	.048
a. Dependent Variable: BusTraveltimeToCentre						

As can be seen from Table B-4, *p-values* for *average standstill distance;* and *speed of bus and car*; and *speed of motorcycle* are smaller than 0.05. This means that these parameters have significant impacts on the average bus travel time based on a significance level of 5%.

Moreover*, b* coefficient for *average standstill distance* is a positive number, which indicates that higher average standstill distance is associated with higher average bus travel time. This seems to be sensible because higher average distance between two vehicles can cause lower capacity in the VISSIM simulation, therefore higher travel time with the same existing traffic volume.

By contrast, both *b* coefficient *for speed of bus and car* and *b* coefficient for *speed of motorcycle are* negative numbers, which indicates that higher vehicle speed distribution is associated with smaller average bus travel time. The reason for that can be explained that car, bus and motorcycle can easily reach desired speed (or speed limit) in the off peak period. Hence, the average bus travel time reduces due to the higher speed.

Additionally, Table B-4 shows the *p*-values for *minimum lateral distance driving* is 0.922, which is much higher than 0.05. This means that this parameter does not have a significant impact on the average bus travel time based on a significance level of 5%. The reason for that can be explained that traffic volume is not high in the off-peak period, vehicles have plenty of spaces in four lanes per direction when overtaking, real lateral distance can be therefore higher than minimum lateral distance. This means that minimum lateral distance cannot have a major influence of infrastructure capacity and hence the vehicle travel time in the off-peak period.

b) Bus travel time on the westbound direction

Similarly, the results of a linear regression model for bus travel time on the westbound direction are shown in Table B-5.

Table B-5 Results of a linear regression model for bus travel time on the westbound direction

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.698[a]	.488	.461	3.55106
a. Predictors: (Constant), MCSpeed, BusCarSpeed, LateralDistance, AvgStandstillDistance				

Coefficients[a]						
		Unstandardized Coefficients		Standardized Coefficients		
Model		B	Std. Error	Beta	t	Sig.
1	(Constant)	129.050	3.743		34.476	.000
	AvgStandstillDistance	1.258	.633	.163	1.988	.050
	LateralDistance	-2.600	2.416	-.088	-1.076	.285
	BusCarSpeed	-.115	.048	-.195	-2.376	.020
	MCSpeed	-.379	.048	-.644	-7.849	.000
a. Dependent Variable: BusTraveltimeToSuburban						

Table B-5 shows that the relationships between the bus travel times on the westbound direction obtained from the simulation model and the calibration parameters are similar to the relationship between the bus travel time on the eastbound direction and calibration parameters. This means that there is significant evidence that *average standstill distance* and *speed distribution of motorcycle, car and bus* have significant impacts on the bus travel times whilst *minimum lateral distance driving* does not have significant impacts on the bus travel times on the westbound direction*.*

B.5.2 Candidate parameter sets

Candidate parameter sets were created with the linear regression model. There is significant evidence that *average standstill distance* and *speed distribution of bus, car and motorcycle* have significant impacts on the bus travel times but *minimum lateral distance driving* does not. However, the linear regression model was created from the results of five VISSIM simulation runs for each candidate parameter set. A sample of five runs seems to be not large enough. Hence, in order to cover all possibilities, *minimum lateral distance driving* should be still considered for choosing the candidate parameter set, which can be the one with an estimated travel time close to the observation value from the field are selected for the evaluation step. The average bus travel times on the eastbound and westbound directions observed from the field are 72.00 and 94.86 seconds respectively. A parameter set is chosen if the differences between the bus travel times in both directions obtained from the VISSIM simulation and the field are less than six seconds. As a result, three combinations of parameters are selected, which are presented in Table B-6.

Table B-6 Candidate parameter sets

Case	Average standstill distance (m)	Minimum lateral distance driving (m)	Desired speed distribution of bus and car (km/h)	Motorcycle desired speed distribution (km/h)	Average bus travel time on the eastbound direction in 5 simulation runs (seconds)	Average bus travel time on the westbound direction in 5 simulation runs (seconds)
1	0.5	0.8	60	50	67.98	100.16
2	0.5	1.0	60	50	68.24	97.42
3	0.5	1.0	50	50	70.01	99.77

B.5.3 Candidate Parameter Set Evaluation

Forty random seeded runs were made for each of the three candidate parameter sets. Each parameter set is evaluated based on two criteria. The first evaluation criterion is distribution of bus travel times produced from VISSIM. The second criterion is visualisation.

a) Travel time distributions

Bus travel times on both directions were collected from 40 random seeded runs. For each simulation run, the average bus travel times are collected and then used to compare vehicle travel times collected from the field. The field data, which was collected in one single day, might represent the average travel time on the corridor but might not. Therefore, the data collected on-site can be average or lower or higher than the true mean. Hence, both comparisons of mean travel time and travel time distribution from the field and the simulation are tested.

Firstly, an independent two-tailed Student's t-test was run to see if the means of vehicle travel time obtained from the field observation and the simulation are equal. Secondly, the Kolmogorov-Smirnov (K-S) test was used to evaluate the goodness-of-fit of the two probability distributions of vehicle travel times. For each candidate parameter set passing the t-test, one simulation run will be chosen and travel time of every single bus in the chosen simulation run is obtained from outputs of VISSIM. Consequently, the distribution of bus travel time for the chosen simulation run is compared with the distribution of the field sample. One candidate parameter set will pass the K-S test if at least one simulation run (out of 40 runs) passes the K-S test. This proves that at least once the distribution of bus travel time for the simulation and the field are the same.

a.1) Student's t test

The test hypotheses are:

H_0: Null Hypothesis is that the means of vehicle travel time from the field survey and the simulation model are the same.

H_1: the means of vehicle travel time from the field survey and the simulation model are not the same.

Through video recordings, forty-five buses were observed at the 182 Quang Trung and 418 Quang Trung stops on the westbound corridor from 12:15 to 13:00 on Monday, 19 March 2018. While thirty-nine buses were observed at the 707 Quang Trung and 521 Quang Trung stops on the eastbound corridor at the same time. Then bus travel times between the two stops in both directions were explored. In each VISSIM simulation run, the average bus travel times between two stops on both directions were obtained. Hence, there are 40 values of the average bus travel times for each direction were collected from 40 VISSIM random seeded runs. The independent two-tailed Student's t-test is run to see if the means of bus travel time obtained from the field observation and the simulation for Case 1, Case 2 and Case 3 are equal for both directions.

Levene's Test and Student’s t test for three Cases are run in the SPSS program and the results are shown in Table B-7 and Table B-8.

Table B-7 Results of Student’s t test and Levene's Test for three Cases with respect to bus travel time on the westbound direction

Group Statistics

	GroupCar	N	Mean	Std. Deviation	Std. Error Mean
BusTravelTime OutCentreCase1	Simulation	40	101.0290	2.78066	.43966
	Observation	45	94.8667	18.26273	2.72245
BusTravelTime OutCentreCase2	Simulation	40	99.1015	3.01751	.47711
	Observation	45	94.8667	18.26273	2.72245
BusTravelTime OutCentreCase3	Simulation	40	99.3680	2.31520	.36607
	Observation	45	94.8667	18.26273	2.72245

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
BusTravelTime OutCentreCase1	Equal variances assumed	100.871	.000	2.111	83	.038	6.16232	2.91906	.35643	11.96822
	Equal variances not assumed			2.235	46.289	.030	6.16232	2.75772	.61226	11.71239
BusTravelTime OutCentreCase2	Equal variances assumed	97.325	.000	1.448	83	.151	4.23487	2.92427	-1.58139	10.05114
	Equal variances not assumed			1.532	46.695	.132	4.23487	2.76394	-1.32641	9.79616
BusTravelTime OutCentreCase3	Equal variances assumed	108.426	.000	1.547	83	.126	4.50131	2.91003	-1.28662	10.28924
	Equal variances not assumed			1.639	45.589	.108	4.50131	2.74695	-1.02936	10.03198

As can be seen from Table B-7, the *sig.* values in the Levene's test for the three Cases are smaller than 0.001. This means that there is significant evidence to reject the null hypothesis of equal variances. Therefore, the *sig.* value in the Student's t test is selected in a situation where equal variances not assumed (in Table B-7).The *sig.* values in the Student's t tests for Case 2 and Case 3 are higher than 0.05. This indicates that the null hypothesis that the mean bus travel time on the westbound for observations and simulation are the same cannot be rejected. On the contrary, for Case 1, the null hypothesis that the mean bus travel time for observations and simulation are the same can be rejected as the *sig.* value is smaller than 0.05.

Table B-8 Results of Student’s t test and Levene's Test for three Cases with respect to bus travel time on the eastbound direction

Group Statistics

	GroupCar	N	Mean	Std. Deviation	Std. Error Mean
BusTravelTime ToCentreCase1	Simulation	40	67.4984	2.87533	.45463
	Observation	39	72.0000	28.51961	4.56679
BusTravelTime ToCentreCase2	Simulation	40	68.1386	2.90704	.45964
	Observation	39	72.0000	28.51961	4.56679
BusTravelTime ToCentreCase3	Simulation	40	68.7669	2.43001	.38422
	Observation	39	72.0000	28.51961	4.56679

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
BusTravelTime ToCentreCase1	Equal variances assumed	59.730	.000	-.993	77	.324	-4.50164	4.53205	-13.52611	4.52282
	Equal variances not assumed			-.981	38.753	.333	-4.50164	4.58937	-13.78641	4.78312
BusTravelTime ToCentreCase2	Equal variances assumed	59.944	.000	-.852	77	.397	-3.86143	4.53257	-12.88693	5.16407
	Equal variances not assumed			-.841	38.770	.405	-3.86143	4.58987	-13.14707	5.42421
BusTravelTime ToCentreCase3	Equal variances assumed	61.953	.000	-.714	77	.477	-3.23311	4.52536	-12.24425	5.77804
	Equal variances not assumed			-.705	38.538	.485	-3.23311	4.58293	-12.50651	6.04029

As can be seen from Table B-8, the *sig.* values in the Levene's test for the three Cases are smaller than 0.001, this means that there is significant evidence to reject the null hypothesis of equal variances. Hence, the *sig.* value in the Student's t test are selected in a situation where equal variances not assumed. The *sig.* values in the Student's t tests for all three cases are higher than 0.05, this indicates that the null hypothesis that means bus travel time on the eastbound direction for observations and simulation are the same cannot be rejected.

To conclude, Case 2 and Case 3 have passed the Student’s t test for both directions. Both these Cases are therefore evaluated by the K-S test.

a.2) Two-Sample Kolmogorov-Smirnov Test

Candidate parameter set Case 2

Simulation run number 40 is chosen initially for K-S test as differences in bus travel times between the simulation and the field for both direction are smallest, which are both smaller than two seconds. In the simulation run number 40, travel times of 39 buses on the eastbound direction are explored while that number for the westbound direction is 45. The sizes of field samples are 39 and

45 for the eastbound and westbound direction respectively. As a result, critical *d*-values in the K-S tests for the eastbound and westbound direction are 0.308 and 0.287 correspondingly.

