# Interaction of demand and supply in transport planning model systems : A comprehensive revisit

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# Interaction of demand and supply in transport planning model systems: A comprehensive revisit

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With the growing trend of transport network worldwide and to support financial and managerial decisions in the transport domain, especially in big cities, the development and application of transport planning model systems (TPMSs) are inevitable. To predict the hypothetical situation of future which is surrounded with unknowns, an ideally developed TPMS should reproduce base year conditions, be sensitive to the policies being tested, and respond logically to changes in input. Accordingly, the performance of TPMSs is highly dependent on the quality of both estimation and calibration processes of the model system. These model systems are usually large-scale so that their development is a complex process.

Focusing on the TPMSs development and enhancement, this thesis has four aims: (1) to review the states of the practice of the TPMSs development and their practical implications, (2) to develop systematic approaches to enhance TPMSs calibration process considering both demand-side and traffic assignment models in a unified structure, (3) to formulate an integrated TPMS to have different model components in a unified structure, and (4) to formulate an emerging model component for conventional TPMSs such as activity-based models. Furthermore, this thesis includes four main chapters. Focusing on the calibration process of TPMSs, the first two main chapters introduce two different calibration models to systematically calibrate and validate large-scale TPMSs. Apart from reproducing the observed statistics, the focus of the first calibration model is on multi-objectivity nature of the calibration process and the validity of TPMSs while the focus of the second calibration model is on building a robust TPMS. Focusing on the asynchronisations among the conventional TPMS model components, the third main chapter explores the possibility of developing an integrated TPMS to rectify the most common problematic issues in conventional TPMSs. It formulates and calibrates novel TPMS which integrates an activity travel pattern generator and multiple traffic assignment. The fourth main chapter does not focus on the whole structure of TPMSs in its big picture; rather, it concentrates on formulating an emerging model component suitable to be embedded in the structure of conventional TPMSs.

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# Abstract

With the growing trend of transport network worldwide and to support financial and managerial decisions in the transport domain, especially in big cities, the development and application of transport planning model systems (TPMSs) are inevitable. The development of TPMSs has become an important topic of research in recent decades so that different generations of model systems have emerged over time.

Due to the huge inherent complexity of transport network behaviour, TPMSs should be developed properly to assure that the planning and management considerations are reliable. To predict the hypothetical situation of future which is surrounded with unknowns, an ideally developed TPMS should reproduce base year conditions and also should be sensitive to the policies being tested; moreover, it needs to respond logically to changes in the input. Accordingly, the performance of TPMSs is highly dependent on the quality of both estimation and calibration processes of the model system. These model systems are usually large-scale so that their development is a complex process.

Focusing on the TPMSs development and enhancement, this thesis has four aims: (1) to review the states of the practice of the TPMSs development and their practical implications, (2) to develop systematic approaches to enhance TPMSs calibration process considering both demand-side and traffic assignment models in a unified structure, (3) to formulate an integrated TPMS to have different model components in a unified structure, and (4) to formulate an emerging model component for conventional TPMSs such as activity-based models. Furthermore, this thesis includes four main chapters. Focusing on the calibration process of TPMSs, the first two main chapters introduce two different calibration models to systematically calibrate and validate large-scale TPMSs. Apart from reproducing the observed statistics, the focus of the first calibration model is on multi-objectivity nature of the calibration process and the validity of TPMSs while the focus of the second calibration model is on building a robust TPMS. The performances of the proposed calibration models are demonstrated via case studies on GTAModel V4.0 model system for the Greater Toronto-Hamilton Area (GTHA). Focusing on the

asynchronisations among the conventional TPMS model components, the third main chapter explores the possibility of developing an integrated TPMS to rectify the most common problematic issues in conventional TPMSs. It formulates and calibrates novel TPMS which integrates an activity travel pattern generator and multiple traffic assignment models and then illustrates the application of the model and its capabilities using numerical experiments. The fourth main chapter does not focus on the whole structure of TPMSs in its big picture; rather, it concentrates on formulating an emerging model component suitable to be embedded in the structure of conventional TPMSs.

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# List of Relevant Publications and Awards

The following provides a list of the award, conference and journal publications that have directly contributed towards the development of the thesis:

**Journal articles**

1. **Najmi, A.**, T. H. Rashidi, J. Vaughan and E. J. Miller (2019). 'Calibration of large-scale transportation planning models: a structured approach'. *Transportation* (Amst), 47(4), 1867–1905.
2. **Najmi, A.**, T. H. Rashidi and E. J. Miller (2018). 'A novel approach for systematically calibrating transport planning model systems'. *Transportation* (Amst). 46(5), 1915–1950.
3. **Najmi, A.**, M. Duell, M. Ghasri, T.H. Rashidi and S.T. Waller (2018). 'How Should Travel Demand and Supply Models Be Jointly Calibrated?' *Transportation Research Record: Journal of the Transportation Research Board*. 2672(47), 114–124.
4. **Najmi, A.**, D. Rey and T. H. Rashidi (2017). 'Novel dynamic formulations for real-time ride-sharing systems'. *Transportation Research Part E: Logistics and Transportation Review*, 108, 122–140.
5. **Najmi, A.**, T. H. Rashidi, A. Abbasi and S. T. Waller (2017). 'Reviewing the transport domain: an evolutionary bibliometrics and network analysis'. *Scientometrics*, 110(2), 1–23.
6. **Najmi, A.**, D. Rey, T. H. Rashidi, and S. T. Waller (2020). 'Model formulation and calibration procedure for integrated multi-modal activity routing and network assignment models'. *Transportation Research Part C: Emerging technologies,* 121(12).

**Conference papers**

7. **Najmi, A.**, T. H. Rashidi, J. Vaughan and E. J. Miller (2019). 'A novel multi-objective approach for calibration of large-scale transportation planning models', In: *98th Annual meeting of Transportation Research Board*, Washington D.C.

**Award**

**Ali Najmi** was the recipient of *Pyke Johnson Award* in 98th *Annual meeting of Transportation Research Board*, 2018. The award was presented at TRB Chairman's Luncheon on 16 January 2019. The prize was awarded in recognition of an outstanding paper in the area of planning and environment – (How Should Travel Demand and Supply Models Be Jointly Calibrated?). It was selected as the overall top paper from among 650 papers. The Pyke Johnson Award is a great honour and privilege since the first award was presented in 1971.

**Ali Najmi** was the recipient of *Faculty Postdoctoral Writing Fellowship* from the University of New South Wales in 2019. Receiving this fellowship is competitive and is given to a limited number of students that have outstanding research output.

The table below summarises the relationship between the publications and the chapters of this thesis. It also briefly describes each problem studied in the corresponding chapter and publications. Please see Chapter 1 for a detailed description of the problems studied in each of the chapters.

| Chapters | Publications | Problems studied |
|---|---|---|
| 2 | 2,3,5 | Reviewing the sequential structure of TPMSs |
| 3 | 3 | Criticising the disjoint calibration of TPMS components |
| 4 | 1,7 | Proposing a systematic calibration model for TPMSs |
| 5 | 2 | Formulating robust TPMSs |
| 6 | 6 | Formulating integrated TPMSs |
| 7 | 4 | Formulating a new model component for TPMSs |

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# List of Abbreviations

| | |
|---|---|
| **ABM** | Activity-based model |
| **ADP** | Adjusted distance proximity |
| **AFT** | Average finalisation time |
| **AKS** | Average total vehicle-kilometres savings |
| **ALAP** | As late as possible |
| **ARP** | Activity routing problem |
| **ASAP** | As soon as possible |
| **ASAα** | As soon as α |
| **ATP** | Activity travel pattern |
| **ATPR** | Activity travel pattern reproduction |
| **BCT** | Base case TPMS |
| **TCT** | Taguchi calibrated TPMS |
| **CCD** | Central composite design |
| **DAT** | Drive access transit |
| **DP** | Distance proximity |
| **DS** | Distance savings |
| **DTA** | Dynamic traffic assignment |
| **EV** | Evening |
| **GARP** | Generalised ARP |
| **GTAModel** | Greater Toronto-Hamilton Area Model |
| **GTHA** | Greater Toronto-Hamilton Area |
| **GVRP** | Generalised VRP |
| **IET** | Initially-estimated TPMS |
| **LR** | Number of links with significant reduction |
| **LRSD** | Number of links with significant reduction in the standard deviation |
| **MD** | Mid-day |
| **MDT** | Modified decision tree |
| **MED** | Mean Euclidean distance |

| | |
|---|---|
| **MR** | Matching rate |
| **MSA** | Method of successive averages |
| **MTWOS** | Multiple time slots without splitting ratios |
| **MTWS** | Multiple time slots with splitting ratios |
| **NM** | Number of matches |
| **NMED** | Normalised mean Euclidean distance |
| **OD** | Origin-destination matrix |
| **ODC** | OD matrices convergence |
| **RSM** | Response surface methodology |
| **S/N** | Signal-to-Noise ratio |
| **SCT** | Structured calibrated TPMS with restricted deviation |
| **SCTR-C** | Structured calibrated TPMS with relaxed deviation in constants |
| **SCTR-C&C** | Structured calibrated TPMS with relaxed deviation in constants and coefficients |
| **SDVRP** | Split delivery vehicle routing problem |
| **SLA** | Statistical Local Areas |
| **SRC** | Splitting ratios convergence |
| **STA** | Static traffic assignment |
| **TASHA** | Travel/Activity Scheduler for Household Agents categorisation |
| **TGC** | Trip generation convergence |
| **TPMS** | Transport planning model system |
| **TTC** | Travel time convergence |
| **UCT** | Unstructured calibrated TPMS |
| **VISTA** | Victorian Integrated Survey of Travel and Activities |
| **WAT** | Walk access transit |
| **1/4/8-TWOS** | 1/4/8 time slot without splitting ratios |
| **1/4/8-TWS** | 1/4/8 time slot with splitting ratios |

# Chapter 1

# Introduction

## 1.1 Motivation

Transport in urban environments is the underlying force on the location, growth, rank-size and functional differentiation of cities. It is an issue that stirs passions among users and others who are impacted by its use. This is due to its central role in society and most activities in day-to-day life, from education and business, to recreation and personal relationships, require transport for facilitation and access. To plan and manage the transport networks' impact and travellers' behaviour, different types of models have been developed. Developing the models is inevitable as transport projects usually involve substantial taxpayer funding and are large enough to disrupt the urban fabric both positively and negatively.

Modern computing and advances in mathematical modelling approaches provide the possibility of developing more accurate models. Therefore, the motivation of this thesis is to enhance the development process of transport planning model systems.

## 1.2 Background

Development of transport planning model systems (TPMSs) has become an important topic of research in recent decades. Different generations of model systems have emerged over time, including four-step models (e.g. NYMTC 2014 and McNally 2000) and activity-based models (e.g. ALBATROSS: Arentze and Timmermans 2004a, ADAPTS: Auld and Mohammadian 2012, and OpenAMOS: Pendyala et al. 2012). Similar to any other model, the fruitfulness of the TPMSs lies in their ability to accurately reproduce observed conditions, which will consequently be used to predict future situations. Specifically, for complicated systems such as TPMSs, the practicality of the model systems and their ability to reliably analyse policy implications depend not only on their development process and the quality of the input data but also on the quality of their calibration and validation processes.

Each TPMS usually consists of several interactive models (categorised as demand-side and network models) within the overall model system. Conventional TPMSs capture the interaction of the two categories of model components, demand-side model and traffic assignment model; however, they are often considered to be completely independent from one another due to differences in their data resources and modelling techniques. On the demand-side, transport demand modellers estimate myriad complex travel demand models based on individual decisions on day-to-day activities, changes in land use, etc. On the traffic assignment model side, transport network modellers model and predict network conditions, usually based on an equilibrium assumption (Wardrop 1952), using a predetermined demand structure.

After development and calibration of the demand-side and traffic assignment models, the models are interacted in the structure of TPMSs to be used for usually strategic planning. However, since estimation and calibration of the demand-side and traffic assignment models are both conducted separately (which is generally due to the different nature of the model components), their outputs most probably may not be synchronised. For example, the OD matrices that are consequences of loading travel times into scheduling models may produce updated travel times that are different from the initially considered travel times to produce OD matrices. Thus, feedback loops are introduced to enhance the structure through an iterative process (using a feedback loop from network to demand in order to update network attributes such as travel time), such that the difference between the observed counts and the simulation results is judged to be within an acceptable gap.

While former research and efforts in the field have been made to join the demand and network models in some advanced integrated transport models, the linkage is primarily limited to a feedback loop where a simulation-based process passes exogenous travel times from the traffic assignment models to the demand-side models. It should be emphasised that applying the feedback loop is limited to the simulation process and consequently the impact of the interaction in the calibration phase is ignored. This approach could sacrifice the accuracy and predictive power of the model due to stability issue, error propagation and transferability of the model (Najmi et al. 2018a).

No matter how TPMSs are developed, they should be calibrated. The standard calibration approach in transport modelling is unstructured such that adjustments are sequentially applied in relatively ad hoc, non-systematic ways mostly based on the modeller's knowledge and expertise, with an aim to reproduce observed statistics. Unstructured calibration approaches can be problematic for many reasons including the computational burden of the calibration, failure to consider interactions among parameters, and also excessive focus on reproducing the statistics observed in the base year. The latter may sacrifice the validity of model systems.

Furthermore, in most of the literature, not only the interconnections between the demand and traffic assignment models in the estimation and calibration processes are missed, but also the linkage among the demand-side model components are not well established. Due to absence of spatiotemporal constraints in a physical network in the unconstrained econometric (dis-)utility minimisation/maximisation modelling approaches, the interactions between the demand-side model components are lost (Jara-Díaz 2003, Recker 2001). Thus, the sequential structure is usually incapable of properly capturing the synchronisations among the model components' outputs.