The results of the K-S test for the simulation run number 40 are shown in Table B-9 and Table B-10.

Table B-9 The results of the K-S test for the eastbound direction

Test Statistics[a]		
		BusTravelTimeToCentreCase2
Most Extreme Differences	Absolute	.205
	Positive	.205
	Negative	-.179
Kolmogorov-Smirnov Z		.906
Asymp. Sig. (2-tailed)		.385
a. Grouping Variable: GroupToCentre		
critical *d*-value = 0.308		

As can be seen from Table B-9, the most extreme difference of 0.205 is smaller than critical d-value of 0.308, therefore, the null hypothesis that the bus travel time distributions from field survey and the simulation run number 40 for the eastbound direction are the same cannot be rejected.

Table B-10 The results of the K-S test for the westbound direction

Test Statistics[a]		
		BusTravelTimeOutCentreCase2
Most Extreme Differences	Absolute	.222
	Positive	.133
	Negative	-.222
Kolmogorov-Smirnov Z		1.054
Asymp. Sig. (2-tailed)		.216
a. Grouping Variable: GroupOutCentre		
critical *d*-value = 0.287		

As can be seen from Table B-10, the most extreme difference of 0.222 is smaller than critical d-value of 0.287, therefore, the null hypothesis that the bus travel time distributions from field survey and the simulation run number 40 for the westbound direction are the same cannot be rejected.

For the first evaluation criterion, which is distribution of bus travel times produced from VISSIM, Case 2 has passed the Student’s t test and the K-S test. In other words, Case 2 has passed for the first criterion. In addition, the simulated result should reflect the field observations at different times of the day. For example, based on time of day, comparisons of the simulation run number 40 results and field data are shown in Figure B-18.

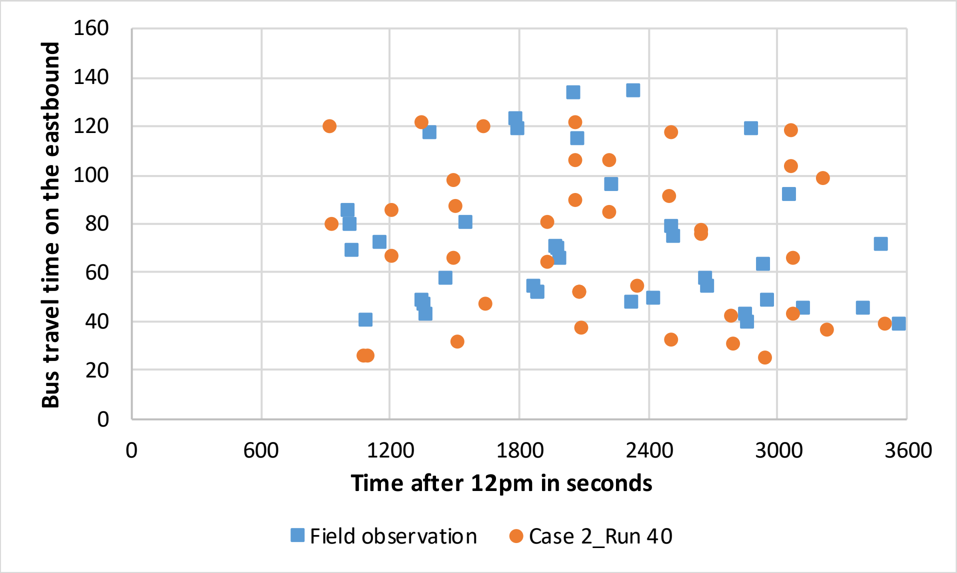


Figure B-18 Comparisons of bus travel time on the eastbound direction between simulation run number 40 and field data based on time of day

Figure B-18 displays that the simulation run 40 results lie in the same range of the field data in term of time of day and bus travel time. It does not appear to show any significant difference compared with the field data.

<u>Candidate parameter set case 3</u>

Simulation run number 24 is chosen initially for K-S test as the differences in bus travel times between the simulation and the field for both directions are smallest, which are both smaller than two seconds. In the simulation run number 24, travel times of 39 buses on the eastbound direction are explored while that number for the westbound direction is 45. The sizes of the field samples are 39 and 45 for the eastbound and westbound direction respectively. As a result, critical *d*-values in K-S test for the eastbound and westbound direction are 0.308 and 0.287 correspondingly.

The results of the K-S test for the simulation run number 24 are shown in Table B-11 and Table B-12.

Table B-11 The results of the K-S test for the eastbound direction

Test Statistics^a		
		BusTravelTimeToCentreCase3
Most Extreme Differences	Absolute	.205
	Positive	.205
	Negative	-.179
Kolmogorov-Smirnov Z		.906
Asymp. Sig. (2-tailed)		.385
a. Grouping Variable: GroupToCentre		
critical *d*-value = 0.308		

As can be seen from Table B-11, the most extreme difference of 0.205 is smaller than critical d-value of 0.308, therefore, the null hypothesis that the bus travel time distributions from the field survey and the simulation run number 24 for the eastbound direction are the same cannot be rejected.

Table B-12 The results of the K-S test for the westbound direction

Test Statistics[a]		
		BusTravelTimeOutCentreCase3
Most Extreme Differences	Absolute	.192
	Positive	.161
	Negative	-.192
Kolmogorov-Smirnov Z		.882
Asymp. Sig. (2-tailed)		.418
a. Grouping Variable: GroupOutCentre		
critical *d*-value = 0.287		

As can be seen from Table B-12, the most extreme difference of 0.192 is smaller than critical d-value of 0.287, therefore, the null hypothesis that the bus travel time distributions from the field survey and the simulation run number 24 for the westbound direction are the same cannot be rejected.

To conclude, for the first evaluation criterion, which is distribution of bus travel times produced from VISSIM, Case 3 has passed the Student's t test and the K-S test. In other words, Case 3 has passed for the first criterion.

b) Visualisation

There are no errors in forty runs for Case 2 and Case 3. As a result, both Parameter Set Case 2 and Case 3 are chosen for the validation process.

B.5.4 Validation process

To perform the validation of the microscopic simulation model, a new set of field data under untried conditions should be collected. This means validation data must be collected for different time periods or conditions. Data for the calibration process are obtained from video recordings from 12:00 to 13:00 on Monday 19th March 2018. Hence, the data for the validation process will be explored from video recordings from 12:00 to 13:00 on Thursday 22nd March 2018. The average bus travel times on the eastbound and westbound directions observed from the field are 78.37 and 93.02 seconds respectively. Forty random seeded runs were made for each of two parameter sets and evaluated based on the Student's t-test in the first place. Because bus travel time is only the key performance indicator for the calibration and validation process of the simulation model for the off-peak period, the K-S test needs to be conducted for the validation process.

a) Student's t test

Student's t test and Levene's Test are run in the SPSS program and the results are shown in Table B-13 and Table B-14.

Table B-13 Results of Student's t test and Levene's Test for Cases 2 and 3 with respect to bus travel time on the westbound direction

	GroupCar	N	Mean	Std. Deviation	Std. Error Mean
BusTravelTime OutCentreCase2	Simulation	40	97.2655	3.30624	.52276
	Observation	44	93.0227	18.10241	2.72904
BusTravelTime OutCentreCase3	Simulation	40	98.0983	3.00700	.47545
	Observation	44	93.0227	18.10241	2.72904

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
BusTravelTime OutCentreCase2	Equal variances assumed	64.910	.000	1.460	82	.148	4.24275	2.90683	-1.53985	10.02536
	Equal variances not assumed			1.527	46.145	.134	4.24275	2.77866	-1.34992	9.83543
BusTravelTime OutCentreCase3	Equal variances assumed	63.916	.000	1.751	82	.084	5.07553	2.89944	-.69238	10.84344
	Equal variances not assumed			1.832	45.604	.073	5.07553	2.77015	-.50179	10.65285

Table B-14 Results of Student's t test and Levene's Test for Cases 2 and 3 with respect to bus travel time on the eastbound direction

	GroupCar	N	Mean	Std. Deviation	Std. Error Mean
BusTravelTime OutCentreCase2	Simulation	40	68.9684	2.38110	.37649
	Observation	39	78.3750	26.51239	4.19198
BusTravelTime OutCentreCase3	Simulation	40	70.5445	1.68702	.26674
	Observation	39	78.3750	26.51239	4.19198

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
BusTravelTime OutCentreCase2	Equal variances assumed	70.035	.000	-2.235	78	.028	-9.40662	4.20885	-17.78580	-1.02745
	Equal variances not assumed			-2.235	39.629	.031	-9.40662	4.20885	-17.91551	-.89774
BusTravelTime OutCentreCase3	Equal variances assumed	74.804	.000	-1.864	78	.066	-7.83046	4.20046	-16.19292	.53200
	Equal variances not assumed			-1.864	39.316	.070	-7.83046	4.20046	-16.32450	.66358

Table B-13 shows both Case 2 and Case 3 have passed the t test while Table B-14 shows only Case 3 has passed the t test. Hence, Case 3 is evaluated with K-S test.

b) Two-sample Kolmogorov-Smirnov test

Simulation run number 19 is chosen initially for the K-S test as differences in bus travel times between the simulation and the field for both direction are smallest, which are both smaller than four seconds. In the simulation run number 19, travel times of 41 buses on the eastbound direction are explored while that number for the westbound direction is 39. The sizes of the field samples are 40 and 44 for the eastbound and westbound direction respectively. As a result, the critical *d*-values in the K-S test for the eastbound and westbound direction are 0.302 and 0.299 correspondingly. The results of the K-S test for the simulation run number 19 are shown in Table B-15 and Table B-16.

Table B-15 The results of the K-S test for the eastbound direction

Test Statistics[a]		
		BusTravelTimeToCentreCase3
Most Extreme Differences	Absolute	.244
	Positive	.244
	Negative	-.163
Kolmogorov-Smirnov Z		1.097
Asymp. Sig. (2-tailed)		.180
a. Grouping Variable: GroupToCentre		
critical *d*-value = 0.302		

As can be seen from Table B-15, the most extreme difference of 0.244 is smaller than critical d-value of 0.302, therefore, the null hypothesis that the bus travel time distributions from field survey and the simulation run number 19 for the eastbound direction are the same cannot be rejected.

Table B-16 The results of the K-S test for the westbound direction

Test Statistics[a]		
		BusTravelTimeOutCentreCase3
Most Extreme Differences	Absolute	.190
	Positive	.190
	Negative	-.059
Kolmogorov-Smirnov Z		.864
Asymp. Sig. (2-tailed)		.445
a. Grouping Variable: GroupOutCentre		
critical *d*-value = 0.299		

As can be seen from Table B-16, the most extreme difference of 0.190 is smaller than critical d-value of 0.299, therefore, the null hypothesis that the bus travel time distributions from field survey and the simulation run number 19 for the westbound direction are the same cannot be rejected.