The focus of this research project is to shed light on the findings of the plausible solutions to enhance TPMSs development process. The interactions among the model components in TPMSs profoundly affect the quality of the outputs. Therefore, proposing different approaches to effectively incorporate the interactions is extremely advantageous in model development practice.

## 1.3 Research problem

To generate more rigorous and precise models, there are a number of options. There can be three solutions for the purpose. An immediate solution could be developing more complicated TPMSs by inclusion of higher number of model components in the TPMSs structure. For example, ride-sharing and car-sharing are the emerging transport modes that are not sufficiently investigated in the body of TPMSs in the literature. Obviously, the more the number of model components and variables results in the higher complexity of the model systems. Thus, the quality and the predictive power of TPMSs would not be necessarily enhanced if a higher number of model components are added in the body of TPMSs.

A more rational solution can be enhancing the development process of the conventional TPMSs. There are 3 main reasons for this: 1) the models usually satisfy the rudimentary requirements of the modellers so using them is very customary, 2) despite the TPMSs' critical problems, their development process is confirmed by many experts as acceptable, and 3) their running speed is relatively fast. These reasons justify the wide usage of the model systems in practice. There could be different possibilities on the improvement of TPMSs one of which is taking into account the interactions among the TPMSs model components; however, the calibration of the already-estimated model components would be a determinant step in development of TPMSs where separation of the demand-side and traffic assignment models is observed. Although the importance of integrating the demand-side and network models in simulation is discussed in transport modelling literature, there are much fewer proposals regarding the integration during the calibration process itself. It is expected that a jointly calibrated model will generate more consistent results than the individually developed and calibrated models.

The third solution would be developing novel TPMSs such that the critical issues in the conventional problems can be resolved. As the sequential development and asynchronisations among the TPMSs model components are of the most problematic issues, an alternative solution would be developing integrated models where multiple choice facets are simultaneously modelled in a unified fashion.

This PhD dissertation argues these solutions which are led to the four research aims.

**Aim 1. Review the states of the practice of the TPMSs development and their potential implications.**

This aim involves reviewing standard practice of developing TMPSs, potential issues that may arise by inappropriate calibration of TPMSs, and common calibration techniques that are used in the calibration process. This will be used to introduce the common procedure of developing large-scale TPMSs, provide context for the research agenda, identify gaps in the literature and determine the requirements of the thesis models.

**Aim 2. Develop systematic approaches to enhance TPMSs calibration process considering both demand-side and traffic assignment models in a unified structure.**

This aim involves proposing novel approaches to calibrate already developed (estimated) TPMSs so that they would enhance the predictive power of the model systems. In the era of emerging large-scale disaggregated transport model systems which encompass large number of model components and parameters, modeller's expertise alone may not result in reliable models. Still, the models have numerous benefits which make replacing them with idealistic model structures not so reasonable if not impossible. Systematic approaches must be designed to steer knowledge and expertise of the modellers when developing the transport model systems. The systematic approaches relate to the development of modelling structure and algorithms, to address the problems identified in Aim 1.

**Aim 3. Formulate an integrated TPMS to have different model components in a unified structure.**

This aim involves proposing novel integrated formulation for the whole TPMSs so that the asynchronisations among the TPMS model components may be minimised. It looks for an ideal structure for TPMSs which is free of problems recognised in Aim 1. The integrated formulation relates to the development of an alternative approach for the currently developed TPMSs in the literature.

**Aim 4. Formulate an emerging model component for conventional TPMSs**

Including more model components is still an immediate approach to generate novel and more advanced TPMSs. Regardless of whether this approach is correct or not, this aim involves proposing a novel formulation for an emerging model component that would be embedded in the body of TPMSs and would not have received enough attention in the TPMSs literature so far.

## 1.4 Thesis overview

The research contributions of this thesis are separated into 4 main chapters, each of which targets solving a certain host of problems existing in current transportation systems in practice.

### 1.4.1 Chapter 2 – Literature Review

Chapter 2 fulfils Aim 1 by reviewing different components of transport planning model systems, their main components, and the standard practice of making connections between the components. Firstly, this chapter provides an overview of TPMS development procedure. Secondly, it explores the standard practice of TPMS calibration process and explains the common calibration techniques that are used in the calibration process. Finally, it briefly discusses the importance of a systematic approach to calibrate and validate TPMSs. Having a specific literature review section in each main chapter of this thesis facilitates this chapter's exploring the main concepts in TPMS development and calibration processes. The content of this chapter is taken from the published papers in *Transportation Research Record* (see Najmi et al. 2018a), *Transportation* (see Najmi et al. 2018b), *Scientometrics* (see Najmi et al. 2017a).

### 1.4.2 Chapter 3 – Inconsistencies in Sequential Models: A Case Study

Chapter 3 complements Chapter 2 and fulfils Aim 1 by providing an example to show the inconsistencies in the sequential models. Thus, Chapter 3 examines the linkage in the calibration process of a simplified TPMS using a case study in Melbourne area followed by a discussion of some possible solutions to address the current limitations in development of an integrated structure. Content of this chapter is taken from the published papers in *Transportation Research Record* (see Najmi et al. 2018a).

### 1.4.3 Chapter 4 – Multi-objectivity and Validation in Calibration Process

This chapter aims to solve some of the practical complexities associated with developing large-scale TPMSs, and it proposes a systematic method for TPMS calibration and validation processes. First, this chapter numerically determines the potential effects of unstructured and sequential calibration processes on model validity and reliability. Second, this chapter addresses the importance of a systematic approach to TPMS calibration in detail. Third, this chapter proposes a tractable approach based on the response surface methodology (RSM) to efficiently calibrate large-scale TPMSs while considering the interactions of their constituent models and parameters to avoid over-calibration in simulation process. Lastly, descriptive results of this chapter offer valuable insights and will help the reader follow the calibration process when the proposed calibration model in this chapter is applied to a real case study using GTAModel for Ontario, Canada, and analysing the results. Content of this chapter is presented in *Transportation Research Board 98th Annual Meeting* (see Najmi et al. 2019) and currently is under publication in *Transportation* journal.

### 1.4.4 Chapter 5 – Robustness in Calibration Process

Similar to Chapter 4, Chapter 5 fulfils Aim 2 through introducing a novel approach for systematically calibrating TPMSs. In addition to introducing a model to guide modellers in the calibration process of large-scale transport planning model systems which is common between chapters 4 and 5, Chapter 5 focuses on minimising the uncertainties of the system output. First, this chapter proposes a systematic approach, based on the Taguchi method, for choosing the most appropriate models and parameters. Second, it examines the capacity of the proposed model for minimising the effects of uncertainty in TPMSs. Finally, this chapter demonstrates the effectiveness of the proposed calibration model on a realistic TPMS for the city of Toronto, Canada. Chapters 4 and 5 contribute to the research on transport modelling, policy-making and strategic planning, both in theory and practice. Content of chapter 5 is already published in the *Transportation* journal (Najmi et al. 2019a).

### 1.4.5 Chapter 6 – Dynamic Transport Planning Model Systems: A Supernetwork Formulation

This chapter fulfils Aim 3 through introducing a novel formulation for TPMSs. Using the concept of supernetworks, it formulates a novel integrated TPMS structure in which a unified demand-side activity travel pattern generator and multiple traffic assignment models are integrated. First, it provides a comprehensive formulation for the unified demand-side model in which it is tried to incorporate spatiotemporal constraints, multi-modality and public transport requirements all together in the body of TPMSs. Second, to simplify supernetwork representation in the modelling, the formulation allows visiting nodes and edges of the network multiple-times which is another novelty of the proposed model. Third, using a number of feedback loops, the developed model of this study iteratively, dynamically and optimally updates the travellers' daily itinerary considering the dynamic travel times (congestions) at different time periods of the day until convergence. Fourth, a novel calibration solution, using splitting ratios, has been proposed to effectively calibrate the proposed TPMS in general. Lastly, the model outputs have been evaluated using some numerical examples which help the reader follow the implementation steps of the proposed TPMS structure. Content of this chapter is submitted to *Transportation Research Part B: Methodological* and it is still under review.

### 1.4.6 Chapter 7 – An Emerging TPMS Model Component: A Ridesharing Formulation

Chapter 7 fulfils aim 4 through introducing a novel ridesharing model focusing on the dynamicity of the model which makes it suitable to be incorporated in the structure of TPMSs. This chapter does not examine TPMSs in its big picture; rather, it tries to provide a new efficient formulation for a ridesharing model which can be embedded in the structure of dynamic large-scale TPMSs. Apparently, there can be many improvement possibilities for TPMSs; in this chapter, it is tried to work on one of the emerging components in the TPMSs. First, this chapter proposes new objective functions for the matching problem arising in ride-sharing systems based on trips' spatial attributes. Second, novel dynamic matching policies are proposed to solve the problem dynamically in a rolling horizon framework. Third, a new clustering heuristic is presented to tackle instances with a large number of participants efficiently. Content of this chapter is already published in *Transportation Research Part E: Logistics and Transportation Review* (Najmi et al. 2017b).

### 1.4.7 Chapter 8 – Conclusion and Future Research

Chapter 8 concludes this thesis. Firstly, this chapter restates the aims of the thesis and then describes how each aim has been fulfilled. Secondly, it discusses future extensions of the research. Finally, the chapter provides the final remarks of the thesis.

# Chapter 2

# Literature Review

*This chapter summarises different types of transport planning model systems. Then, it explores the sequential structure of conventional TPMSs. In this thesis, as the main chapters of 4 to 7 have their own literature review and problem definition specific to themselves, the focus of the current chapter is on providing a general view on some specific parts of transport modelling on which the other chapters are built on.*

## 2.1 Introduction

An efficient transport system has a crucial role on the growth and development of economy of a nation (Zhong et al. 2015). In line with this, travel models are created to support decision making by providing quantitative information about the transport system performance which can be used to evaluate alternatives and make informed decisions. A travel model, so-called a transport planning model system (TPMS) in this thesis, is an analysis tool that provides a systematic framework to simulate the changes in travel demand and network in response to different input scenarios (Castiglione et al. 2014). The history of the development of the model systems goes back more than half a century and different generations of the models have been developed.

The transport planning model systems can be categorised into two main groups: 1) sequential-based, and 2) direct optimisation-based through a combined or integrated model. The model systems in the first category contain some model components (including several demand-side and traffic assignment models) that are sequentially connected to each other using iterative feedback mechanisms, which iteratively feeding back output (for example, the congested link travel times) from traffic assignment model to the demand-side models (usually to destination choice models). It should be mention that the sequential relationship is not limited to the interaction between demand-side and traffic assignment models; the demand-side models themselves usually are sequentially connected to each other. These model system iterations are continued until convergence happens, meaning that the speed/time values used in the demand-side models and those output from traffic assignment model have converged. Conventional models such as activity-based models and trip-based models are under the category of sequential-based models.

In the models of the second category, almost all components of a TPMS are solved simultaneously and in an integrated structure to solve the inconsistencies in the sequential model. These models can be further decomposed into two sub-categories: 1) mathematically combined models, and 2) expanded network-based model. General approach in mathematically combined models is to translate the behavioural assumptions into mathematical conditions, and seek solutions that satisfy the conditions (Bar-Gera and Boyce 2003). These models are complicated and require more rigorous technical knowledge than sequential models to be developed and implemented (Boyce 2002). Furthermore, these models cannot capture the disaggregated behavioural facet of travellers' decisions. Expanded network-based, which can be further categorised into supernetwork-based (Liao et al. 2013, Liao 2016) and vehicle routing problem-based (Chow and Djavadian 2015, Chow 2014) models are other integrated models which were originally developed to represent the transition and interactions between multiple modes. Later, their application was extended to model activity-travel scheduling decisions of travellers so that multiple choice facets are simultaneously modelled in a unified fashion (Liu et al. 2015). In the literature, expanded network-based models are usually developed by expanding the networks, over space and time. Specifically, in supernetworks-based models, different choices are turned to indifferent path choice (Nagurney et al. 2003) and having the start and end nodes of supernetwork, any path connecting these nodes represents a feasible ATP, which can express the activity location, sequence of activities, and choice of mode and route. The integrated models are much less commonly implemented than the conventional models (Reeder et al. 2012). Despite these models are theoretically well-defined, the direct optimisation approach is still remained in theory and not commonly used in practice.

In the rest of this chapter, the sequential structure of conventional TPMSs and their calibration process are summarised. As the main chapters of 4 to 7 are written in such a way that reading the chapters does not required reading the other chapters in advance. The chapters have their own literature review and problem definition specific to themselves. Thus, in the current chapter, the focus is on providing a general view on some specific parts of transport modelling on which the other chapters are built on.

## 2.2 Transport planning model systems (TPMSs)

TPMS refers to a system of model components that are used jointly for transport planning and travel forecasting. Each model component can be labelled as demand-side or network-side (traffic assignment) model. While *demand-side* models reflect the travel decisions of agents in the transport system and the resulting travel demand, *network-side* models deal with the interaction between travel demand and the network of infrastructure and transport services (Bliemer et al. 2013).

Different generations of model systems have emerged over time, including four-step models (e.g. NYMTC 2014, McNally 2000), tour-based models, and activity-based models (e.g. ALBATROSS: Arentze and Timmermans 2004a, ADAPTS: Auld and Mohammadian 2012, OpenAMOS: Pendyala et al. 2012, CEMDAP: Bhat et al. 2004).

Trip-based models use trips as the basic unit of analysis. A trip is defined as a unit of travel connecting two locations. In a trip-based model, knowledge of trips context beyond their endpoints is missed. Incorporating trip chains in the modelling process, tour-based models overcome much of the knowledge loss associated with trip-based models. An activity-based model goes further by recognising travel as a derived demand. That is, the demand for travel is derived from the desire to participate in activities, rather than the desire to travel for the joy of being in the car. (NCHRP 2010).

Despite the well-introduced advantages of more advanced models such as activity-based modelling in the academic context, traditional four-step travel demand modelling are still the most popular modelling approach in practice in a majority of the Metropolitan Planning Organisations (MPOs) worldwide (e.g. TBRPM 2015).

## 2.3 Sequential models

Traditionally, sequential TPMSs were recognised as four-step model which include trip generation (travel choice), trip distribution (destination choice), modal split (mode choice) and traffic assignment (route choice) sequentially in a top-down sequential process (Ortúzar S. and Willumsen 2011). Later, this definition is extended to activity-based models because not only are not the choices of travel facets fully independent, but also the demand-side and network models are sequentially connected to each other (Najmi et al. 2018a,b). In sequential modelling, the outputs of one step serve as the inputs of the next step.

The sequential model systems may result in many inconsistencies in travel times and congestion effects in various steps of these sequential models and are criticised in many studies (Garrett and Wachs 1996, Boyce and Xiong 2007). To remedy these inconsistencies, a 'feedback' mechanism is introduced into the computational procedures in early 1990s. Nonetheless, the convergence is not guaranteed.

Sequential process with feedback loop where travel times and costs in demand-side models and the results of the traffic assignment (network) model are brought into consistent agreement in an iterative process is the common structure for travel forecasting which is widely accepted in theory and practice (Boyce et al. 2007). The sequential structure with feedback loop is not limited to four-step models but it is widely employed in almost all the conventional TPMSs (tour-based and activity-based models) where the output of network model is fed back to the demand-side models.

Thus, in this thesis, sequential terminology refers to the transport model systems where their model components are priorities in the development or calibration processes of the model systems. The sequential models, whether they are four-step models or activity-based models, suffers from some common problems in their development and calibration processes (these issues are fully addressed in the next chapters) so that their prediction power.

### 2.3.1 Travel demand-side model development

Some of travel demand-side models seek to comprehensively represent multiple, interrelated aspects of regional travel behaviour, such as what activities people engage in, where and when these activities occur, and how people get to these activities. Other models are more limited in scope, addressing a smaller transport market such as airport-related travel, travel within a corridor or a particular district of a city (Castiglione et al. 2014).

Traditional travel demand-side models are developed separately for system level and user level properties in which the individual trips are usually the units of analysis. Furthermore, demand-side models are generally developed using travel diary data at the disaggregate level of individuals/households. These models are mainly based on the utilitarian concept that travellers either maximise their utility (Random Utility Maximisation: McFadden 1980), or minimise their regret (Random regret Minimisation: Chorus et al. 2008). In developing each of the demand-side model components, goodness-of-fit tests are usually employed to assess the effectiveness of the model estimations.

### 2.3.2 Network models development

The network model is the component of the transport planning process that outputs link flows as an estimation of the network conditions that will result from the modelled travel demand. The network model represents the providers of road services, by assigning the routes between origin-destination trips. Most often the travel demand is in the form of the OD matrix. Equilibrium is typically sought when the travel time on all routes between an origin and destination are equal (within an acceptable gap function) and minimal (Sheffi 1985). While numerous updated approaches exist to expand the traditional equilibrium assumptions, most notably stochastic user equilibrium to address the assumption of perfect information (Daganzo and Sheffi 1977) and dynamic traffic assignment to capture the time dependent nature of many traffic flow phenomena (Peeta and Ziliaskopoulos 2001), the traditional static approach continues to be far more prevalent especially in practice, for reasons such as solution uniqueness and stability.

### 2.3.3 Feedback loop

One typical problem of many four-step models is the inconsistency between the inputs into earlier steps of the model systems and the model outputs at later stages. For example, the travel times/speed used in trip distribution step have a considerable difference with the calculated travel times/speed in the traffic assignment model. To remedy the inconsistencies, the feedback loop mechanism is introduced and later is applied in activity-based models as well. The TPMSs with feedback loop are expected to have better performance than the TPMSs with no feedback loops, when there is traffic congestion during certain times of the day (Avner 2009).

Implementation of feedback mechanism in TPMSs is currently under study by many researchers. There is a general agreement that the feedback loop provides a better solution than a single sequential application of the traditional three- or four-step model systems. Nonetheless, there is no consensus on the right way to implement the feedback loop and to measure the convergence of the iterative sequential TMPSs (Avner 2009). There are several common approaches for updating the basis attribute that is fed back from one iteration to the next. These include naïve feedback, fictive cost, MSA (Evans 1976, Feng et al. 2010), constant weight methods (Loudon et al. 1997, Boyce and Xiong 2007). For more information, the reader is referred to (Reeder et al. 2012). The feedback mechanism is fully discussed in (Reeder et al. 2012) for four step models and in (Lin et al. 2008a) for activity-based models.

In a nutshell, the purpose of a feedback mechanism is to iteratively "feedback" times from assignment model into the earlier stages (Trip Distribution and Mode Choice) until more consistent travel times being used for all the model stages.

### 2.3.4 Demand and network models in the sequentially structured TPMS

In many applications of transport planning models, the policy options that are being examined require a connection between the network and demand-side models (i.e., demand and network models cannot be treated as completely independent). In trip based, tour based and many ABMs, the linkage between demand and network is the OD matrix.

As Figure 2-1 illustrates, there are two separate parts to the development of TPMSs. First, the demand-side models are estimated and calibrated against observed statistics (e.g. observed OD matrix). The calibration is locally as there is no interaction between the models and traffic assignment model in this phase. The output of this process is the OD matrix which is input to the traffic assignment model. However, the link flows that result when an OD matrix is applied with the traffic assignment model can be substantially different from the observed traffic count data. This is due to a variety of reasons, including the differences in time scale between the demand data and the observed counts. Therefore, a second calibration process based on the assignment model and the OD matrix is often employed, as shown in the figure.

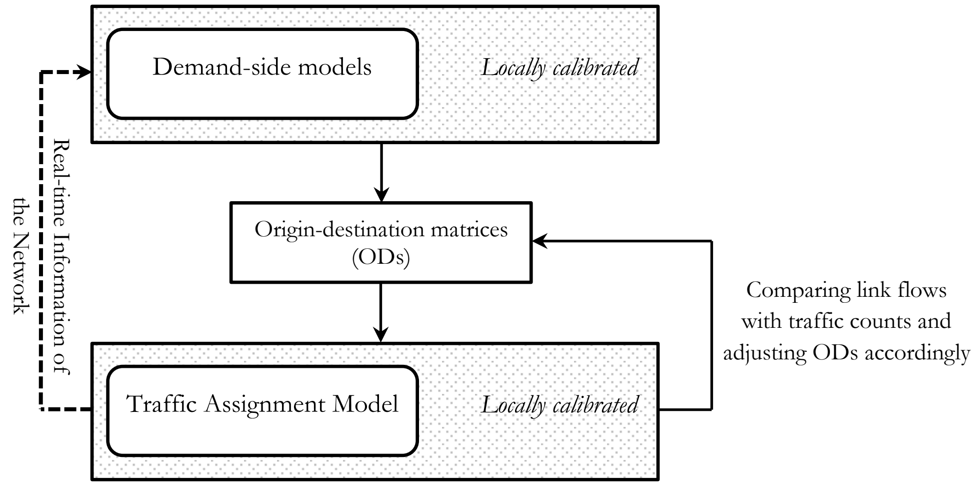



Figure 2-1 Framework of individually calibrated demand and network models

More advanced four step models include an iterative process in which the calibrated demand and network models communicate. As can be seen in the Figure 2-1 using a dotted line, in each iteration, the network level attributes such as path travel times are considered exogenous information to be used in the demand-side model. The updated demand-side model feeds a new OD matrix to the traffic assignment model, which produces new network attribute data (i.e., a new set of path travel times or link cost. Including a feedback loop creates a stronger linkage between the demand and network but still faces limitations due to the fact that the connection is only through updating variables like travel time, not related to the calibration of either model component.

The calibration process for ABMs is similar to four step models. For calibration of ABMs, demand modellers use a travel diary of a sample of travellers to develop a model reproducing the behaviour of people. In a technical way, the likelihood of modelling the observed decisions is maximised given the sample. The sample is then expanded to reproduce the population assuming that the parameters of the model developed on the sample are unbiased estimators of the true parameters of the population. Then trips (tours or daily activity itinerary) are inputted to the traffic assignment model. The network modellers calibrate the traffic assignment model using the link flows. In the so-called joint structures proposed in the literature (the difference between this so-called integrated structure and an ideal integrated structure will be elaborated in Chapter 2), a feedback loop is again proposed to join demand-side and traffic assignment models (Auld and Mohammadian 2009, Lin et al. 2008). Similar to Figure 2-1, the role of the feedback loop is to provide network level information such as path travel times to the already calibrated travel demand-side models (for example to the activity purpose, mode choice and destination choice models) in which travel time plays a significant role. As shown in Figure 2-2a, the feedback loop is mainly used during the simulation, while during the calibration exercise the role of the feedback loop is like before to update *variables* used in the demand-side model. In line with using the feedback loop in four-step models, Auld and Mohammadian (Auld and Mohammadian 2009) and Lin et al. (Lin et al. 2008a) suggest feedback mechanisms between ABM and traffic assignment models. In these models, the time-dependent ABM is fed into a traffic assignment model at specific time intervals. The predicted travel times resulted from running traffic assignment is then returned to the ABM in order to be used for rescheduling activities. This process is repeated until a state of convergence is reached.

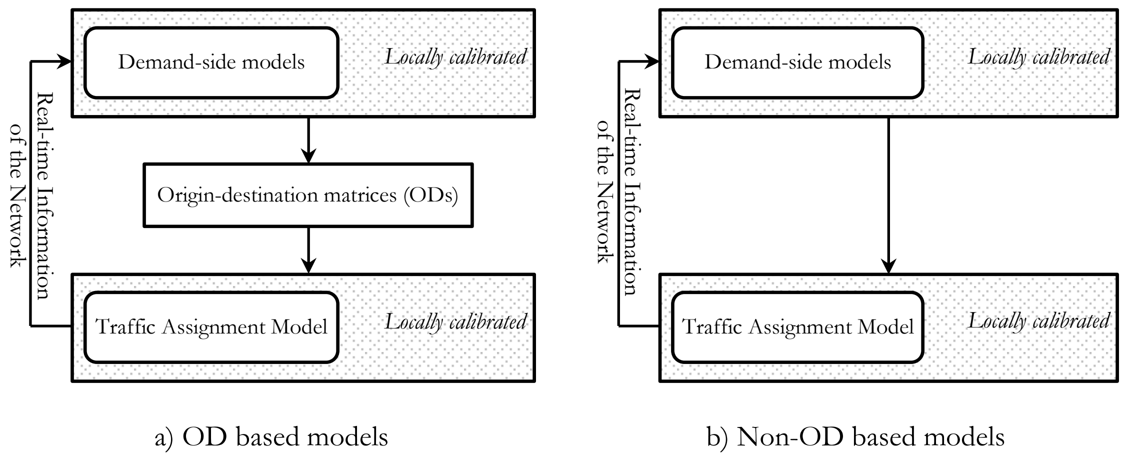



Figure 2-2 The linkage of ABM and TA in simulation

As shown in Figure 2-2b, the recent direction of demand and network models such as activity-based models and dynamic traffic assignment models, provides an agent-based alternative to the OD based approach. Nonetheless, similar to Figure 2-1, the calibration process is still done in an independent manner for both demand and network models. As Figure 2-2b shows, each model would still be separately calibrated and then joined in a sequential manner, similar to what happened during the simulation process.

In practice, the majority of models that are applied by real transport planning agencies around the world are OD based, and the demand and network models are calibrated separately. Moreover, while there is a feedback loop between demand and network models in some models, it is almost universally used in simulation phase.

### 2.3.5 Calibration techniques

In practice, different techniques have been used for making adjustments in TPMS parameters are as follows:

- Zone specific scaling factors: The scaling factors can be used for some specific zones to adjust generation and attraction rates upward or downward (Parsons Brinckerhoff 2014). This technique can bring the simulated and observed statistics closer together.

- OD K-factors: K-factors are constant values added to the origin-destination county-to-county constants of the utility functions of destination choice models. OD K-factors adjust the magnitude of modelled trip rates between pairs of zones. Zero is the reference value in the K-factors matrix. Positive and negative values correspond to utility and disutility of selection of a destination respectively. K-factors can produce high correspondence between predicted traffic counts and observed district-level origin-destination flows. Therefore, K-factors can be very tempting to be used to resolve the gaps between predicted and observed origin-destination flows without scrutinising the possibility of exploring the source of such discrepancy. As a result, while the K-factors technique is a prevalent adjustment tool (Cambridge Systematics 2008), like zone specific scaling factors, they must be cautiously used to choose relatively small values which then obviate the whole purpose of using them (Cambridge Systematics 2010).