To conclude, the parameter set Case 3 has passed the K-S test and is used for the VISSIM simulation model for the off-peak period.

Appendix C Comparative Economic Assessment Application

C.1 Congestion Charge for the Hanoi Case Study

Congestion charge coefficients in the utility functions are estimated below.

Calculation examples for car

*U_{car_before} (U_{car_0}) = 1.325391 - 0.0216*tt_car_0 - 0.0001628*cf_car_0*

- Existing car fuel cost (fc_car_0) = 2,376 (VND/Km).

- Existing motorcycle, car and bus share are 77.38%, 13.83% and 8.79% respectively. P_{mc_0} = 77.38%, P_{car_0} = 13.83%, P_{bus_0} = 8.79%.

- Existing demands of all modes, motorcycle, car and bus are Q, Q_{mc_0}, Q_{car_0}, Q_{bus_0}, correspondingly.

If the total demand of all modes is unchanged, the following equations are consistent.

$$\frac{Q_{Car\_1}}{Q_{Car\_0}} = \frac{P_{Car\_1} * Q}{P_{Car\_0} * Q} = \frac{P_{Car\_1}}{P_{Car\_0}}$$

$$\frac{\Delta Q_{Car}}{Q_{Car\_0}} = \frac{P_{Car\_1} - P_{Car\_0}}{P_{Car\_0}}$$

Percentage change in fuel price and percentage change in car fuel cost are the same, which is:

$$\frac{\Delta cf\_car}{\text{cf\_car\_0}} = \frac{(\text{cf\_car\_1} - \text{cf\_car\_0})}{\text{cf\_car\_0}}$$

Express an equation of the elasticity of car demand with respect to fuel price below if the change in car fuel cost is 1.0 VND/km (cf_car_1 - cf_car_0).

$$E_{cf} = \frac{\frac{P_{Car\_1} - P_{Car\_0}}{P_{Car\_0}}}{\frac{1}{\text{cf\_car\_0}}} = \frac{(P_{Car\_1} - P_{Car\_0}).\,\text{cf\_car\_0}}{P_{Car_0}}$$

Then, change in car utility (ΔU_{car}) is fuel cost parameter value (cf_coefficient = -0.0001628). Changes in utilities of motorcycle and bus are assumed to be unchanged.

Probability of choosing car is estimated as:

$$P_{Car\_1} = \frac{P_{Car\_0}\exp(\Delta U_{Car})}{P_{Car\_0}\exp(\Delta U_{Car}) + P_{MC\_0}\exp(\Delta U_{MC}) + P_{Bus\_0}\exp(\Delta U_{Bus})}$$

$$\Delta U_{MC} = \Delta U_{Bus} = 0$$

So,

$$P_{Car\_1} = \frac{P_{Car\_0}\exp(\Delta U_{Car})}{P_{Car\_0}\exp(\Delta U_{Car}) + P_{MC\_0} + P_{Bus\_0}}$$

$$P_{MC\_0} + P_{Bus\_0} = 1 - P_{Car\_0}$$

Hence,

$$P_{Car\_1} = \frac{P_{Car\_0}\exp(\Delta U_{Car})}{P_{Car\_0}\exp(\Delta U_{Car}) + 1 - P_{Car\_0}}$$

$$P_{Car\_1} - P_{Car\_0} = \frac{P_{Car_0}\exp(\Delta U_{Car})}{P_{Car_0}\exp(\Delta U_{Car}) + 1 - P_{Car\_0}} - P_{Car\_0}$$

Divide by P_{Car_0} in both sides of the equation, the equation is rearranged as:

$$\frac{(P_{Car_1} - P_{Car\_0})}{P_{Car\_0}} = \frac{\exp(\Delta U_{Car})}{P_{Car_0}\exp(\Delta U_{Car}) + 1 - P_{Car_0}} - 1$$

$$\frac{(P_{Car_1} - P_{Car\_0})}{P_{Car\_0}} = \frac{\exp(\Delta U_{Car}) - P_{Car\_0}\exp(\Delta U_{Car}) - 1 + P_{Car\_0}}{P_{Car\_0}\exp(\Delta U_{Car}) + 1 - P_{Car\_0}}$$

$$\frac{(P_{Car_1} - P_{Car\_0})}{P_{Car\_0}} = \frac{[\exp(\Delta U_{Car}) - 1].(1 - P_{Car\_0})}{P_{Car\_0}\exp(\Delta U_{Car}) + 1 - P_{Car\_0}}$$

Now, the elasticity of car demand with respect to fuel price is estimated as:

$$E_{cf} = \frac{[\exp(\Delta U_{Car}) - 1].(1 - P_{Car\_0})}{P_{Car\_0}\exp(\Delta U_{Car}) + 1 - P_{Car\_0}}.\text{cf\_car\_0}$$

$$E_{cf} = \frac{[\exp(\text{cf\_coefficient}) - 1].\left(1 - P_{Car\_0}\right).\text{cf\_car\_0}}{P_{Car\_0}\exp(\text{cf\_coefficient}) + 1 - P_{Car\_0}}$$

Substitute P_{Car_0}= 13.83%, cf_car_0 = 2,376 (VND/vehicle-km), cf_coefficient =-0.0001628, cc_car_0 = 1,250.7 (VND/vehicle-km) in the equation above, the elasticity of car demand with respect to fuel price is estimated as -0.175. This value can be consistent. Because Goodwin, Dargay and Hanly (2004) reviewed the effects of fuel price on traffic levels and showed that the elasticity of car demand with respect to fuel price is -0.16 for the short-term estimation.

Similarly, the elasticity of car demand with respect to congestion charge is estimated as:

$$E_{cc} = \frac{[\exp(\text{cc\_coefficient}) - 1].\left(1 - P_{Car\_0}\right).\text{cc\_car\_0}}{P_{Car\_0}\exp(\text{cc\_coefficient}) + 1 - P_{Car\_0}}$$

Santos (2004) studied the London Congestion Charge Scheme and showed the elasticity of car demand with respect to the generalised cost is -2.5. A congestion charge of £5 was a component of the generalised cost of £23. This can imply the elasticity of car demand with respect to the congestion charge is around -0.54. Assume that Ecc = -0.54 for the Hanoi case study. Substitute P_{Car_0} = 13.83%, cf_car_0 = 2,376 (VND/vehicle-km), cf_coefficient =-0.0001628, cc_car_0 = 1,250.7 (VND/ vehicle-km) in the equation above, the congestion charge coefficient in the car utility is estimated as -0.000501.

Calculation examples for motorcycle

U_{mc_before} (U_{mc_0}) = 1.630348 - 0.048*tt_mc_0 - 0.0002116*fc_mc_0

- Existing motorcycle fuel cost (fc_mc_0) = 760 (VND/Km).

- P_{mc_0} = 77.38%, cc_mc_0 = 1,250.7 (VND/ vehicle-km).

The elasticity of motorcycle demand with respect to fuel price is estimated as:

$$E_{cf} = \frac{[\exp(\text{cf\_coefficient\_mc}) - 1] . \left(1 - P_{mc\_0}\right) . \text{cf\_mc\_0}}{P_{mc\_0} \exp(\text{cf\_coefficient\_mc}) + 1 - P_{mc\_0}} = -0.036$$

The motorcyclists seem to very insensitive to fuel price due to the following reasons. Firstly, fuel consumption of motorcycle is around one third that number of car, which are adapted from data in the study of Bray and Holyoak (2015). Secondly, motorcycles are dominant with a share of around 77%. Thirdly, motorcyclists are mainly lower middle-income and upper middle-income people, who neither have any car and nor be attracted by existing bus services (Vu, 2015).

Based on studies of Santos (2004) and Goodwin, Dargay and Hanly (2004), assume that the elasticity of motorcycle demand with respect to congestion charge are three times (0.54/0.175) as high as the elasticity of motorcycle demand with respect to fuel price for the Hanoi case study. E_{cc} for motorcycle is assumed as -0.1111. The congestion charge coefficient in the motorcycle utility is estimated as -0.000393.

C.2 An Example Calculation for the Completed Assessment

This appendix shows an example calculation for the Metro option – Scenario 2 with the congestion charge scheme for the peak period. The process of the first two iterations of the completed assessment in Figure 8-6 is illustrated below.

C.2.1 For the first iteration after an introduction of Metro

Existing situation

The following parameters are obtained from the VISSIM simulation model and social cost model.

- Existing motorcycle travel time (tt_mc_0) = 5.593876 minutes.

- Existing motorcycle fuel cost (cf_mc_0) = 760 VND/Km.

- Existing car travel time (tt_car_0) = 6.046047 minutes.

- Existing car fuel cost (cf_car_0) = 2,376 VND/Km.

- Existing bus travel time (tt_bus_0) =6.795102 minutes.

- Existing bus wait time (wt_bus_0) = 0.4184 minutes.

Notes that the average journey length is 7.2 km in the study of Bray and Holyoak (2015) and the length of the simulated segment is 1.5km. The utilities of motorcycle (mc), car and bus are estimated as:

$U_{mc\_before}\ (U_{mc\_0}) = 1.630348 - 0.01*(7.2/1.5)*tt\_mc\_0 - 0.0002116*cf\_mc\_0 = 1.201$

$U_{car\_before}\ (U_{car\_0}) = 1.325391 - 0.0045*(7.2/1.5)*tt\_car\_0 - 0.0001628*cf\_car\_0 = 0.808$

$U_{bus\_before}\ (U_{bus\_0}) = 0.665548 - 0.005149*(7.2/1.5)*tt\_bus\_0 - 0.0112216*wt\_bus\_0 = 0.4929$

Incremental elasticity analysis after an introduction of Metro

After the introduction of Metro, the following parameters are obtained from the VISSIM simulation model and social cost model.

- Motorcycle travel time (tt_mc_1) = 5.4657 minutes.

- Motorcycle fuel cost (cf_mc_1) = 755.48 VND/km.

- Car travel time (tt_car_1) = 5.9849 minutes.

- Car fuel cost (cf_car_1) = 2,360.88 VND/km.

- Remaining bus travel time (tt_bus_1) = 6.7643 minutes.

- Remaining bus wait time (wt_bus_1) = 0.4683 minutes.

- Metro travel time (tt_metro_1) = 3.4012 minutes.

- Metro wait time (wt_metro_1) = 0.918 minutes.

Hence, the utilities of each mode in the after situation are estimated as:

U_{mc_after} (U_{mc_1}) = 1.630348 - 0.01*(7.2/1.5)*tt_mc_1 - 0.0002116*cf_mc_1 = 1.2081

$U_{car\_\ after}$ (U_{car_1}) = 1.325391 - 0.0045*(7.2/1.5)*tt_car_1 - 0.0001628*cf_car_1 = 0.8118

$U_{bus\_\ after}$ (U_{bus_1}) = 0.665548 - 0.005149*(7.2/1.5)*tt_bus_1 - 0.0112216*wt_bus_1 = 0.4931

U_{Metro} (U_{metro_1}) = 0.996184 - 0.004496*(7.2/1.5)*tt_metro_1-0.0112216*wt_metro_1= 0.9125

The utility of PT in the upper nest is:

$U_{pt} = 0.7532 \times \ln (e^{Umetro} + e^{Ubus\_after}) = 1.067$

Change rate in a logsum and total demand is:

$$\frac{\Delta Logsum}{Logsum\_before} = \frac{Logsum_{after} - Logsum\_before}{Logsum\_before}$$

$$Logsum\_before = Ln\left(e^{Ucar\_before} + e^{Umotorcycle\_before} + e^{Ubus\_before}\right) = 1.97459$$

$$Logsum\_after = Ln\left(e^{Ucar_{after}} + e^{Umotorcycle_{after}} + e^{U_{pt}}\right) = 2.14104$$

So,

$$\frac{\Delta Q}{Q} = \frac{Q_1 - Q_0}{Q_0} = \frac{\Delta Logsum}{Logsum\_before} = 0.0843$$

As existing demand ($Q_{\_0}$) is 19,000 pax in both directions, new total demand after the introduction of Metro ($Q_{\_1}$) is 19,000*(1+0.0843) = 20,601 pax.

Incremental nested logit model

Existing motorcycle, car and bus share are 77.38%, 13.83% and 8.79% respectively. These values are shown in Table 7-4. P_{mc_0} = 77.38%, P_{car_0} = 13.83%, $P_{PT\_0} = P_{bus\_0}$ = 8.79%.

Using equations in the study of Preston (1991), public transport's share in the upper nest is:

Appendix C

$$P_{PT\_1} = \frac{P_{PT\_0}\left[\exp\left(U_{metro\_1} - U_{bus\_0}\right) + \exp\left(U_{bus\_1} - U_{bus\_0}\right)\right]^{\emptyset}}{P_{PT\_0}\left[\exp\left(U_{metro\_1} - U_{bus\_0}\right) + \exp\left(U_{bus\_1} - U_{bus\_0}\right)\right]^{\emptyset} + \left[1 - P_{PT\_0}\right]}$$

where,

P_{PT_1} (P_{PT_0}) is the proportion choosing public transport in the after (before) the introduction of Metro;

$\emptyset$ is EMU parameter (or structural parameter for public transport nest). This value is 0.7532 for the Hanoi case study, based on the study of Hensher and Rose (2007) and modal share data in the study of Japan International Cooperation Agency (2007).

$$P_{PT\_1} = \frac{8.79\%.\left[\exp(0.9125 - 0.4929) + \exp(0.4931 - \ 0.4929)\right]^{0.7532}}{8.79\%.\left[\exp(0.9125 - 0.4929) + \exp(0.4931 - \ 0.4929)\right]^{0.7532} + [1 - 8.79\%]}$$

So, $P_{PT\_1} = 16.206\%$

The lower nest are therefore:

$$P_{metro_1} = \frac{\exp(\,U_{metro_1} - U_{bus_0})}{\exp(\,U_{metro_1} - U_{bus_0}) + \exp(\,U_{bus_1} - U_{bus_0})}.P_{PT_1}$$

$$P_{metro_1} = \frac{\exp(0.9125 - 0.4929)}{\exp(0.9125 - 0.4929) + \exp(0.4931 - \ 0.4929)}.0.16206 = 9.777\%$$

and

$$P_{bus\_1} = \frac{\exp(\,U_{bus\_1} - U_{bus\_0})}{\exp(\,U_{metro\_1} - U_{bus\_0}) + \exp(\,U_{bus\_1} - U_{bus\_0})}.P_{PT\_1}$$

$$P_{bus_1} = \frac{\exp(0.4931 - \ 0.4929)}{\exp(0.9125 - 0.4929) + \exp(0.4931 - \ 0.4929)}.0.16206 = 6.429\%$$

The probabilities for motorcycle (P_{mc_1}) and car (P_{car_1}) in the upper nest are estimated as:

$$P_{mc\_1} = P_{mc\_0}\frac{1 - P_{PT\_1}}{1 - \ P_{PT\_0}} = \ 77.38\%\frac{1 - 16.206\%}{1 - \ 8.79\%} = 71.088\%$$

$$P_{car\_1} = P_{car\_0}\frac{1 - P_{PT\_1}}{1 - \ P_{PT\_0}} = 13.83\%\frac{1 - 16.206\%}{1 - \ 8.79\%} = 12.706\%$$

As new total demand after the introduction of Metro ($Q_{\_1}$) is 20,601 pax, new motorcycle, car, bus and Metro demands are 14,645; 2,618; 1,324 and 2,014 pax correspondingly.

For the first iteration of the completed assessment, the changes in motorcycle and car utilities are used to estimate the total general demand after the introduction of Metro in the incremental elasticity analysis, whilst they are not considered in the equations in the study of Preston (1991) in the incremental nested logit model. The congestion charge in the first iteration only impacts on the total general demand but do not affect modal shares. Hence, the congestion charge impacts on both the total general demand and modal shares from the second iteration.

C.2.2 For the second iteration after an introduction of a congestion charge scheme

Incremental elasticity analysis

After the introduction of the congestion charging, the following parameters are obtained from the VISSIM simulation model and social cost model.

- Motorcycle travel time (tt_mc_2) = 5.20603 minutes.

- Motorcycle fuel cost (cf_mc_2) = 728.10 VND/km.

- Car travel time (tt_car_2) = 5.64104 minutes.

- Car fuel cost (cf_car_2) = 2275.32 VND/km.

- Remaining bus travel time (tt_bus_2) = 6.95001 minutes.

- Remaining bus wait time (wt_bus_2) = 0.47144 minutes.

- Metro travel time (tt_metro_2) = 1.7475 minutes.

- Metro wait time (wt_metro_2) = 0.3113 minutes.

- Congestion charge = £0.114/vehicle-km = 1250.7 (VND/ vehicle-km) by using the PPP rate in 2015 prices.

Hence, the utilities of each mode in the after situation are estimated as:

$U_{mc\_2} = 1.630348 - 0.01*(7.2/1.5)*tt\_mc\_2 - 0.0002116*cf\_mc\_2 - 0.0002116*3.375*1250.7 = 0.3332$

$U_{car\_2}=1.325391- 0.0045*(7.2/1.5)*tt\_car\_2 - 0.0001628*cf\_car\_2 - 0.0001628*3.375*1250.7 = 0.1459$

$U_{bus\_2} = 0.665548 - 0.005149*(7.2/1.5)*tt\_bus\_2 - 0.0112216*wt\_bus\_2 = 0.4885$

$U_{metro\_2} = 0.996184 - 0.004496*(7.2/1.5)*tt\_metro\_2-0.0112216*wt\_metro\_2= 0.9550$

The utility of PT in the upper nest is:

$U_{pt\_2} = 0.7532 \times \ln (e^{U_{metro\_2}} + e^{U_{bus\_2}}) = 1.08599$

$$\frac{\Delta Logsum}{Logsum\_before} = \frac{Logsum_{after} - Logsum\_before}{Logsum\_before}$$

$$= \frac{Ln\left(e^{Ucar_2} + e^{Umc_2} + e^{U_{pt_2}}\right) - Ln\left(e^{Ucar\_1} + e^{Umc\_1} + e^{Upt\_1}\right)}{Ln\left(e^{Ucar\_1} + e^{Umc\_1} + e^{Upt\_1}\right)}$$

$$= \frac{1.97459 - 2.14104}{1.97459}$$

$\frac{\Delta Q}{Q} = \frac{Q_2 - Q_1}{Q_1} = \frac{\Delta Logsum}{Logsum} = -0.2025$

As $Q\__1$ = 20,601 pax, the new total demand after the introduction of the congestion charge scheme ($Q\__2$) is 20,601 *(1-0.2025) = 16,430 pax.

Incremental nested logit model

As a result, the following equations can be used for estimating the probability of choosing transport mode in the INLM from the second iteration (Department for Transport, 2017d). The changes in utility functions at the lower level are:

$\Delta U_{bus\_2} = U_{bus\_2} - U_{bus\_1} = 0.4885 - 0.4931 = -0.0046$

$\Delta U_{metro\_2} = U_{metro\_2} - U_{metro\_1} = 0.9550 - 0.9125 = 0.0425$

Moreover, the utilities of bus and the new PT mode (at the lower level) can be estimated in the completed assessment, which are shown above. As a result, the change in the utility of public transport at the highest level is as:

$$\Delta U_{PT\_2} = U_{PT_2} - U_{PT_1} = 1.08599 - 1.067 = 0.01899$$

Additionally, the congestion charge is taken into account in the changes in utility of private transport at the highest level, which are as:

$\Delta U_{car\_2} = U_{car\_2} - U_{car\_1} = 0.1459 - 0.8118 = - 0.6659$

$\Delta U_{mc\_2} = U_{mc\_2} - U_{mc\_1} = 0.3332 - 1.2081 = -0.8749$

Note that the change in the congestion charge is equal to zero from the third iteration of the completed assessment.

Probability of choosing PT at the higher split is estimated as:

$$P_{PT\_2} = \frac{P_{PT\_1}\exp(\Delta U_{PT\_2})}{P_{PT\_1}\exp\left(\Delta U_{PT\_2}\right) + P_{car\_1}\exp\left(\Delta U_{car\_2}\right) + P_{mc\_1}\exp\left(\Delta U_{mc\_2}\right)}$$

Appendix C.2.1 shows $P_{PT\_1} = 16.206\%$, $P_{mc\_1} = 71.088\%$ and $P_{car\_1} = 12.706\%$, as well as $P_{metro\_1} = 9.777\%$ and $P_{bus\_1} = 6.429\%$. Probabilities of choosing PT, car and motorcycle at the higher split are estimated as:

$$P_{PT\_2} = \frac{16.206\%. \exp(0.01899)}{16.206\%. \exp(0.01899) + 12.706\% \exp(-0.6659) + 71.088\% \exp(-0.8749)} = 0.3133$$

$$P_{car\_2} = \frac{12.706\% \exp(-0.6659)}{16.206\%. \exp(0.01899) + 12.706\% \exp(-0.6659) + 71.088\% \exp(-0.8749)} = 0.1239$$

$$P_{mc\_1} = 1 - 0.3133 - 0.1239 = 0.5628$$

Probabilities of choosing Metro or bus at the lower split are estimated as:

$$P_{metro\_2} = P_{PT_2}. \frac{P_{metro\_1} * \exp(\Delta U_{metro\_2})}{P_{metro\_1} * \exp(\Delta U_{metro\_2}) + P_{bus\_1} * \exp(\Delta U_{bus\_2})}$$

$$P_{metro\_2} = 0.3133 . \frac{9.777\% * \exp(0.0425)}{9.777\% * \exp(0.0425) + 6.429\% * \exp(-0.0046)} = 0.1926$$

and $P_{bus\_2} = P_{PT\_2} - P_{metro_2} = 0.3133 - 0.1926 = 0.1207$

C.3 Time of Day Demand Splits

To estimate ASC of mixed traffic in the mixed transport social cost modal, time of day demand splits need to be identified. The demand is defined as mixed traffic demand, which either includes motorcycle and car for Scenario 1 or consists of motorcycle, car and partial existing bus for Scenario 2. Because the demand for the new PT mode is used in the public transport social cost model. As mentioned in Chapter 5, the core operating day time services are assumed as from 06:00 to 21:00 and the daily passenger demands are split into four periods including Pear Hour (2 hours), Peak Period (3 hours), Mid-day Off-peak (7 hours) and Morning-evening Off-peak (3 hours). The peak periods include the Pear Hour and Peak Period while the off-peak periods cover the Mid-day Off-peak and Morning-evening Off-peak. Split rates for one hour period for the existing situation are shown in Table 5-7. However, the VISSIM simulations are run for one peak hour and one off-peak period separately. Assume that the rate of demand between the Peak Hour and the Peak Period are unchanged, as well as the rate of demand between the Mid-day Off-peak and Morning-evening Off-peak. In addition, the cross-effects between the peak and off-peak periods are not considered in this thesis. Table C-1 displays the differences of mixed traffic demand split rate for the one-hour period among the existing situation, the Metro options for Scenario 1 with and without the congestion charge scheme.