- OD matrix estimation (updating): The OD matrix estimation methods should be used with care since they are best employed as an error checking method. It means, ideally, the methods should be used for identifying and correcting the errors in the OD inputs (the components that their results affect the OD pairs). As an instance, the OD matrix estimation method may be used to identify the possible sources of errors in trip distribution inputs requiring adjustments in parameters of the distribution model. Nonetheless, the OD matrix estimation methods are widely applied for TPMS calibration. If the methods are used for calibration, forecasting future year matrices requires careful attention so that the forecasted matrices would also be affected by the adjustments that are performed on the observed OD matrices in the base year. A simple method is to apply the absolute difference between the simulated OD matrices in the base year and adjusted (using OD estimation) base year matrices to the future year forecasted (simulated) matrices (NZ Transport Agency 2014). This way, the effects of the errors and unobserved variables which affect the base year matrices are brought through to the forecasted OD matrices. In this method, the modeller should ensure that negative trips are not produced in the forecasted OD matrices. The percentage of change is another method to transfer the difference between simulated OD matrices and adjusted matrices for the base year to the forecasted matrices. Numerous OD estimation models are developed in the literature two of which are Asakura et al. (2000) and Cascetta and Postorino (2001).

- Alternative-specific constants adjustments: Adjusting the constants in the utility functions, especially for mode share adjustments, is a commonly used technique for TPMS calibration. The adjustment may result in over-calibration where large constants dominate the utility values. The over-calibration enervates the basic model elasticities and behavioural properties. Therefore, the modellers must avoid excessively large constants adjustments in utility functions. The adjustment of alternative-specific constants is meaningful only when the person-trip tables, highway and transit networks, and observed patterns are sufficiently accurate (Cambridge Systematics 2008). When large adjustments in alternative-specific constants are needed, it is usually an indication of problems in the models that need to be addressed before calibration process can continue (Cambridge Systematics 2008).

- Data manipulation: Sometimes, some data such as personal/household information, zonal information etc. are altered to achieve a better correspondence to the base year (Cools et al. 2010). Data manipulation may include adjusting fields or adding or deleting records in datasets. Data manipulation must be avoided due to concerns about the validity and the credibility of the calibrated TPMSs.

- Weighting agents and activity patterns: The goal of weighting techniques is to procure the highest match between the observed traffic counts and the simulated traffic counts. The inverse of the sample size is the reference value for all the weights in TPMSs. Weighting agents and activity patterns are two approaches that can help modellers to reproduce observed statistics (Cools et al. 2010). For example, by adjusting the weights of persons, the OD pairs are changed. Feeding the adjusted OD into assignment model can produce closer simulated results to observed statistics. In some cases, where the number of simulated agents or activity patterns is large, weighting technique can become computationally very intensive.

In a nutshell, all discussed techniques are related to weighting techniques applied to different parts of TPMSs e.g. origin, destinations, origin-destination pairs, and agents. However, changing these weights is similar to changing the data. Since the surveys are the most reliable data available, significant adjustment of weights based on activities and agents is not recommended unless there is a valid reason. A valid reason, as an example, can be the change in the attractiveness of a zone because of opening a shopping centre after the year the surveyed data are collected. In these cases, higher weights can be given to agents in the zone and its surrounding area. Although changing the data is not recommended, the modellers are interested in reproducing observed statistics. However, due to the complex relationships of the parameters and the significant effects of the calibration techniques, applying the calibration techniques to different parts of a TPMS can be problematic (Cools et al. 2010).

## 2.4 Demand and network models in integrated models

Since the 1970s, the limitations of sequentially structured transport planning model systems have been discussed. Inconsistency of the resulting predictions is the typical problem frequently occurs in the sequential transport planning process (Zhou et al. 2009). In recent years, the problems of the sequential models have been addressed by many researchers who have sought to either reduce the inconsistencies among the model components. Combining the trip distribution and traffic assignment model, the trip distribution and mode choice model are the common efforts in this direction (Tsekeris and Tsekeris 2011). Further extension of the combined transport planning models includes the efforts to integrate all the model components in a unified structure to consider travellers' choice facets on different stages simultaneously. For an overview of the potential problems of the sequential models, the reader is referred to (Najmi et al. 2019a)

Similar to sequential TPMSs models, developing fully integrated models are far from new. Beckmann et al. (1956) is the first that mathematically formulate user-equilibrium assignment with elastic demand. Its assumption is the dependency of the flow of travellers on the level of service between every pair of origin and destination. Later, their convex optimisation is extended by the introduction of origin and destination constraints (Evans 1976). Later, more advanced combined model emerged where the user classes and mode split and, in some research, the destination choice components were combined with the traffic assignment models (see Boyce et al. 1983, Lam and Huang 1992, Bar-Gera and Boyce 2003). Assuming the travel cost structure as either separable of symmetric, these models formulation are convex; therefore, these models have the advantage of unique solutions and readily available convergent solution algorithms. For the cases with asymmetric interactions, more general integrated models are formulated as variational inequalities (VI) problem (e.g. Florian et al. 2002, García and Marín 2005, Hasan and Dashti 2007, Zhou et al. 2009). For a comprehensive review on the combined TPMSs, the reader is referred to Boyce and Bar-gera (2004). Also, In chapter 6, the integrated models are discussed in details.

## 2.5 Bibliometric analysis

This section explores a part of a bibliometric analysis that has been conducted in Najmi et al. (2017) which is related to the thesis topic. The results confirm the insignificant relationship between the demand-side and network models. The results also reveal a new mode (ride-sharing) that would be an emerging model component in TPMSs. This output was a clue to develop a ride-sharing model component to fulfil Aim 4.

### 2.5.1 Methodology

This section discusses the procedure applies to conduct this bibliometric analysis, as shown in Figure 2-3: 1) source selection and data collection; 2) tools evaluation and selection; 3) data cleaning; and finally 4) data analysis and reporting the results.

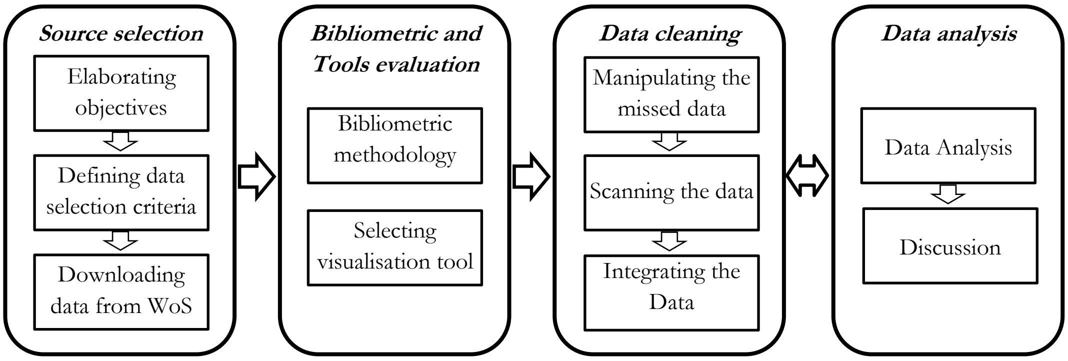



Figure 2-3 The research methodology structure

A description of different parts of the research procedures is discussed in the following subsections.

### 2.5.2 Source selection and data collection

Having a general and at the same time a holistic view of the transport in one framework demands to review tens of thousands of papers. This is somehow impossible unless using bibliographic data of such a large number of publications.

The data is collected based on defining some boundaries which are journal-centric criteria in this study. Scientific Journal Rankings[1] (SJR) of journals under the subject category of "Transportation" and at the same time Web of Science (WoS) indexed list of journals, as the first criterion, are used in order to select a list of target journals. In other words, the top 40 ranked journals listed in SJR which are also indexed in WoS are selected. Then, journals being less relevant to 'transport planning operations and management' are excluded. In addition, two journals of "Transportation Research Record" and "Accident Analysis and Prevention" that have strong roles in the transport research but not listed in SJR (but indexed in WoS) are added to the data source. The full list of selected journals is shown in Table 2-1. Then, to download data from WoS, the time span was set to "all years" and the bibliographic records consist of totally 35,712 papers were retrieved on September 11th, 2015. The dataset encompasses 154 countries, 7,833 institutes, 46,061 authors and 443,475 cited references. Although the extracted database is not inclusive of all papers published in

1 http://www.scimagojr.com/journalrank.php

the field of transport, it is important to note that for bibliometrics analysis, the highly ranked articles (Feng et al. 2015), reflect the most about a paradigm. As the pool of articles used in the analysis of this study includes more than 35,000 articles published in high ranked transport journals, and also more than 400,000 references (of those articles), it may provide a holistic view of the whole domain of transport planning operations and management.

Table 2-1 The target list of journals in the database (data is extracted in 2015)

| Row | Title | No. of publications | IF (WoS) |
|---|---|---|---|
| 1 | Accident Analysis and Prevention | 4,761 | 2.07 |
| 2 | European Journal of Transport and Infrastructure Research | 195 | 0.818 |
| 3 | International Journal of Sustainable Transportation | 213 | 2.548 |
| 4 | Journal of Public Transportation | 120 | 0.587 |
| 5 | Journal of Transport Economics and Policy | 1,254 | 1.182 |
| 6 | Journal of Transport Geography | 1,136 | 2.65 |
| 7 | Journal of Transportation Engineering | 271 | 0.797 |
| 8 | Research in Transportation Economics | 202 | 1.196 |
| 9 | Transport Policy | 861 | 1.492 |
| 10 | Transport Reviews | 1,081 | 2.903 |
| 11 | Transportation | 1,458 | 2.358 |
| 12 | Transportation Journal | 1,334 | 0.275 |
| 13 | Transportation Planning and Technology | 584 | 0.512 |
| 14 | Transportation Research Record | 12,445 | 0.544 |
| 15 | Transportation Research, Part A: Policy and Practice | 2,412 | 2.789 |
| 16 | Transportation Research, Part B: Methodological | 1,919 | 2.952 |
| 17 | Transportation Research, Part C: Emerging Technologies | 1,256 | 2.818 |
| 18 | Transportation Research, Part D: Transport and Environment | 1,065 | 1.937 |
| 19 | Transportation Research, Part E: Logistics and Transportation Review | 1,080 | 2.676 |
| 20 | Transportation Research, Part F: Traffic Psychology and Behaviour | 685 | 1.473 |
| 21 | Transportation Science | 1,229 | 3.043 |
| 22 | Transportmetrica A: Transport Science | 112 | 1.333 |
| 23 | Transportmetrica B: Transport Dynamics | 39 | 2.417 |

### 2.5.3 Bibliometric and Tools evaluation

#### 2.5.3.1 Bibliometric visualisation (science mapping)

The idea of visualising bibliometric networks or science mapping has received great attention since the emergence of bibliometric research. Since then, science mapping has been a powerful approach to analyse a large variety of bibliometric networks, using bibliometric data. Bibliometric data include several items of a paper such as title, authors, affiliations, publication venue (journals or conferences titles), keywords and references. References themselves include all the previous items. A bibliometric network, like all other networks, consists of edges and vertices (or nodes). The vertices can be each of the items in the bibliometric data (i.e., publications, journals, authors, and keywords) while edges correspond to the relations between pairs of vertices (van Eck and Waltman 2010).

Three main types of relationships among the bibliometric items (vertices) can be considered (which can form three bibliometric networks): 1) co-occurrence, 2) bibliographic coupling and 3) direct citation. Co-occurrence happens when two bibliometric items (e.g., authors, institutes, journals and keywords) exist in a publication. In another word, co-occurrence networks, depending on the unit of analysis, can be 1-1) co-keyword, 1-2) co-author or 1-3) co-citation. Therefore, in a co-occurrence network, vertices represent a bibliometric item (i.e., publications, journals, authors) and links represent existence of at least a co-occurrence relationship among each pair of vertices. In a weighted network analysis, the co-occurrence frequency is considered as the weight of the link. Moreover, there exist three kinds of co-citation network: paper co-citation (references as the unit of analysis), journal co-citation (journal of the reference as the unit of analysis) and author co-citation (authors of the reference as the unit of analysis).

Bibliographic coupling relationship happens when two bibliometric items cite a third item (Kessler 1963). For instance, a bibliographic coupling link among two publications exists if both are citing a third publication. Another well-known analysis is direct citation analysis and it results when any bibliometric item (publication, author, and journal) is citing another. Among the bibliometric relations, in this analysis, only the co-occurrence networks are used for further analysis.

This relationship information can be demonstrated in a matrix format and then mapped to a variety of (weighted) network in which nodes are the items and links are the relationships (based on different relations).

#### 2.5.3.2 Tools evaluation and selection

For bibliometric analysis and visualisation of the results, different software packages have been developed including CiteSpace (Chen 2006), CoPalRed (Bailón-Moreno et al. 2005), Sci2 (Sci2 Team 2009), VantagePoint (Porter and Cunningham 2005), and VOSViewer (van

Eck and Waltman 2010). For a comprehensive overview concerning details and capabilities of the bibliometric visualisation software packages, the reader is referred to (Cobo et al. 2011).

At the second phase, after deciding on the type of analysis, the capabilities and features of the tools were examined among which Citespace was chosen for domain visualisation. Citespace uses different colours to mark nodes and edges. For instance, the colours represent the period of time that co-occurrence frequency of lines reached the threshold for the first time. Moreover, the thickness of links in a network is proportional to the co-occurrence frequencies. Moreover, Citespace uses a time-slicing mechanism to generate a synthesised panoramic network visualisation based on a series of snapshots of the evolving network across consecutive time slices (Chen and Guan 2011) which facilitates discovering salient evolving patterns of scientific literature from a diverse range of visual attributes (Chen et al. 2008). The coloured rings around the nodes across the series of time slices represent the citation characteristics of the nodes at various time periods. The rule of colours in Citespace is: oldest in blue, and newest in red and a spectrum of colours indicates the temporal orders of occurrence and co-occurrence in between. These rules of colours are applied in Figure 2-4 and Figure 2-5.

### 2.5.4 Data cleaning

Publications data (e.g., authors name and their affiliations, keywords) are often not quite organised and consistent due to misspelling or use of not standard characters, etc. Therefore, as the third phase, before conducting any analysis, the data needs to be cleaned. Although cleaning can be done by both CiteSpace and manually, for this analysis the process is performed manually. Cleaning includes integrating different forms of titles employed for authors, their respective institutes and combining the synonyms, acronyms, and single and plural forms of the keywords.

### 2.5.5 Data analysis

In this section, a part of the publication co-citation and keyword co-occurrence networks which is taken from (Najmi et al. 2017a) is provided to justify the gaps in the literature.

#### 2.5.5.1 Publication co-citation analysis

Analysing references is the most commonly conducted type of analysis in the area of bibliometrics. In thus analysis, the top 200 publications (from the references dataset of more than 400,000 cited publications) of every 2 years (slices of 2 years) during 1990 and 2015 are selected based on their citation frequencies. The co-citation network of the cited publications has been formed and visualised in Figure 2-4. Nodes in the networks represent the cited publications and the links appear among any pair of nodes if they have been co-cited frequently enough.

Citespace clusters the co-cited network based on the co-citation relationships and network attributes. To name the clusters, the nature of each cluster should be identified. CiteSpace can extract noun phrases from the titles, keywords, and abstracts of papers that cited the particular cluster, to name the clusters automatically. However, to name the clusters in Figure 2-4, more accurate investigations are employed. The titles, keyword lists, and abstracts of papers in each cluster of cited papers and also papers that cited them are reviewed to extract the core content and nature of the clusters.

By looking closely at the colour of the links and the width and colour of the rings around cited references, several interesting findings can be obtained, but in this section, only outputs that are related to TPMSs are investigated. For further information, the interested reader is referred to Najmi et al. (2017). Among the recognised clusters, “Traffic equilibrium model” (#0), “Congestion pricing” (#1), “Discrete choice modelling” (#3), and “Activity scheduling” (#5) are the main topics of research that form the TPMSs literature. The figure reveals some implications. First, these are among the biggest clusters in the transport domain which show the significance of the research areas. It should be noted that these clusters’ numbers are sorted in a descending order. Second, in these clusters, there is no new link but new rings (based on the colours of the nodes and links). It means a majority of the survived nodes in these clusters appeared in the 1990s while they have received many citations until now. This shows that the research areas in TPMSs still focus on ideas created in the past. Third, the research in these clusters has actively started appearing in the past and maintained the clusters’ significance in the literature. Fourth, these clusters neither have emerged recently, nor have they lost their attractiveness until now. Fifth, there is not a significant relationship between the clusters “Traffic equilibrium model” (#0) and “Activity scheduling” (#5) which reflects the insignificant contribution of the traffic models on activity scheduling. Sixth, the linkage between "Traffic equilibrium model" (#0) and "Discrete choice modelling" has been intensified since 2008 which could be because more attention has been paid to integration of the demand-side and network models (discussed in section 2.3).

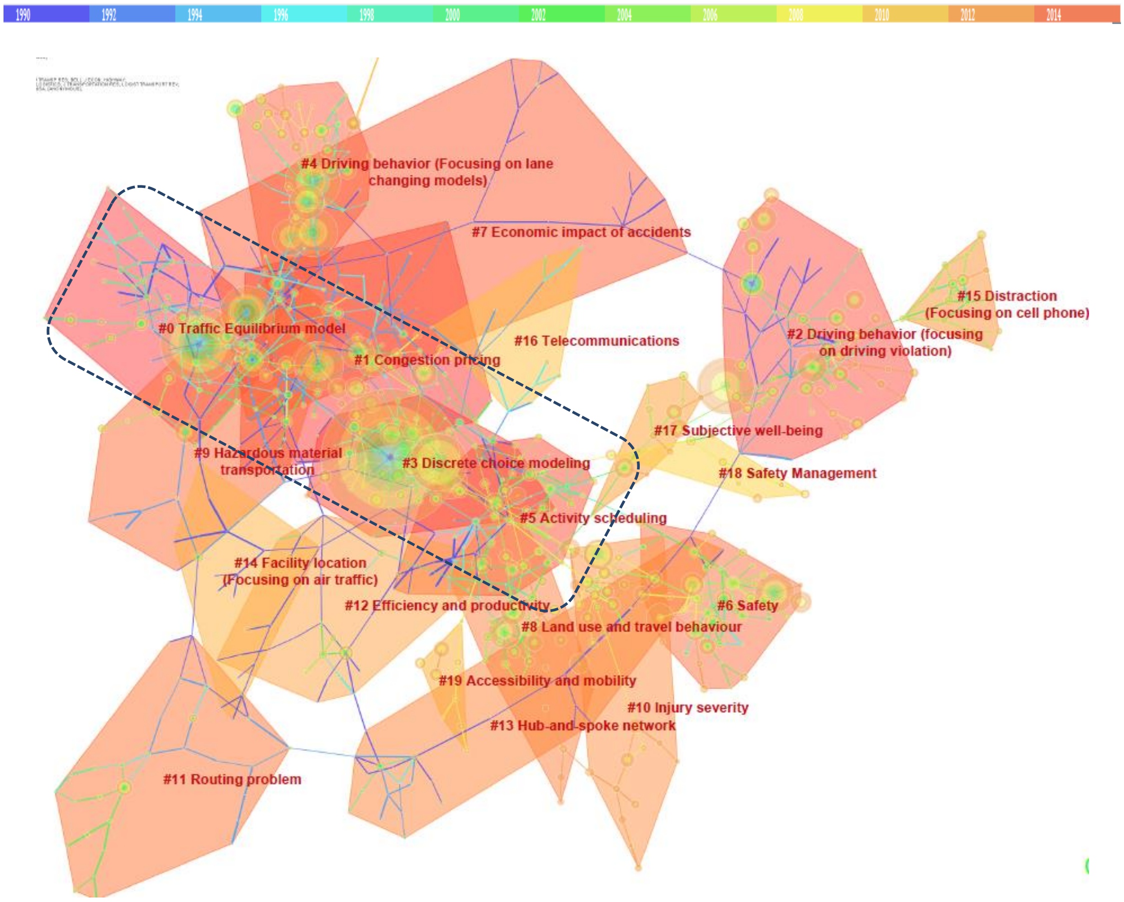



Figure 2-4 Co-citation network of cited publications during 1990 – 2015. Note: Slice length is 2 and top 200 highly connected (co-cited) references are selected per slice.

#### 2.5.5.2 Keyword co-occurrence network

Since keywords contain information regarding the core content of academic documents, the co-occurrence of keywords (i.e., the appearance of keywords in a publication) can reveal information about the formation of multidisciplinary evolving research frontiers of a knowledge domain (He 1999, Lee and Su 2010). The higher co-occurrence frequency of the two keywords can be translated to their closer relationship, which is represented by a thicker linking line between the two keywords in the network (Chen and Guan 2011). While analysing the co-occurrence network of keywords, the keywords are combined with their synonyms, acronyms, and single and plural forms in a manual endeavour. The minimum spanning tree algorithm is used to generate the simplified merged network in

Figure 2-5. Each node in the figure represents a keyword and the colour of each link represents the first time that the co-occurrence of the corresponding keywords happens.

Similar to publication co-citation network analysis, only a part of co-occurrence network in Najmi et al. (2017), which is in line with this thesis topic, is discussed here. Analysing the colours generated by CiteSpace reveals two modes of transport that their co-keyword occurrences are in red, which means that they have relatively high frequencies in the last few years. In other words, these red lines reveal the emerging areas of research in the field of transport. The lines connect: {"Time window" with "ride problem" and "Travel salesman problem"} and {"Cycling" with "Bicycle"}. For instance, the {"Time window" with "ride problem" and "Travel salesman problem"} co-occurrences seem to be quite interesting as the ride-sharing topic is opted for in the literature possibly due to the widespread usage of  smart phones with GPS. These technologies enable matching agencies to communicate with participants in the ride-sharing mode and detect their current locations. The output of the analysis steers the author of this thesis to tackle Aim 4 by developing a dynamic ride-sharing model component which can be incorporated in TPMSs.

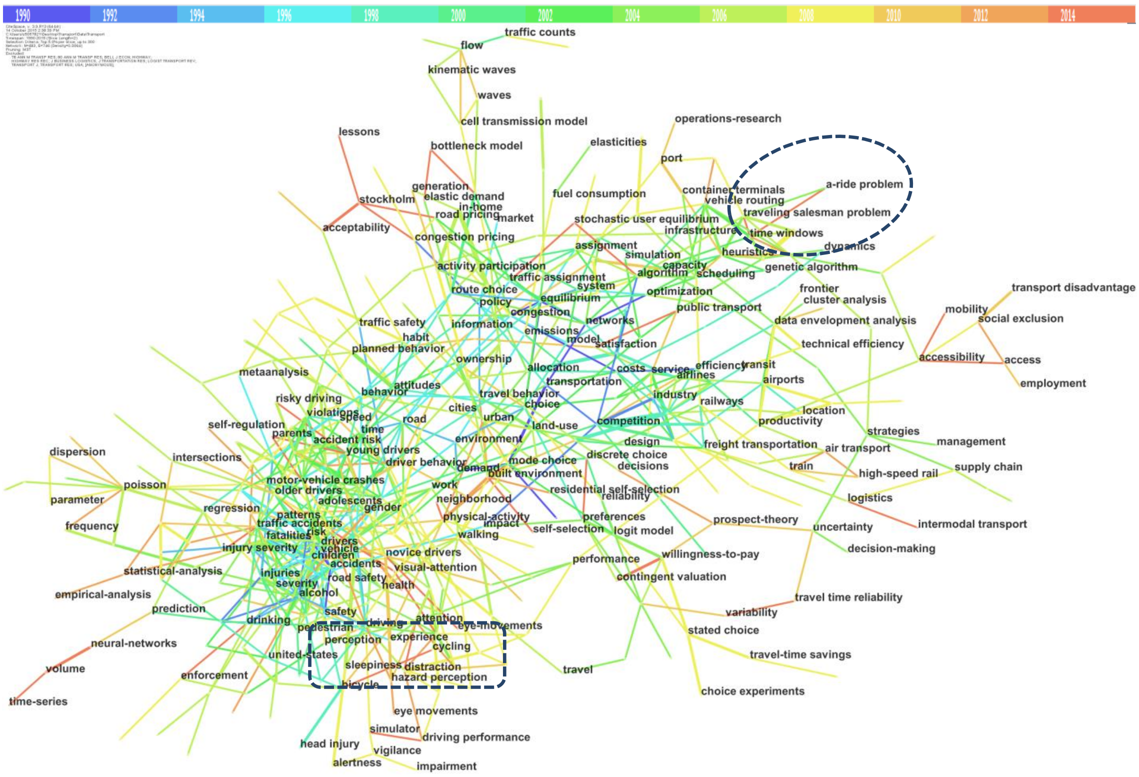



Figure 2-5 The co-occurrence network of keywords in the "transport planning operations and management" field during 1990 – 2015. Note: Slice length is 2 and top 5% limited to 300 keywords are selected per slice.

## 2.6 Conclusion

In this chapter, different structures of TPMSs were presented. Despite the interdependent relationship between demand and network, in transport planning models the two aspects are often treated separately and sequentially. In spite of the problems in the conventional sequential models, their reputation has made them as a cornerstone of the transport domain. However, there could be some possibilities to enhance the performance of the model. Following the general discussion in this chapter about the structure of transport model, the chapters 4 to 7 present the problem statement of the models from different perspectives. These chapters are then present novel approaches to circumvent and fix the problems.

# Chapter 3

# Inconsistencies in Sequential Models: A Case Study

***This chapter is in line with Aim 1 which is introducing the research gap in the literature. In the previous chapter, the existing processes of developing and integrating demand and supply models were discussed. So, in this chapter, the process is examined using a case study in Melbourne area followed by a discussion of some possible solutions to address the current limitations in development of an integrated structure.***

*Calibration is a critical aspect of model development that has long been recognised by researchers as a challenging issue. In particular, difficulties arise when the observed data used for calibration does not match the model output, which is the case in the majority of transport planning models. In the traditional calibration process, the origin-destination (OD) matrices are the key interface between demand and supply models, which could lead to issues when observed traffic link counts are used to update the OD matrix causing a loss of key demand characteristics in the process. Developing a unified structure for modelling both demand and supply requires a calibration process that meets the requirements of both types of models, a serious issue which has received less attention in the literature. To examine the effects of a traditional calibration technique, this chapter applies OD calibration technique to adjust OD matrix. The numerical results show that the standard OD calibration procedure causes unrealistic changes in the OD matrix.*

## 3.1 Introduction

The calibration of transport planning models plays a crucial role in model application and decision-making. It is generally considered that the effectiveness of a model lies in its ability to accurately reproduce actual conditions, which will then be used to produce estimates regarding future situations. Thus, the usefulness of the models and their ability to reliably analyse policy scenarios depends on the quality of calibration. Inadequate calibration can result in significant issues regarding stability, error propagation, and the transferability capacity of the model. For example, Bloomberg et al. (2003) conducted a study on six different software programs and found that the calibration differences of 13% in the predicted freeway speeds for existing conditions increased to differences of 69% in the forecasted freeway speeds for future conditions.

Traditional planning models capture the interaction of two components, demand and supply, in a way that is often considered to be completely independent from one another, due to differences in their data resources and modelling techniques. On the demand side, transport demand modellers estimate the myriad complexities of travel demand based on individual decisions on day-to-day activities, changes in land use, etc. On the supply side, transport network modellers predict network conditions that will result from a predetermined demand, usually based on an equilibrium assumption (Wardrop 1952). Despite the interdependence between demand and supply (i.e., network conditions are both determined by and influence travel decisions), traditionally the calibration of each remains largely separated. Moreover, the calibration of both demand and supply is further confused by questions regarding both the calibration procedures and their practical application. From a technical perspective one of the issues is, given a set of macroscopic observations such as travel survey data and road traffic counts, which macroscopic or microscopic rules should be applied to move the simulation or assignment closer to the observations? Typically traffic counts for areas of the network and trip diaries for a part of population are available.