Table C-1 Mixed traffic demand split into different times for the existing situation and the Metro options with Scenario 1

Period	One hour period	Period duration	Split rate for one hour period (Existing situation)	Split rate for one hour period (The Metro option, Scenario 1, without congestion)	Split rate for one hour period (The Metro option, Scenario 1, with congestion)
Early morning off-peak	6:00-7:00	1	4.0%	4.1%	4.6%
Morning Peak Hour	7:00-8:00	1	10.0%	9.8%	7.9%
Morning Peak Period	8:00-9:00	1	7.5%	7.4%	5.9%
Mid-day Off-peak	9:00-16:00	7	6.5%	6.6%	7.5%
Afternoon Peak Period	16:00-17:00	1	7.5%	7.4%	5.9%
Afternoon Peak Hour	17:00-18:00	1	10.0%	9.8%	7.9%
Evening Peak Period	18:00-19:00	1	7.5%	7.4%	5.9%
Late evening off-peak	19:00-21:00	2	4.0%	4.1%	4.6%

Table C-1 indicates that there are minor changes in demand split into different times after the introduction of only Metro mode whilst significant differences occur after the introduction of both the Metro technology and the congestion charge scheme. The reason can be that the congestion charge and the introduction of Metro causes a dramatic decrease in car and motorcycle demand in the peak periods whilst there is a small reduction in the mixed traffic demand in the off-peak periods. That implies that traffic in the Mid-day Off-peak periods is higher than that level in the Peak Period between 16:00 and 17:00. Although mixed traffic demands between 7-8 AM and 5-6 PM are still busiest after the introduction of the congestion charge scheme. The split rate shown in Table C-1 are inserted in the mixed transport social cost model. The general trend of mixed traffic demand split rate for the Monorail and BRT options are similar to the Metro options.

C.4 Modal Shares

Figure C-1 and Figure C-2 show modal shares for the BRT options for both Scenarios with and without the congestion charge scheme in the peak and off-peak periods respectively. Figure C-3 and Figure C-4 illustrate modal shares for the Monorail options for both Scenarios with and without the congestion charge scheme in the peak and off-peak periods correspondingly.

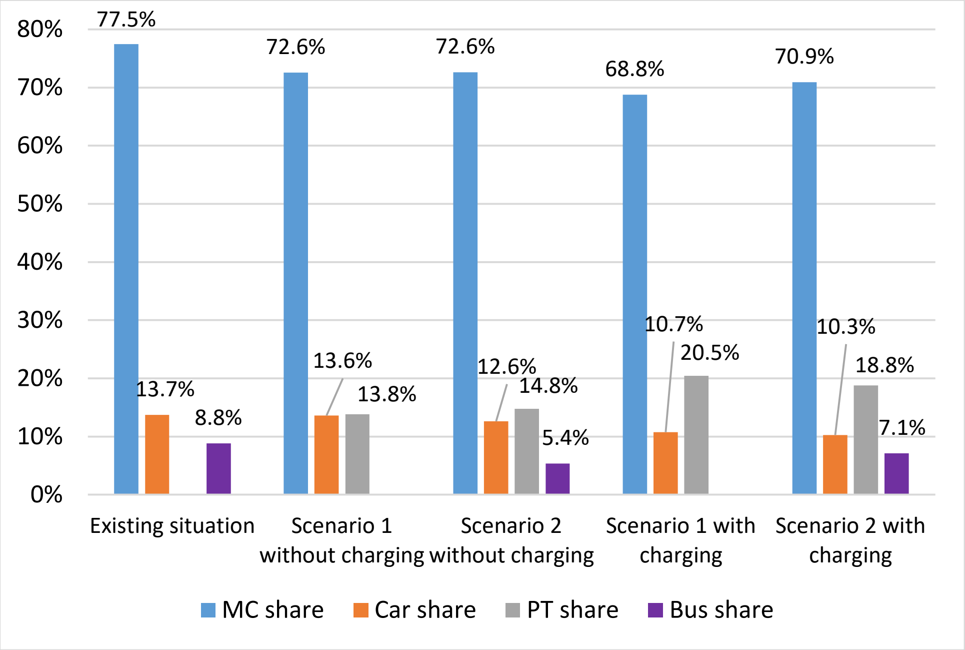


Figure C-1 Modal shares in the peak period for the BRT options for both Scenarios with and without the congestion charge scheme

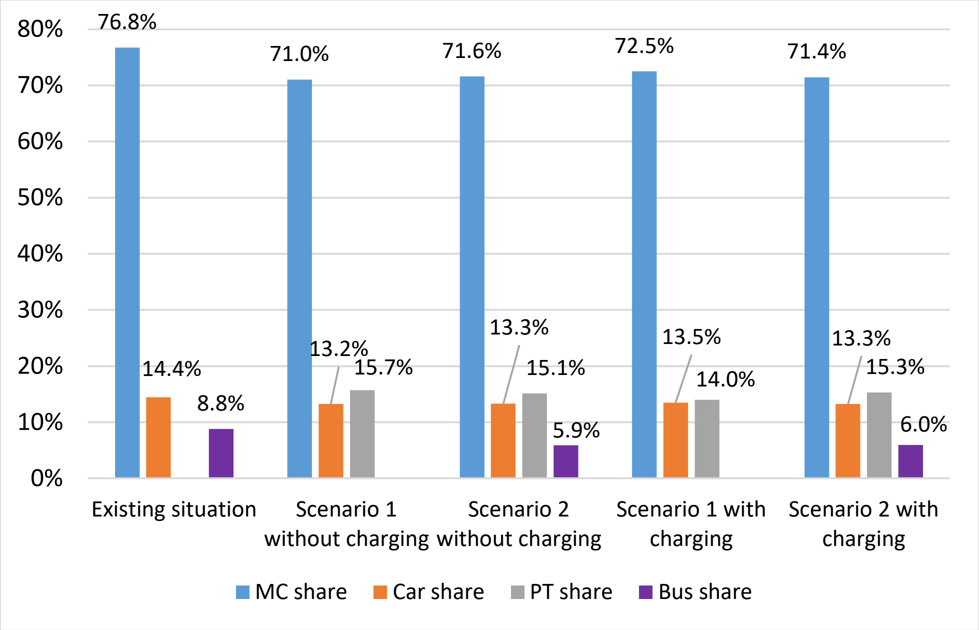


Figure C-2 Modal shares in the off-peak period for the BRT options for both Scenarios with and without the congestion charge scheme

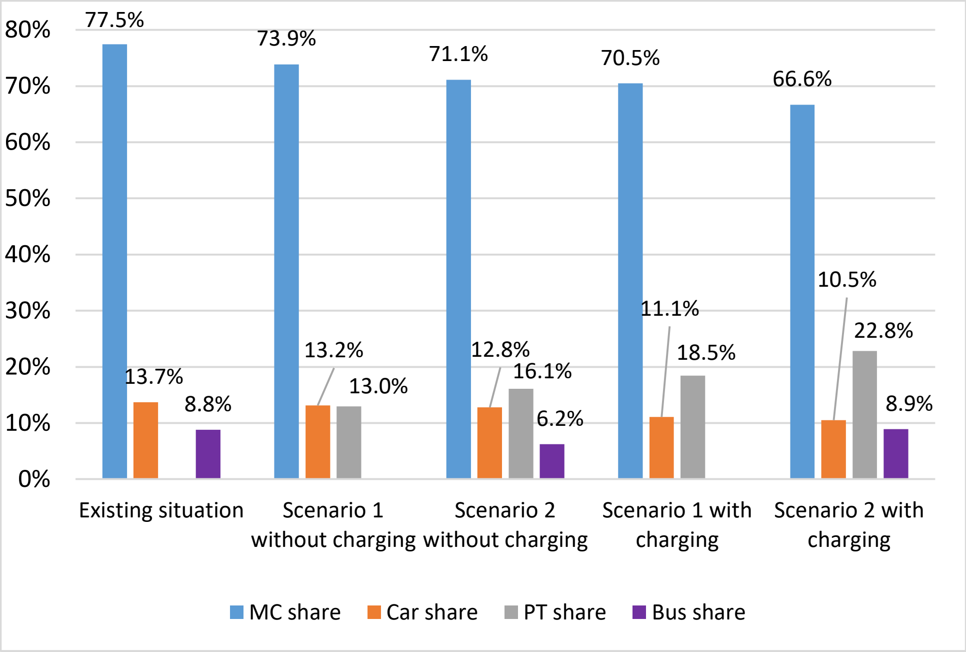


Figure C-3 Modal shares in the peak period for the Monorail options for both Scenarios with and without the congestion charge scheme

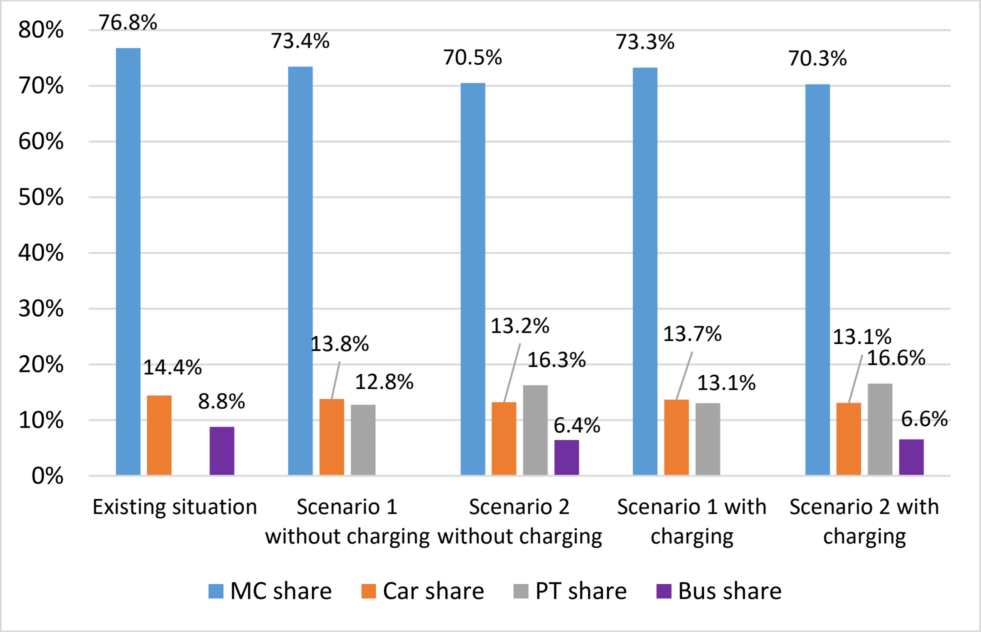


Figure C-4 Modal shares in the off-peak period for the Monorail options for both Scenarios with and without the congestion charge scheme

List of References

Abrantes, P. and Wardman, M. (2011) 'Meta-analysis of UK Values of Travel Time: An Update', *Transportation Research Part A: Policy and Practice*, 45(1), pp. 1-17.