Traditionally, the calibration process of a planning transport model includes separate exercises to estimate parameters of demand models that generate the OD matrix and to estimate the network parameters (i.e., link capacities). Once both demand and supply models are calibrated, the structure can be further enhanced through an iterative process (using a feedback loop from supply to demand to update network attributes such as travel time), such that the difference between the observed counts and the simulation results is judged to be within an acceptable gap.

Considering different views to OD matrices can elaborate the disjoint calibration processes. From the view of demand modellers, OD matrix is not calibrated while it is the output of the calibrated demand models. If the luxury of knowing an observed OD matrix exists, it is then used to assess the precision of the calibrated demand models. On the other hand, from the perspective of supply modellers an OD is considered properly calibrated if it can optimally reproduce the observed traffic counts. However, due to the temporal difference between when the survey data (for the demand) was collected and the time when link counts were observed, there is conflicting output between the assignment model and the observed link counts. Therefore, using OD calibration methods is very common by traffic assignment modellers to modify the OD matrices to what is desirable. Many OD calibration methods have been proposed in the literature for OD calibration (Spiess 1990, Juarez and Chavez 2015, Cascetta and Nguyen 1988). The central part of all the OD calibration methods is the target/initial OD. In many of the methods, the weighted distance between the updated OD matrix and the target matrix provided from demand models, and also the weighted distance between simulated link flows and observed flows, are minimised subject to flow constraints (Lundgren and Peterson 2008).

The motivation for the research in this chapter stems from a central research question: Do traditional transport models where the demand and supply is primarily connected via OD matrices produce biased results? A critical issue is that when the OD matrix is changed, important characteristics that were directly represented in the demand model but no longer modelled in the OD matrix will be lost. This means, the connection between the calibrated traffic assignment models and the original demand-side models is no longer exist which can be problematic later when they are used in the body of TPMSs. Therefore, the contribution of this chapter can be summarised as follows:

- Based on a large-scale, realistic case study of Melbourne Australia, the potential downfalls of traditional OD calibration techniques are illustrate and their implications for models in practice are discussed; and
- Some possibilities from the demand modelling perspective for the unified calibration of demand and network approaches are suggested.

## 3.2 OD updating

OD matrix updating (also called estimation or calibration) is the common approach to minimise the discrepancy between the modelled and observed link flows, due to the fact that updating of the survey data underlying the travel demand-side model is difficult and costly. OD matrix updating is usually based on current traffic count data collected on a set of links. The established approaches can be categorised into four modelling approaches including Maximum Entropy, Maximum Likelihood estimator, Bayesian inference, and Generalised Least Square estimator (Caggiani et al. 2013). However, the accuracy of the estimated matrices depends on the updating model used, the input data errors, and the set of links with collected traffic counts (Bera and Rao 2011). The OD matrix updating problem has many solutions due to the fact in any practically-sized network, the number of OD pairs will by far exceed the number of links with observed traffic counts, and thus the equation system for estimating the OD matrices is underspecified (Abrahamsson 1998). Therefore, to estimate the proper OD matrices, in the literature, two indices of the distance between the updated OD and target OD (or the observed OD if available) and the distance between the estimated link flows and observed link flows are applied.

Based on their applications, the OD matrix updating models can be categorized as static and dynamic. In static methods, the traffic flows are considered as time-independent and an average OD demand is determined for long-time transport planning and design purpose. However, from last two decades different dynamic approaches have been proposed which are used for short-term strategies like route guidance, traffic control on freeways, intersections etc. The assignment matrix which provides an approximate trip proportions based on the route choice behavior of the trip makers is the complicated part in the updating problem. Another aspect, on which the reliability of the updated OD matrix largely depends, is the optimum traffic counting locations. The traffic counts collected should provide as much traffic information as possible saving subsequent manpower requirement in data collection (Bera and Rao 2011).

## 3.3 or the accuracy of the estimated ODM. Case study

A case study of the city of Melbourne is used to investigate the impact of network based OD updating on the OD matrix itself. In the case study, the changes in an OD matrix that result from two common approaches are compared. The first approach is based on a demand model estimation, while the second method uses a network based OD updating approach. In order to explore the impact of both approaches, a relative comparison on how each method changes the OD matrix is performed. This section explains the details of this experiment and discusses the findings.

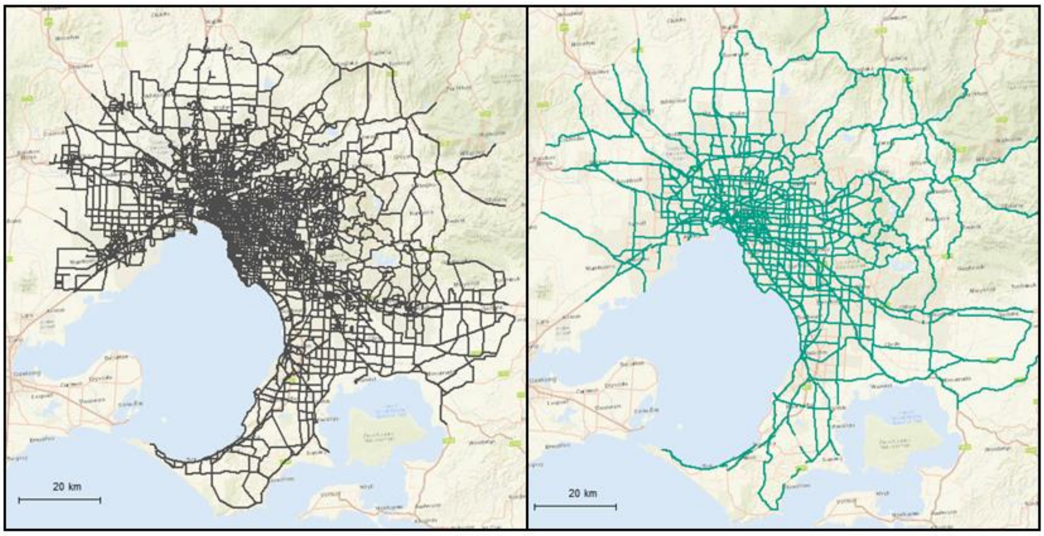
### 3.3.1 Data

#### 3.3.1.1 Household travel survey

The main data source for demand in this study is the household travel surveys collected in the Victorian Integrated Survey of Travel and Activities (VISTA) in 2007, from which several different OD matrices are generated, as explained in the following section. The zoning system in this matrix is defined based on the Census Collection Districts in Melbourne. However, to expand the OD matrix to the population level, a larger zoning system of Statistical Local Areas (SLA) is used.

#### 3.3.1.2 Network and traffic counts

This case study focuses on the greater area of Melbourne, Australia illustrated in Figure 3-1. The network consisted of approximately 44,000 links and 16,000 nodes, which would be considered a very large scale regional network. The original network data was obtained courtesy of CityX at the Monash University (CityX), which included the link parameters for the conventional BPR travel cost function (Bureau of Public Roads 1964). The data was then processed to extract the vehicle-only network. The traffic counts are based on annual SCATS signal averages and are publically available from VicRoads Open Data Portal (VicRoads 2015). The demand centroids were based on Census Collection Districts as obtained from the Australia Bureau of Statistics.




a) Melbourne network links b) publically available traffic estimates

Figure 3-1 Melbourne network

Two map matching processes were necessary to complete the dataset. First, the Census Collection District centroids were created and spatially matched to the nearest network node via the creation of a centroid connector, using ArcGIS. Second, the traffic counts were matched to the network links based on spatial location and their geometric angle. Due to various disparities between the datasets (the roads in the traffic dataset covered greater distances than network links but could only be matched to a single network link), the final processed dataset resulted in 3,655 network links with counts to use as benchmarks of observed link flows.

### 3.3.2 Methodology of the case study

For this case study, we are interested in exploring what is a reasonable change in the OD matrix and then we want to examine the changes that result from a common OD matrix updating approach.

First, a hypothetical forecasted OD matrix should be generated. We used the household travel data from VISTA and an approach introduced by Ghasri et al. (2017), where trip purpose, travel mode, time of day, commute distance and attributes of trip destination are jointly modeled using Modified Decision Tree (MDT), which was previously shown to produce the best aggregate fit to data. Using this demand model, two matrices for the target 2009 are produce. The first is for normal conditions, which is called $OD^P$ and the second for an extreme condition, which is called $OD^E$.

The extreme condition is presented as an upper bound for the reasonable change in an OD matrix that would be produced by a demand model. For the extreme condition, it is assumed that the entire population are full time workers. This is not intended to be a realistic scenario; instead, the extreme assumption creates a suitable benchmark for measuring the impact of OD calibration/updating method on an OD matrix. The difference between $OD^P$ and $OD^E$ is defined as a matrix of changes $p'$. The matrix of changes $p'$ is an indicator of the largest potential change under an extreme condition of a demand scenario. According to the analysis with the case study dataset, the daily total number of trips under the extreme condition has increased 7% compared to the estimate under the normal conditions.

In the next step, the impact of a traditional OD matrix updating method will be explored. The base case (generated from the VISTA dataset) is defined as $OD^0$, which will be updated using the set of observed flow counts. The equilibrium assignment for the OD matrix is solved using the TAPAS solution approach (Bar-Gera 2010) and then compare the observed flows with the model output. As expected, equilibrium flows from the traffic assignment model do not match the observed link flows and calibration is necessary.

The OD updating method by Juarez and Chavez (2015), the modified version of the method in Spiess (1990), is used to calibrate the input $OD^0$. This method updates the demand of OD pairs in order to match the count flows. The updating process is conducted in a bi-level optimisation process. The sub-problem is the user equilibrium problem which guarantees the user equilibrium condition for the assigned flows to the network (solved using TAPAS in the current implementation). The upper level minimises an objective function (Eq. (3-1)) with two parts: 1) the difference between count flows and assigned flows $(\Delta v)$ and 2) the difference between target and updated OD demands $(\Delta g)$. The combination of these two terms in the objective function is weighted using the parameter $\alpha$. By definition, larger values of $\alpha$ would result in higher weight for the difference between count flows and assigned flows. For $\alpha = 1$, the updating method is exactly the same Spiess method which is widely used in the literature.

$$\min Z(g) = \frac{\alpha}{2}\sum(\Delta v)^2 - \frac{1-\alpha}{2}\sum(\Delta g)^2 \qquad 0 \le \alpha \le 1 \tag{3-1}$$

The output of the updating method is an updated OD matrix $OD^U$. At this stage, a comparison between the elements of $OD^O$ and $OD^U$ would result in a matrix of changes of $p$ which represent the magnitude of changes from the OD updating process. The case study analysis compares the results for $p$ and $p'$ in the next section.

### 3.3.3 Effectiveness of the OD calibration method

Intuitively, $p$ values are expected to be considerably smaller than $p'$ values because the magnitude of changes from the calibration process is expected to be lower than the changes resulting from a change as extreme as the assumption of full employment. However, the results suggest otherwise. In this study, when $\alpha = 1$, nearly 30% of the $p$ values are larger than their corresponding $p'$values. This means, for 30 percent of OD pairs, the calibration procedure has a higher impact compared to the extreme condition of full employment.

Table 3-1 presents a cross-classification of $p$ versus $p'$ for $\alpha = 1$, $\alpha = 0.9$, and $\alpha = 0.5$. Assigning lower values to $\alpha$, the calibration algorithm would consider higher weights for differences between target and updated OD. In contrast, the higher weights for $\alpha$ would be considered for matching the count flows.

Ideally, a transport modeller does not expect the OD calibration to modify the initial values significantly because there are characteristics in the target/initial OD matrix that are important for any policy analysis. Therefore, all of the elements of $p$ matrix should ideally fall into the category of -25% $\leq p <$ 25% in Table 3-1. However, Table 3-1 shows that this is not the case. It should be noted that the limits in the table are chosen intentionally for better elaboration of the changes in $p$ and $p'$. In Table 3-1, for $\alpha = 0.5$ the number of elements in the favorable category of $p$ is higher than those for $\alpha = 0.9$ and $\alpha = 1$. This is because when $\alpha = 0.5$, changes in the OD matrix is more penalised in the calibration process.

Table 3-1 Percentage of changes in OD pair - Updating method versus extreme scenario

| Change in p | $-100\% \le p' < -75\%$ | $-75\% \le p' < -50\%$ | $-50\% \le p' < -25\%$ | $-25\% \le p' < 25\%$ | $25\% \le p' < 50\%$ | $50\% \le p' < 75\%$ | $75\% \le p' < 100\%$ | $100\% \le p' < 200\%$ | $200\% \le p' < 500\%$ | $500\% \le p'$ | Sum |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Alpha = 0.5 | | | | | | | | | | | |
| -100% $\le p <$ -75% | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| -75% $\le p <$ -50% | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 2 |
| -50% $\le p <$ -25% | 2 | 4 | 4 | 4 | 1 | 5 | 0 | 1 | 5 | 1 | 27 |
| -25% $\le p <$ 25% | 133 | 401 | 296 | 703 | 88 | 161 | 58 | 130 | 125 | 42 | 2137 |
| 25% $\le p <$ 50% | 8 | 9 | 3 | 23 | 3 | 4 | 3 | 5 | 2 | 2 | 62 |
| 50% $\le p <$ 75% | 1 | 2 | 1 | 6 | 0 | 3 | 1 | 1 | 0 | 2 | 17 |
| 75% $\le p <$ 100% | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 1 |
| 100% $\le p <$ 200% | 0 | 0 | 0 | 2 | 0 | 0 | 0 | 0 | 0 | 0 | 2 |
| 200% $\le p <$ 500% | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 500% $\le p$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Sum | 144 | 416 | 304 | 738 | 93 | 174 | 62 | 137 | 132 | 48 | 2248 |
| Alpha = 0.9 | | | | | | | | | | | |
| -100% $\le p <$ -75% | 0 | 0 | 1 | 0 | 0 | 3 | 0 | 0 | 0 | 1 | 3 |
| -75% $\le p <$ -50% | 1 | 3 | 3 | 4 | 0 | 3 | 0 | 0 | 2 | 1 | 17 |
| -50% $\le p <$ -25% | 6 | 17 | 8 | 19 | 4 | 2 | 0 | 8 | 6 | 0 | 70 |
| -25% $\le p <$ 25% | 119 | 359 | 282 | 644 | 80 | 151 | 55 | 118 | 119 | 37 | 1964 |
| 25% $\le p <$ 50% | 10 | 27 | 8 | 44 | 6 | 11 | 3 | 6 | 4 | 5 | 124 |
| 50% $\le p <$ 75% | 6 | 4 | 0 | 14 | 2 | 1 | 2 | 2 | 0 | 2 | 33 |
| 75% $\le p <$ 100% | 2 | 4 | 1 | 8 | 0 | 2 | 2 | 2 | 1 | 2 | 24 |
| 100% $\le p <$ 200% | 0 | 2 | 1 | 4 | 1 | 1 | 0 | 1 | 0 | 0 | 10 |
| 200% $\le p <$ 500% | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| 500% $\le p$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Sum | 144 | 416 | 304 | 738 | 93 | 174 | 62 | 137 | 132 | 48 | 2248 |
| Alpha = 1 (Spiess 1990) | | | | | | | | | | | |
| -100% $\le p <$ -75% | 12 | 21 | 8 | 46 | 7 | 12 | 4 | 4 | 4 | 9 | 127 |
| -75% $\le p <$ -50% | 9 | 25 | 18 | 46 | 2 | 11 | 4 | 13 | 5 | 3 | 136 |
| -50% $\le p <$ -25% | 25 | 53 | 29 | 91 | 8 | 34 | 10 | 15 | 23 | 7 | 295 |
| -25% $\le p <$ 25% | 74 | 241 | 200 | 439 | 57 | 87 | 32 | 72 | 63 | 20 | 1285 |
| 25% $\le p <$ 50% | 8 | 21 | 17 | 43 | 7 | 5 | 4 | 11 | 19 | 2 | 137 |
| 50% $\le p <$ 75% | 3 | 10 | 6 | 15 | 1 | 7 | 4 | 6 | 4 | 2 | 58 |
| 75% $\le p <$ 100% | 2 | 5 | 4 | 10 | 1 | 2 | 1 | 4 | 2 | 1 | 32 |
| 100% $\le p <$ 200% | 5 | 23 | 8 | 34 | 7 | 4 | 1 | 5 | 4 | 2 | 93 |
| 200% $\le p <$ 500% | 4 | 14 | 7 | 9 | 1 | 6 | 2 | 5 | 6 | 1 | 55 |
| 500% $\le p$ | 2 | 3 | 7 | 5 | 2 | 6 | 0 | 2 | 2 | 1 | 30 |
| Sum | 144 | 416 | 304 | 738 | 93 | 174 | 62 | 137 | 132 | 48 | 2248 |

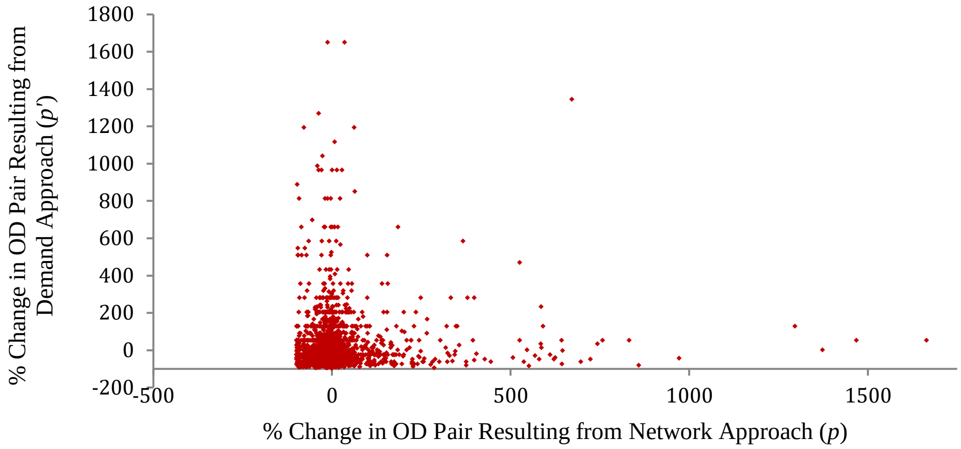
The most problematic cases are highlighted in Table 3-1. These cases represent the situations where the calibration process has generated considerably larger changes in demand compared the changes that would occur from an extreme change in the demand model itself (as represented by $OD^P$and $OD^E$). When $\alpha = 1$, in 497 out of 2248 cases, while the extreme condition cause a minor change in demand (changes less than 25%), the updating procedure produce a change of more than 25%. Furthermore, the updating process changes 159 of the OD pairs more than 100%, 29 of which are even changed more that 500%. However, this condition would be better, when the results of $\alpha = 0.9$ and $\alpha = 0.5$ are considered. For these cases, the number of OD pairs with minor changes in extreme demand condition and major changes in calibration process would reach to 144 and 37, respectively.

Figure 3-2 visualises the relationship between $p$ and $p'$ for the cases of $\alpha = 0.5$ and $\alpha = 1$. Each point in this plot corresponds to one of the elements in OD table. The horizontal axis represents $p$ values and the vertical axis represents $p'$ values. Ideally, one would expect the updating not to make major changes to OD elements which would mean the points would be scattered close to the vertical axis in this plot. Note that, there would be no limitation on the $p'$ values, as the impact of the extreme scenario on travel demand is unknown. Figure 3-2 shows a noticeable number of points are far from the vertical axis and very close to the horizontal axis. These points represent a major change in the OD calibration process for the OD pairs with minor changes under extreme demand condition.

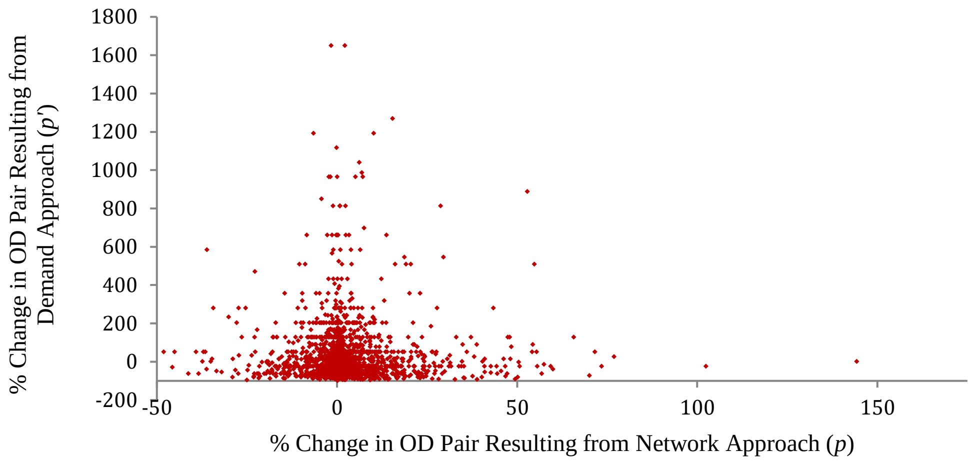
Therefore, while OD updating plays a critical role in connecting the demand side and supply side models in the literature, it cannot transfer the OD demand truly and completely. This leads to an interruption in the linkage between these two sorts of models.

## 3.4 Discussion

While previous efforts have been made to join the demand and network models in some advanced integrated transport models, the linkage is primarily limited to a feedback loop where a simulation-based process passes exogenous travel times to the demand from the network. Section 0 demonstrated that established calibration methods may significantly change the OD demands. This approach could sacrifice the accuracy and predictive power of the demand model and also lose the reciprocal relationship with network model.




a) In the case of $\alpha = 1$




b) In the case of $\alpha = 0.5$

Figure 3-2 The percent of the changes in OD pair by updating method versus extreme scenario

This situation can be made worse when the OD matrix is considered as the sole connection between supply and demand. When tours/trips are summarised into the OD matrix, variables used in the process of generating the OD matrix that may represent important characteristics such as stochasticity and adaptivity are no longer present. As a result, some information about the demand is lost if an OD matrix represents demand. However, due to lack of a better solution, OD matrices remain the most common representative of demand to be used in traffic assignment models.

From the network perspective, it is necessary to update the OD matrix due to the temporal difference between when the survey data (for the demand) was collected and the time when link counts were observed, which creates conflicting output between the assignment model and the observed link counts. However, when the OD matrix is changed, important characteristics that were directly represented in the demand model but no longer modelled in the OD matrix will be lost.

It is expected that a joint model will generate more consistent results when demand and supply are jointly calibrated. Figure 3-3 depicts a desirable structure for an integrated demand and supply model. As discussed in Section 0, the OD updating/calibrating method, as an integral part of OD based models development, significantly affects demand outputs. Therefore, a sequential model calibration process which directly links demand and supply models is expected to produce more reasonable results. This is the situation where the models are simultaneously calibrated and fully integrated so that they can be used for running scenarios for forecasting as the demand model is completely sensitive to changes in input variables and is capable of directly information the supply model about consequences of these changes.

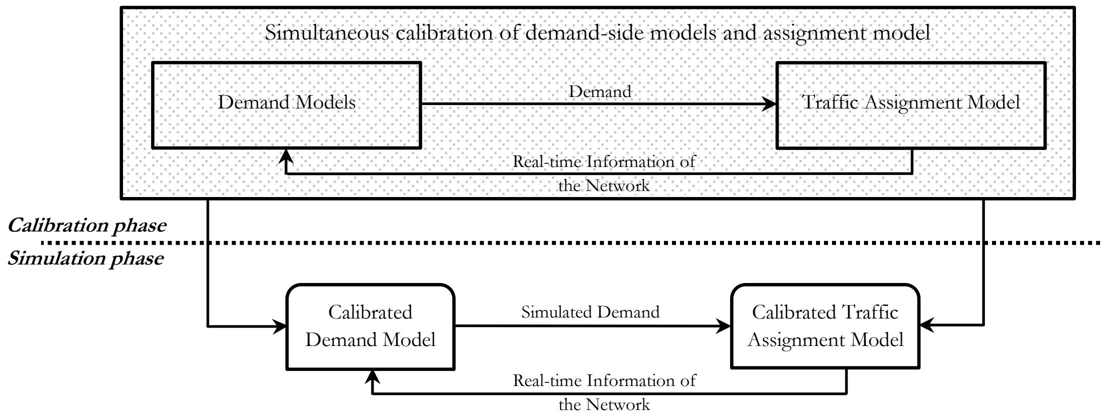



Figure 3-3 The desirable structure in developing a fully integrated transport model

When trying to unify demand and supply models, some modifications to the demand model will be necessary, although as previously discussed, these modifications should not be applied (or at least with very limited magnitude applied) to the OD matrix but to structure of the demand model. The first option is to change the parameters resulted from fitting the demand-side models on surveyed data so that they can reproduce the observed traffic counts. Updating the parameters can include adjusting the constants in the demand-side models and adjusting the sensitivity of each of the models in choosing an alternative to some variables. As an example, a modeller can adjust the auto availability constants (Bowman et al. 2006) and also adjust the sensitivity of choosing a destination for doing a recreational activity to the distance between origin and destination zones, such that the downstream assignment model provides better fit to the observed link flows. It is important to note here that by doing so, the fit to the observed travel behaviour data is decreasing at the cost of having better fit to the observed network data. One may also argue that after updating parameter the model is not any more behavioural as it used to be when it was calibrated by only looking at the demand data. A solution to this problem is to update the underlying assumptions about the error term components reflecting unobserved factors not captured in the parameters of the demand model. This way the behavioural feature of the demand model is not touched while the unobserved components are expected to reflect some features of the network. Although updating the error term assumptions seems effective in developing a fully integrated transport model, it is very complicated.

It is also possible, less desirable though, to weight the agents and the activities of travellers in the joint calibration of demand and supply models. This can procure a high resemblance between the link flows and observed traffic counts (Cools et al. 2010). Examples of the possible changes include changing the trip generation rates for different individuals. Changing these weights is similar to changing data. Since the surveyed data are the most reliable data that is available, weighting the activities and agents is not recommended, unless there is a valid reason. A valid reason, as an example, can be the change in the attractiveness of a zone because of opening a shopping centre after the year the surveyed data are collected. The higher weights can be given to the agents in the zone and its surrounding area.

## 3.5 Conclusion

Despite the interdependent relationship between demand and supply, in transport planning models the two aspects are often treated separately. The result may be unrealistic and unpredictable changes in the travel demand, which could result in biased policy predictions. Although the literature shows a growing recognition of the importance of integrating the demand and supply models in the simulation phase, there are fewer proposals regarding integration during the calibration process itself. Certainly the accuracy of the transport models in forecasting various scenarios is highly affected by the procedures taken in the linking the demand and supply models and the calibration afterward.