Allen, R. and Lerner, A. (1934) 'The Concept of Arc Elasticity of Demand', *The Review of Economic Studies*, 1(3), pp. 226-230.

Annema, J.A., Mouter, N. and Razaei, J. (2015) 'Cost-Benefit Analysis (CBA), or Multi-criteria Decision-making (MCDM) or Both: Politicians’ Perspective in Transport Policy Appraisal', *Transportation Research Procedia*, 10, pp. 788-797.

Asian Development Bank (2007) *Greater Mekong Subregion Southern*

Coastal Corridor Project. Report and Recommendation of the President to the Board of Directors. Asian Development Bank, Manila.

Asian Development Bank (2008) *Bus Rapid Transit (BRT): Toolkit for Feasibility Studies* Available at: https://sti-india-uttoolkit.adb.org/mod2/se2/004_10.html (Accessed: 22 December 2020).

Asian Development Bank (2013) *Cost-Benefit Analysis for Development - A Practical Guide*. Asian Development Bank, Manila.

Asian Development Bank (2014) *Proposed Loan and Administration of Loan Socialist Republic of Viet Nam: Sustainable Urban Transport for Ho Chi Minh City Mass Rapid Transit Line 2 Project*. Available at: https://www.adb.org/sites/default/files/project-document/80128/45200-002-rrp.pdf (Accessed: 29 May 2017).

Asian Development Bank (2017) *Guidelines for the Economic Analysis of Projects*. Asian Development Bank, Manila.

Balcombe, R. *et al.* (2004) *The demand for public transport: a practical guide*. Crowthorne, UK.

Bangkok Mass Transit System Public Company Limited (2018) *Lift Up Your Life*. Annual Report 2017-2018. Bangkok: Bangkok Mass Transit System Public Company Limited.

Barbosa, S. *et al.* (2017) 'Multi-criteria Analysis Model to Evaluate Transport Systems: An Application in Florianópolis, Brazil', *Transportation Research Part A: Policy and Practice*, 96, pp. 1-13.

Barceló, J. (2010) 'Models, traffic models, simulation, and traffic simulation', in *Fundamentals of Traffic Simulation*. Springer, pp. 1-62.

Bates, J., Ashley, D. and Hyman, G. (1987) *15th PTRC Summer Annual Meeting, University of Bath, England*.

Ben-Akiva, M. and Bierlaire, M. (1999) 'Discrete Choice Methods and Their Applications to Short Term Travel Decisions', in *Handbook of transportation science*. Springer, pp. 5-33.

Ben-Akiva, M. and Morikawa, T. (2002) 'Comparing Ridership Attraction of Rail and Bus', *Transport Policy*, 9(2), pp. 107-116.

Bickel, P. *et al.* (2005) *Developing Harmonised European Approaches for Transport Costing and Project Assessment Deliverable 2 'State-of-the-art in Project Assessment'*. Stuttgart: IER, University of Stuttgart.

Biswas, S., Chandra, S. and Ghosh, I. (2017) 'Use of Lambert W Function in Determining Speed for Macroscopic Traffic Flow modes', *European Transport*, (63), pp. 1-10.

Brake, J., Mulley, C. and Nelson, J. (2006) *Good Practice Guide for Demand Responsive Transport Services using Telematics*. Available at: https://eprint.ncl.ac.uk/file_store/production/12981/B9C57C8D-4AD9-4ED6-80E7-C05258B34516.pdf (Accessed: 11 July 2018).

Brand, C. and Preston, J. (2003) *The Software Tool: Specification and Case Study Validation*. TSU Working Paper (Ref. 948). Oxford: Transport Studies Unit, University of Oxford.

Bray, D. and Holyoak, N. (2015) 'Motorcycles in Developing Asian Cities: A Case Study of Hanoi', *Paper presented at the 37th Australasian Transport Research Forum (ATRF)*. Sydney, New South Wales, Australia, September 30 - October 2.

Broniewicz, E. and Ogrodnik, K. (2020) 'Multi-criteria Analysis of Transport Infrastructure Projects', *Transportation research part D: transport and environment*, 83, p. 102351.

Bruun, E.C. (2007) *Better Public Transit Systems*. Chicago: Planners Press, American Planning Association.

Burghout, W. (2004) *Hybrid Microscopic-mesoscopic Traffic Simulation*. KTH.

Cacciabue, P. (2007) *Modelling Driver Behaviour in Automotive Environments: Critical Issues in Driver Interactions with Intelligent Transport Systems*. Springer.

Chang, H.-L. and Yeh, T.-H. (2006) 'Regional Motorcycle Age and Emissions Inspection Performance: A Cox Regression Analysis', *Transportation Research Part D: Transport and Environment*, 11(5), pp. 324-332.

Chen, K. *et al.* (2003) 'Motorcycle Emissions and Fuel Consumption in Urban and Rural Driving Conditions', *Science of The Total Environment*, 312(1-3), pp. 113-122.

Cheu, R.L., Tan, Y. and Lee, D. (2003) *83rd Annual Meeting of the Transportation Research Board*.

Chu, C.M., Sano, K. and Matsumoto, S. (2005) 'The Speed, Flow and Headway Analyses of Motorcycle Traffic', *Journal of the Eastern Asia Society for Transportation Studies*, 6, pp. 1496-1508.

Cooper, J. (2007) *Review of the Components and Structure Applied to Updating City of Glasgow Taxi Tariffs*. Available at: https://www.glasgow.gov.uk/councillorsandcommittees/viewSelectedDocument.asp?c=P62AFQDNDNZ3ZLDX (Accessed: 25 July 2018).

Cooper, J. and Mundy, R. (2010) *Taxi! Urban Economies and the Social and Transport Impacts of the Taxicab*. London: Routledge.

Cowie, J. (2009) *The Economics of Transport: A Theoretical and Applied Perspective*. Oxford: Routledge.

Cowie, J. and Ison, S. (2017) *The Routledge Handbook of Transport Economics*. Oxford: Routledge.

Currie, G. (2005) 'The Demand Performance of Bus Rapid Transit', *Journal of public transportation*, 8(1), pp. 41-55.

Danaher, A.R. *et al.* (2007) 'TCRP Report 118: Bus Rapid Transit Practitioner’s Guide', *Transportation Research Board of the National Academies, Washington, DC*.

De Jong, G. *et al.* (2007) 'The Logsum as an Evaluation measure: Review of the Literature and New Results', *Transportation Research Part A: Policy and Practice*, 41(9), pp. 874-889.

Department for Transport (2014) *TAG UNIT M3.1 Highway Assignment Modelling*. London.

Department for Transport (2017a) *TAG Data Book* London.

Department for Transport (2017b) *TAG UNIT A1.3 User and Provider Impacts*. London.

Department for Transport (2017c) *TAG UNIT M1 Principles of Modelling and Forecasting*. London.

Department for Transport (2017d) *TAG UNIT M2 Variable Demand Modelling*. London.

Department for Transport (2018a) *TAG Unit A1.1 Cost-Benefit Analysis*. London.

Department for Transport (2018b) *TAG UNIT A2.1 Wider Economic Impacts Appraisal*. London.

Dimitriou, H., Ward, J. and Dean, M. (2016) 'Presenting the Case for the Application of Multi-criteria Analysis to Mega Transport Infrastructure Project Appraisal', *Research in Transportation Economics*, 58, pp. 7-20.

Dissanayake, D. *et al.* (2012) 'Inter-regional and Inter-temporal Analysis of Travel Behaviour for Asian Metropolitan Cities: Case Studies of Bangkok, Kuala Lumpur, Manila, and Nagoya', *Transport Policy*, 19(1), pp. 36-46.

DMJM Harris (2001) *Monorail Technology Assessment*. Available at: https://www.montgomerycountymd.gov/DOT-Transit/Resources/Files/techreportfinalreport.pdf (Accessed: 14 July 2018).

Dobes, L. and Bennett, J. (2009) 'Multi-criteria Analysis: "Good Enough" for Government Work?', *Agenda: A Journal of Policy Analysis and Reform*, pp. 7-29.

Dowling, R.G. (2005) *Predicting Air Quality Effects of Traffic-flow Improvements: Final Report and User's Guide* (NCHRP report 535).

Duong, H.H. (2005) *Highway Design. [Thiết kế đường ô tô]*. 2nd edn. Hanoi: Education publishing.

Euler, L. (1927) 'De Formulis Exponentialibus Replicatis', *Opera Mathematica*, 15, pp. 268-297.

European Environment Agency (2015) *Occupancy Rates of Passenger Vehicles*. Available at: https://www.eea.europa.eu/data-and-maps/indicators/occupancy-rates-of-passenger-vehicles/occupancy-rates-of-passenger-vehicles-1 (Accessed: 6 September 2017).

Federal Transit Administration (2012) *2012 National Transit Summaries and Trends*. Washington, D.C. Available at: https://www.transit.dot.gov/sites/fta.dot.gov/files/docs/NTST%20for%20RY%202012.pdf.

Feng, Y., Perrin, J. and Martin, P.T. (2003) *Transportation Research Board 82nd Annual Meeting*.

Flores, O. and Rayle, L. (2017) 'How Cities Use Regulation for Innovation: The Case of Uber, Lyft and Sidecar in San Francisco', *Transportation Research Procedia*, 25, pp. 3756-3768.

General Statistic Office of Vietnam (2020) *Population and Employment* Available at: https://www.gso.gov.vn/en/px-web/?pxid=E0201&theme=Population%20and%20Employment (Accessed: 24 March 2021).

Goodwin, P., Dargay, J. and Hanly, M. (2004) 'Elasticities of Road Traffic and Fuel Consumption with Respect to Price and Income: A Review', *Transport reviews*, 24(3), pp. 275-292.

Government of South Australia (2013) *Aimsun Traffic Simualtion Model Development Mannual* Available at: https://www.dpti.sa.gov.au/__data/assets/pdf_file/0014/322007/11542739-v1-AIMSUN_Model_Development_Manual_V7_130913.pdf (Accessed: 20 May 2018).

Government of Vietnam (2014) *Regulation on Businees of Transportation services*.

Government of Vietnam (2016) *Approval of Transportation Master Plan in Hanoi up to 2030 with a Vision Towards 2050*. Available at: http://vanban.chinhphu.vn/portal/page/portal/chinhphu/hethongvanban?class_id=2&mode=detail&document_id=184101 (Accessed: 28 April 2017).

Grab (2018) *Grab Merges with Uber in Southeast Asia*. Available at: https://www.grab.com/vn/en/press/business/uber-dong-nam-a-chinh-thuc-sap-nhap-vao-grab/ (Accessed: 29 November 2019).

Greenberg, H. (1959) 'An Analysis of Traffic Flow', *Operations research*, 7(1), pp. 79-85.

Grimaldi, R., Laurino, A. and Beria, P. (2010) *The Choice Between Bus and Light Rail Transit: A Stylised Cost-benefit Analysis Model*. Available at: https://mpra.ub.uni-muenchen.de/24872/1/MPRA_paper_24872.pdf (Accessed: 25 October 2017).

Gwilliam, K., Kojima, M. and Johnson, T. (2004) *Reducing Air Pollution from Urban Transport*. Available at: http://documents.worldbank.org/curated/en/989711468328204490/pdf/304250PAPER0Reducing0air0pollution.pdf (Accessed: 30 June 2017).

Hall, J.V. and Krueger, A.B. (2018) 'An Analysis of the Labor Market for Uber's Driver-Partners in the United States', *ILR Review*, 71(3), pp. 705-732.

Hanna, R., Kreindler, G. and Olken, B. (2017) 'Citywide Effects of High-occupancy Vehicle Restrictions: Evidence from "Three-in-one" in Jakarta', *Science*, 357(6346), pp. 89-93.

Hanoi Transport & Services Corporation (2017) *Car Parking*. Available at: http://www.transerco.vn/Default.aspx?pageid=197 (Accessed: 8 May 2017).

Hanoi Transport Management and Operation Centre (2011) *Detailed Plan for the Bus Network System in Hanoi from 2010 to 2020*. Hanoi: Hanoi Department of Transport.

Hansen, A. (2016) 'Capitalist Transition on Wheels: Development, Consumption and Motorised Mobility in Hanoi'.

Hansen, A. and Nielsen, K.B. (2014) 'Cars of Future Past in Vietnam and India', *Tvergastein*, 4, pp. 72-79.

Hellinga, B.R. (1998) 'Requirements for the Calibration of Traffic Simulation Models', *Proceedings of the Canadian Society for Civil Engineering*, 4, pp. 211-222.

Hensher, D. and Golob, T. (2008) 'Bus Rapid Transit Systems: A Comparative Assessment', *Transportation*, 35(4), pp. 501-518.

Hensher, D.A. and Rose, J.M. (2007) 'Development of Commuter and Non-commuter Mode Choice Models for the Assessment of New Public Transport Infrastructure Projects: A Case Study', *Transportation Research Part A: Policy and Practice*, 41(5), pp. 428-443.

Hicks, J.R. (1946) *Value and Capital: an Inquiry Into Some Fundamental Principles of Economic Theory*. Oxford: Clarendon Press.

Hussain, H., Radin Umar, R.S. and Ahmad Farhan, M.S. (2011) 'Establishing Speed–flow–density Relationships for Exclusive Motorcycle Lanes', *Transportation Planning and Technology*, 34(3), pp. 245-257.

Independent Evaluation Group (2010) *Cost-Benefit Analysis in World Bank Projects*. Washington, DC: World Bank. Available at: https://openknowledge.worldbank.org/handle/10986/2561 (Accessed: 27 May 2020).

Independent Pricing and Regulatory Tribunal of New South Wales (2012) *2012 Review of Taxi Fares in New South Wales*. Sydney. Available at: https://www.ipart.nsw.gov.au/files/sharedassets/website/trimholdingbay/final_report_-_2012_review_of_taxi_fares_in_nsw_-_maximum_fares_from_july_2012.pdf (Accessed: 7 May 2018).

IT Transport (2002) *The Value of Time in Least Developed Countries* Report to the Department for International Development (UK), Oxon.

IT Transport (2005) *The Value of Time in Least Developed Countries: The African Studies*. Report to the Department for International Development (UK), Oxon.

Jakob, A., Craig, J. and Fisher, G. (2006) 'Transport Cost Analysis: A Case Study of the Total Costs of Private and Public Transport in Auckland', *Environmental Science & Policy*, 9(1), pp. 55-66.

Japan International Cooperation Agency (2007) *The Comprehensive Urban Development Programme in Hanoi Capital City of the Socialist Republic of Vietnam (HAIDEP). Final report (in Vietnamese).*

Japan International Cooperation Agency (2016) *Data Collection Survey on BRT in Hanoi. Final report*. Available at: http://open_jicareport.jica.go.jp/pdf/12266391_01.pdf (Accessed: 2 May 2017).

Johnson, R.A. and Bhattacharyya, G.K. (2014) 'Statistics: Principles and Methods'.

Joseph, H. (1960) 'Construction Costs of Urban Expressways', *CATS Research News*, 4(1).

Kaparias, I. and Bell, M. (2012) 'London Congestion Charging: Successes, Gaps and Future Opportunities Offered by Cooperative ITS', *15th International IEEE Conference on Intelligent Transportation Systems*, pp. 134-139.

Karathodorou, N., Graham, D.J. and Noland, R.B. (2010) 'Estimating the effect of urban density on fuel demand', *Energy Economics*, 32(1), pp. 86-92.

Kittelson & Associates *et al.* (2013) *Transit Capacity and Quality of Service Manual*. 3rd edn. Transit Cooperative Research Program, Report 165. Washington, D.C: Transportation Research Board.

Lambert, J.H. (1758) 'Observationes Variae in Mathesinpuram', *Acta Helvetica physico mathematico anatomico botanico medica*, 3, pp. 128-168.

Lee, D. (2000) 'Demand Elasticities for Highway Travel', *Highway Economic Requirements System*, 4.

Levinson, H. *et al.* (2003) 'TCRP Report 90, Vol II:"Bus Rapid Transit-Implementation Guidelines."', *Transportation Research Board, Washington*.

Li, X. (2015) *A Comparative Assessment for Innovative Public Transport Technologies*. PhD thesis, University of Southampton.

Li, X. and Preston, J. (2015) 'Reassessing the Financial and Social Costs of Public Transport', *Proceedings of the ICE-Transport*, 168(4), pp. 356-369.

Link, H. *et al.* (2016) 'A Generalized Approach for Measuring the Marginal Social Costs of Road Transport in Europe', *International Journal of Sustainable Transportation*, 10(2), pp. 105-119.

Litman, T. (2019) *Understanding Transport Demands and Elasticities*. Victoria. Available at: https://www.vtpi.org/elasticities.pdf.

Litman, T. (2020) *Transportation Cost and Benefit Analysis – Travel Time Costs*. Victoria. Available at: https://www.vtpi.org/tca/tca0502.pdf.

Litman, T. and Doherty, E. (2011) *Transportation Cost and Benefit Analysis: Techniques, Estimates and Implications, Second Edition (2009): Executive Summary*. Victoria Transport Policy Institute.

Long, G. (2000) 'Acceleration Characteristics of Starting Vehicles', *Transportation Research Record: Journal of the Transportation Research Board*, (1737), pp. 58-70.

Macharis, C., De Witte, A. and Ampe, J. (2009) 'The Multi-actor, Multi-criteria Analysis Methodology (MAMCA) for the Evaluation of Transport Projects: Theory and Practice', *Journal of Advanced transportation*, 43(2), pp. 183-202.

Mackie, P., Nellthorp, J. and Laird, J. (2005) *Where to Use Cost Effectiveness Techniques rather than Cost Benefit Analysis* (25 May 2018). World Bank, Washington, DC. Available at: https://openknowledge.worldbank.org/handle/10986/11795.

Mageean, J. and Nelson, J.D. (2003) 'The Evaluation of Demand Responsive Transport Services in Europe', *Journal of Transport Geography*, 11(4), pp. 255-270.

Maibach, M. *et al.* (2007) *Handbook on Estimation of External Cost in the Transport Sector*. Delft: CE Delft.

Malaysia Economic Planning Unit (2010) *Tenth Malaysia Plan 2011 - 2015*. Available at: https://www.pmo.gov.my/dokumenattached/RMK/RMK10_Eds.pdf (Accessed: 20 September 2018).

Manoratna, D.A., Kawata, K. and Yoshida, Y. (2017) 'Environmental Impact and Travel Time Savings of a New Monorail System in Colombo’s Commuting Traffic', *Transportation Research Part D: Transport and Environment*, 51, pp. 122-128.

Mathworks (n.d) *Lambert W Function*. Available at: https://uk.mathworks.com/help/symbolic/lambertw.html (Accessed: 25 September 2017).

Meyer, J.R., Kain, J.F. and Wohl, M. (1965) *The Urban Transportation Problem*. London: Oxford University Press.

Ministry of Construction (2016) *Circular of Identifying and Managing Construction Costs*. Available at: http://www.xaydung.gov.vn/web/guest/home/-/legal/2pBh/vi_VN/18/295208/37 (Accessed: 1 June 2017).

Mohring, H. (1972) 'Optimization and Scale Economies in Urban Bus Transportation', *The American Economic Review*, 62(4), pp. 591-604.

Molt, W. (2016) 'Hanoi Public Transport—Transformation by Management Using Action Research and Behavior Setting Theory', *Journal of Traffic and Transportation Engineering*, 4, pp. 320-338.

Mouter, N. (2020) *Standard Transport Appraisal Methods*. Cambridge: Academic Press.

Nellthorp, J., Bristow, A.L. and Day, B. (2007) 'Introducing Willingness-to-pay for Noise Changes into Transport Appraisal: An Application of Benefit Transfer', *Transport Reviews*, 27(3), pp. 327-353.

Nguyen, C.Y. and Sano, K. (2012) 'Estimating Capacity and Motorcycle Equivalent Units on Urban Roads in Hanoi, Vietnam', *Journal of Transportation Engineering*, 138(6), pp. 776-785.

Nguyen, C.Y., Sano, K. and Chu, C.M. (2007) 'Dynamic Motorcycle Unit and Mean Stream Speed under Mixed Traffic Conditions on Urban Roads', *Journal of the Eastern Asia Society for Transportation Studies*, 7, pp. 2439-2453.

Office of Rail and Road (n.d.) *Railway Networks*. Available at: http://orr.gov.uk/about-orr/who-we-work-with/railway-networks (Accessed: 26 October 2018).

Ortuzar, J.d.D. and Willumsen, L.G. (2011) *Modelling Transport*. 4th edn. West Sussex: John Wiley & Sons Ltd.

Papageorgiou, G. *et al.* (2009) 'Modelling and Simulation of Transportation Systems: a Scenario Planning Approach', *Automatika: Journal for Control, Measurement, Electronics, Computing & Communications*, 50.

Park, B. and Schneeberger, J. (2003) 'Microscopic Simulation Model Calibration and Validation: Case Study of VISSIM Simulation Model for a Coordinated Actuated Signal System', *Transportation Research Record: Journal of the Transportation Research Board*, (1856), pp. 185-192.

Preston, J. (1991) 'Demand Forecasting for New Local Rail Stations and Services', *Journal of Transport Economics and Policy*, 25(2), pp. 183-202.

Preston, J. (2021) 'The Total Social Cost (TSC) of Public Transport Modes', in Currie, G. (ed.) *Handbook of Public Transport Research*. 1 edn. Cheltenham: Edward Elgar, pp. 156-171.

PTV AG (2011) *VISSIM 5.40 User Manual*. Karlsruhe, Germany.

Rogers, M. and Duffy, A. (2012) *Engineering Project Appraisal*. Chichester: John Wiley & Sons.

Sacks, J. *et al.* (2002) 'Statistically-based Validation of Computer Simulation Models in Traffic Operations and Management', *Journal of Transportation and Statistics*, 5(1), pp. 1-24.

Sansom, T. *et al.* (2001) *Surface Transport Costs and Charges: Great Britain 1998*. Report commissioned by the Department of Environment, Transport and the Regions. Leeds: Institute for Transport Studies, University of Leeds and AEA Technology Environment.

Santos, G. (2004) *Road pricing: Theory and evidence*. Oxford: Elsevier.

Santos, G. and Fraser, G. (2006) 'Road Pricing: Lessons from London', *Economic Policy*, 21(46), pp. 264-310.

Santos, G. and Shaffer, B. (2004) 'Preliminary Results of the London Congestion Charging Scheme', *Public Works Management & Policy*, 9(2), pp. 164-181.

Satiennam, T. *et al.* (2011) 'Public Transport Planning for a Motorcycle Dominated Community', *Journal of the Eastern Asia Society for Transportation Studies*, 9, pp. 970-985.

Scherer, M. (2010) 'Is Light Rail More Attractive to Users than Bus Transit? Arguments Based on Cognition and Rational Choice', *Transportation Research Record*, 2144(1), pp. 11-19.

Schneider, H. (2017) *Uber: Innovation in Society*. Switzerland: Springer.

Small, K.A. (1983) 'Bus Priority and Congestion Pricing on Urban Expressways', *Research in Transportation Economics*, 1, pp. 27-74.

Small, K.A. and Verhoef, E.T. (2007) *The Economics of Urban Transportation*. New York: Routledge.

Sugiyanto, G. *et al.* (2010) 'Estimation of Congestion Cost of Private Passenger Car Users in Malioboro, Yogyakarta', *Civil Engineering Dimension*, 12(2), pp. 92-97.

Sugiyanto, G. *et al.* (2011) 'Estimation of Congestion Cost of Motorcycles Users in Malioboro, Yogyakarta, Indonesia', *International Journal of Civil & Environmental Engineering (IJCEE-IJENS)*, 11(01), pp. 56-63.

Taipei Department of Transportation (2013) *Annual Report 2013, Taipei City Government, Taiwan*. Available at: http://www-ws.gov.taipei/001/Upload/public/Attachment/4117177248.pdf (Accessed: 29 October 2018).

Taxi Group (2018) *Taxi group ban xe taxi thuong quyen san bay noi bai*. Available at: https://taxigroup.net/taxi-group-ban-xe-taxi-thuong-quyen-san-bay-noi-bai/ (Accessed: 25 July 2018).

Timan, P.E. (2015) 'Why Monorail Systems Provide a Great Solution for Metropolitan Areas', *Urban Rail Transit*, 1(1), pp. 13-25.

Tirachini, A., Hensher, D.A. and Jara-Díaz, S.R. (2010) 'Comparing Operator and Users Costs of Light Rail, Heavy Rail and Bus Rapid Transit over a Radial Public Transport Network', *Research in transportation economics*, 29(1), pp. 231-242.

Toledo, T. *et al.* (2004) 'Calibration of Microscopic Traffic Simulation Models with Aggregate Data', *Transportation Research Record*, 1876(1), pp. 10-19.

Trang, T.T., Van, H.H. and Oanh, N.T.K. (2015) 'Traffic Emission Inventory for Estimation of Air Quality and Climate Co-benefits of Faster Vehicle Technology Intrusion in Hanoi, Vietnam', *Carbon Management*, 6(3-4), pp. 117-128.

Transport Department of Hanoi (2020) *Proposing congestion charge for private transport in Hanoi from 2025*. Hanoi.

Transport Engineering Design Incorporated (2013) *Transportation Master Plan in Hanoi up to 2030 with a Vision Towards 2050*. Hanoi: Department of Transport.

Transport for London (2010) *Traffic Modelling Guidelines. TfL Traffic Manager and Network Performance Best Practice. Version 3.*

Transport for London (2021) *Congestion Charge*. Available at: https://tfl.gov.uk/modes/driving/congestion-charge (Accessed: 16 February 2021).

Transport Research Partners (2016) *Glasgow Taxi Cost Model 2016 - Review of Taxi Tariffs in the City of Glasgow for the period February 2015 - February 2016*. Glasgow: Glasgow City Council.

Transport Simulation Systems (2014) *Aimsun 8 Users' Manual*. Spain.

Transportation Research Board (2010) *HCM 2010: Highway Capacity Manual*. 5th edn. Washington, D.C.

Tsai, J.-H. *et al.* (2005) 'Development of a Local Real World Driving Cycle for Motorcycles for Emission Factor Measurements', *Atmospheric Environment*, 39(35), pp. 6631-6641.

Tzeng, G.-H., Lin, C.-W. and Opricovic, S. (2005) 'Multi-criteria Analysis of Alternative-fuel Buses for Public Transportation', *Energy Policy*, 33(11), pp. 1373-1383.

U.S. Department of Transportation (1997) *1997 Federal Highway Cost Allocation Study. Final Report.*

Uber (2018) *What Is the Uber Fee?* Available at: https://help.uber.com/h/5704e643-6df8-47ce-bcb2-a3968a445bcc (Accessed: 06 August 2018).

US Department of Transportation (1987) *Fully Allocated Cost Analysis Guidelines for Public Transit Providers*. 2nd edn. Washington.

Vovsha, P. (1997) 'Application of Cross-Nested Logit Model to Mode Choice in Tel Aviv, Israel, Metropolitan Area', *Transportation Research Record*, 1607(1), pp. 6-15.

Vu, A.T. (2015) 'Mode Choice Behavior and Modal Shift to Public Transport in Developing Countries-the Case of Hanoi City', *Journal of the Eastern Asia Society for Transportation Studies*, 11, pp. 473-487.

Vu, V.H. *et al.* (2013) 'Health Risk Assessment of Mobility-Related Air Pollution in Ha Noi, Vietnam', *Journal of Environmental Protection*, 04(10), pp. 1165-1172.

Vuchic, V.R. (2007) *Urban Transit: Operations, Planning, and Economics*. New Jersey: John Wiley & Sons.

Walters, A. (1961) 'The Theory and Measurement of Private and Social Cost of Highway Congestion', *Econometrica: Journal of the Econometric Society*, pp. 676-699.

Wang, R. (2011) 'Autos, Transit and Bicycles: Comparing the Costs in Large Chinese Cities', *Transport Policy*, 18(1), pp. 139-146.

Ward, E.J., Dimitriou, H.T. and Dean, M. (2016) 'Theory and Background of Multi-criteria Analysis: Toward a Policy-led Approach to Mega Transport Infrastructure Project Appraisal', *Research in Transportation Economics*, 58, pp. 21-45.

Ward, E.J. *et al.* (2016) 'Application of policy-led multi-criteria analysis to the project appraisal of the Northern Line Extension, London', *Research in Transportation Economics*, 58, pp. 46-80.

Wardman, M., Chintakayala, P.K. and de Jong, G. (2016) 'Values of Travel Time in Europe: Review and Meta-Analysis', *Transportation Research Part A: Policy and Practice*, 94, pp. 93-111.

White, P.R. (2002) *Public Transport: Its Planning, Management, and Operation*. 4th edn. London: Spon. The natural and built environment series.

World Bank (2005a) *Valuation of Accident Reduction*. Available at: http://siteresources.worldbank.org/INTTRANSPORT/Resources/336291-1227561426235/5611053-1231943010251/trn-16EENote2.pdf (Accessed: 26 June 2017).

World Bank (2005b) *Valuation of Time Savings*. Available at: https://openknowledge.worldbank.org/bitstream/handle/10986/11800/339360rev0trn0150EENote2pdf.pdf?sequence=1&isAllowed=y (Accessed: 24 May 2018).

World Bank (2015a) *International Development Association Project Appraisal Document on a Proposed Credit in the Amount of SDR 88.2 million (US$124.0 million) to the Socialist Repuplic of Vietnam for the Ho Chi Minh City Green Transport Development Project*. Available at: http://documents.worldbank.org/curated/en/558961468179946764/pdf/PAD1305-PAD-P126507-IDA-R2015-0120-1-Box391444B-OUO-9.pdf (Accessed: 30 May 2017).

World Bank (2015b) *PPP Conversion Factor, GDP* Available at: http://data.worldbank.org/indicator/PA.NUS.PPP?end=2015&start=2011 (Accessed: 22 May 2017).

World Bank (2019) *Classifying Countries by Income*. Available at: https://datatopics.worldbank.org/world-development-indicators/stories/the-classification-of-countries-by-income.html (Accessed: 30 September 2019).

Wunsch, P. (1996) 'Cost and Productivity of Major Urban Transit Systems in Europe: An Exploratory Analysis', *Journal of Transport Economics and Policy*, pp. 171-186.

Wuppertal (n.d.). Available at: https://www.wuppertal.de/microsite/en/tourism/schwebebahn/102370100000140310.php#Njk5MTU4MjYw (Accessed: 26 October 2018).

Zeldin, W. (2016) *Vietnam: Document on Taxation of Uber Services Issued*. Available at: https://www.loc.gov/law/foreign-news/article/vietnam-document-on-taxation-of-uber-services-issued/#:~:text=Uber%20drivers%2C%20%E2%80%9Cindividuals%20who%20have,1.5%25%20for%20individual%20income%20tax. (Accessed: 29 November 2020).