In this chapter, the adverse effect of OD updating, as the main tool for the linkage, was discussed using the case study of Melbourne area. The results revealed that the impact of OD updating in changing a considerable number of the OD pairs is higher compared to the extreme condition of full employment. Therefore, it is important to continue research in other approaches for calibrating the unified structure of demand and supply models, with more focus on demand components instead of on ODs and network attributes. Finally, some possible solutions to improve the quality of the calibration, focusing of demand model, were discussed.

# Chapter 4

# Multi-objectivity and Validation in Calibration Process

***This chapter is in line with Aim 2 and proposes a systematic approach to enhance TPMSs calibration process considering both demand-side and traffic assignment models in a unified structure.***

*Traditionally, transport planning model systems are estimated and calibrated sequentially, which does not allow for interactions among included parameters to be considered. Furthermore, the computational burden of model systems plays a key role in choosing a calibration approach, and usually forces modellers to calibrate demand-side and network models separately. Also, trial-and-error methods and expert opinion are currently the backbones of transport model calibration, which leaves room for error in the calibrated parameters. This chapter addresses these challenges and suggests an analytical approach for determining optimal calibrated transport model parameters. This approach involves joint estimation and calibration of demand and network models, with a major focus on avoiding any manipulation of the OD matrix. The approach can be applied to static or dynamic traffic assignments. The approach is applied by calibrating the GTAModel—an example of a large-scale agent-based model system from Toronto, Canada.*

## 4.1 Introduction

The development of transport planning model systems (TPMSs) has become an important topic of research in recent decades. Different generations of model systems have emerged over time, including four-step models (e.g. NYMTC 2014, McNally 2000) and activity-based models (e.g. ALBATROSS: Arentze and Timmermans 2004a, ADAPTS: Auld and Mohammadian 2012, OpenAMOS: Pendyala et al. 2012, CEMDAP: Bhat et al. 2004). Each TPMS usually consists of several interactive models (categorised as demand-side and network models) within the overall model system. While *demand-side* models reflect the travel decisions of agents in the transport system and the resulting travel demand, *supply-side* models deal with the interaction between travel demand and the supply of infrastructure and transport services (Bliemer et al. 2013). The models may include sub-models for things such as trip generation, destination choice, departure time, mode choice and network assignment.

Model parameter *estimation* is the first step in TPMS development, and usually involves maximisation of certain functions—such as a likelihood function, a simulated likelihood function, or squared moment conditions—to find a parameter set that maximises the model's fit to a set of observed data (Train 2003). Generally, the initial structures of TPMSs are created by linking a sequence of estimated models together. Usually, the estimated models require adjustment when they are combined into an overall TPMS structure. This necessitates iterative calibration and validation of the TPMS. According to NYMTC (2014), *calibration* refers to the process by which the models (with estimated parameters) comprising each TPMS are adjusted to best approximate observed data from a "base year". *Validation*, however, is the assessment of the effectiveness of a TPMS in reflecting travel market characteristics and traveller choices and behaviours in years subsequent to the base year. In practice, calibration and validation processes are usually iterative, with model validation revealing issues that require further calibration to overcome (Donnelly et al. 2010). In this chapter, the iterative processes of calibration and validation are called the *calibration process*. When the calibrated and validated models are used to analyse scenarios, policies or hypothetical situations, the outputs are generated in the simulation process.

In spite of the importance of the TPMS calibration process in practice, little academic attention has been paid to this problem although the calibration of TPMS model components has been well discussed. An ideally calibrated TPMS should reproduce base year conditions, be sensitive to the policies being tested, and respond logically to changes in inputs. Nonetheless, in practice, the focus of model calibration efforts is usually on reproducing the base year conditions (Donnelly et al. 2010). This may result in over-calibrated TPMSs which, consequently, make misleading predictions. This, unfortunately, means that the validation of TPMSs has not received enough attention in the literature.

*Unstructured/classic* approaches are still the standard in transport modelling, in which adjustments are sequentially applied in relatively ad hoc, non-systematic ways. These adjustments are based on the modeller's knowledge and expertise, with an aim to reproduce observed statistics. The tools used in unstructured calibration include origin-destination (OD) "K-factors", alternative-specific constant adjustments, and adjustments of agent and activity weightings. Unstructured calibration approaches can be problematic for many reasons, including the computational burden of the calibration, failure to consider interactions among parameters, and excessive focus on reproducing the statistics observed in the base year. The latter may sacrifice the validity of model systems. These core complications, along with some other potential problems, are discussed in Section 0. Furthermore, as the number of parameters in a TPMS increase, the number of interactions between them increase exponentially, making the calibration process ever more difficult.

While the development of different transport planning models has garnered increasing industrial and academic attention (Bao et al. 2014), the existing literature about their calibration remains deficient in some aspects. This is the motivation for this study, which makes several theoretical contributions and highlights their practical implications. First, this study is among the first to solve the practical complexities associated with developing large-scale TPMSs. Although the individual calibration of demand-side and network models is well-discussed in the literature, calibration of a TPMS has its own requirements, and there is no systematic or standard calibration method. Second, this study numerically determines the potential effects of unstructured calibration processes on model validity and reliability. The unstructured/classic calibration process used for transport planning models—which applies calibration techniques based only on the modeller's expertise—has been criticised by many researchers. Nonetheless, conducting numerically-based research to identify, examine and compare the potential effects of unstructured calibration processes on model validity and reliability is necessary. Third, this study addresses the necessity for a systematic approach to TPMS calibration. It proposes a tractable approach based on the response surface methodology (RSM) to efficiently calibrate large-scale TPMSs while considering the interactions of their constituent models and parameters. The central composite design (CCD) is chosen as the design matrix because it allows reliable identification of first-order interactions between parameters while providing a second-order polynomial model to predict their optimum levels (Myers et al. 2009). By modelling and optimising the parameters, it is possible to investigate their effects on the TPMS output. Fourth, this work contributes to the research on transport modelling, policy-making and strategic planning, both in theory and practice. Lastly, the descriptive results offer valuable insights and will help the reader follow the calibration process when applying it to a real case study using data from the City of Toronto, Canada.

The rest of the chapter is structured as follows. Section 4.2 reviews the relevant existing literature. Section 4.3 presents the problem statement and outlines the significant drawbacks of unstructured calibration in practice. In Section 04.4, central composite methodology is briefly introduced and then, in Section 4.5, a model is set up to calibrate TPMSs efficiently and effectively. Following this, the application of the model and its capabilities are illustrated in Section 4.6. Finally, the findings and their possible extensions are summarised in Section 4.7.

## 4.2 Literature review

The calibration method presented in this chapter is relevant to many aspects of transport modelling. These include: studies of demand-side model development, especially agent-based models, OD matrix estimation, network model calibration, and TPMS development and calibration in practice. The focus of this chapter is on the fourth of these, TPMS calibration.

### 4.2.1 Demand modelling

Travel demand modelling has attracted significant interest from academia and practice with considerable literature in this area. Separate travel demand models have been developed to account for system-level and user-level properties. Demand models are typically estimated/calibrated using travel diary data at the disaggregated level of individuals.

The classical demand models are mainly focused on individual models for different travel attributes such as mode, time of day and destination while the connectivity between models is overlooked (Zhao and Kockelman 2002). Further, the literature is rather slim when it comes to estimation of the demand models while properties of the network models are accounted for (Najmi et al. 2018).

### 4.2.2 Origin-destination matrix calibration

The final output of the demand models (the OD matrix) is commonly adapted to find a better fit for the network model. This procedure is known as OD estimation/calibration, and there has been extensive research on OD calibration methods. In general, the calibration procedure in these cases includes a bi-level optimisation formulation, the upper-level estimates the OD matrices under the assumption of known OD path flows, whereas the lower-level solves an assignment problem under the assumption of a given OD (from the upper-level). The calibration solution is usually addressed using variational inequality (Nie and Zhang 2008), numerical gradient-based methods (Spiess 1990) and stochastic approaches (Cipriani et al. 2011, Asakura et al. 2000, Kattan and Abdulhai 2006). To address the deployment of dynamic traffic assignment models, research in OD estimation methods has shifted towards development of time-dependent OD estimation models, which is still a vibrant research area.

One main shortcoming of these studies pertains to neglecting performance measures other than minimising the discrepancy between modelled and observed traffic counts or screen lines. Furthermore, instead of adjusting the ODs, adjusting the demand-side parameters that affect the output (including the OD) of the models is something that has been dismissed in the literature.

### 4.2.3 Network calibration

Speed-density models are usually at the core of network calibration. Such calibration typically recognises the time-lagged response of speed to density, and also to autocorrelated system noise. Speed-density models capture essential traffic streams on highways and form the basis for macroscopic and mesoscopic traffic simulations (Qin and Mahmassani 2004). Parameter estimation and calibration of these models are usually performed by using regression techniques with observed traffic data. There is an implicit assumption in these applications: traffic measurements taken over consecutive intervals are independent, and there are no dynamic effects. For further details, the reader is referred to Qin and Mahmassani (2004) and Huynh et al. (2002).

Similar to the discussion of the previous two subsections, ignoring the link between network and demand models can result in substantial discrepancies which unavoidable in a large-scale TPMS.

### 4.2.4 Joint calibration of OD and network

There are few studies on the joint calibration of OD flows and dynamic traffic assignment models. Early calibration efforts are based on iteration between the demand and network components where 1) the O-D flows and route choice model parameters and 2) the driver behaviour parameters are iteratively adjusted until convergence (e.g. Doan et al. 1999, Toledo et al. 2003). More recent calibration approaches have focused on the simultaneous calibration of both the demand and network components (e.g. Balakrishna 2006, Balakrishna et al. 2007, Antoniou et al. 2005). The results in Balakrishna (2006) reveal that simultaneous calibration, leads to better results because of the interactions between demand and supply. The calibration solutions can also be categorised into off-line and online calibrations. While the off-line calibration is used to ensure the model's capability to reproduce average conditions, the online calibration is used for real-time predictions of traffic conditions. Online calibration uses the off-line calibration results as a priori estimations during the calibration process. For a comprehensive review of these joint calibration efforts, the readers are referred to Balakrishna (2006) and Omrani and Kattan (2012).

A critical problem in this area of research is that the output of the demand models (or OD matrices being generated through the first three steps of a 4-step model), and not the demand models themselves, is considered to be the responsibility of the demand component of the structure. For example, if only the OD matrices are considered in the calibration process, then no trace of details of destination choice and mode choice models are utilised in the calibration process. As shown in Najmi et al. (2018a), the OD calibration may fall short in transferring information on how the OD matrices are formed, which then may lead to something that cannot be used for forecasting.

### 4.2.5 Large-scale TPMS calibration

Recent urban development and the need for mid-term and long-term transport planning have triggered great interest in people's responses to changes in policy and infrastructure. Accordingly, many TPMSs have been developed. Two important generations of such model systems are *four-step* and *activity-based* models. To calibrate such model systems, adjustment of the network parameters is rare; instead, the network models are considered to be already calibrated. In contrast to the other before-mentioned streams of research, there is no coherent method for the calibration of these large-scale models. In these models, some calibration techniques, such as zone-specific scaling factors, OD K-factors, alternative-specific constant adjustment, weighting agents and activity patterns, and data manipulation, are applied to the demand-side model with the aim of simultaneously calibrating the demand-side and network models.

A comprehensive example of such a calibration method for a four-step model system is provided in NYMTC (2014). In this report, the calibration process focuses on adjusting the inputs, network and demand-side model parameters, with a focus on using utility constants to reproduce the base year travel statistics. In the model system, journey production and attraction models are calibrated using scaling factors, and applied to the zone of residence according to trip purpose. Furthermore, county-to-county K-factors and utility constant adjustments are used to shape the OD distribution and daily journey mode shares, respectively. Parsons Brinckerhoff (2005) calibrated the Mid-Ohio regional planning commission (MORPC) model system to reproduce OD flows and mode shares using OD K-factors and scaling factors, respectively. That study also introduced several general rules for calibrating TPMSs. The rules include making small adjustments in each iteration of the calibration process, spreading minimal adjustments over the maximum possible number of segments, and selecting the alternative-specific constants for adjustment.

Furthermore, there is little research on the calibration of more disaggregated model systems. Bowman et al. (2006) presented a calibration procedure for the Sacramento activity-based travel demand model. According to their calibration process, some constant terms in the utility function of the demand-side models were adjusted to reproduce screenline counts, transit boarding counts, and transit trip observations. Cools et al. (2010) also highlighted a framework to link demand-side models in general, and activity-based models in particular, using traffic counts. In their study, activity-based model parameters were adjusted by weighting chosen activity patterns and agents to reproduce the observed OD matrix. Availability of a full observed OD table was a unique feature of their modelling context. To review experiences in the development and application of TPMSs in practice, the reader is referred to Davidson et al. (2007). The authors point out the general technical issues that appear when developing and implementing such model systems. As can be understood, transport modellers have used a handful of techniques for TPMS calibration. However, no analytical framework for the calibration process has yet been reported in the literature.

The focus of the current study is on the TPMS calibration category, with potential implications for other categories. However, if differs from the TPMS calibration studies in several ways. Firstly, a formal calibration structure is proposed. Secondly, the interaction between demand-side and network models is considered. Thirdly, in the calibration process, the network model plays a more prominent role in the calibration of TMPSs in comparison with unstructured TPMS calibration. Finally, this study is also the first to propose a systematic procedure for calibration and validation of TPMSs.

## 4.3 Problem statement

The calibration process is not simply a predefined process or a purely mathematical exercise in adjusting model parameters to fit observed statistics; rather, it is generally an unstructured process. An unstructured calibration approach may be problematic, since it may force modellers of practical applications to override theoretical standards and rules. Problems with this standard approach are discussed in the following paragraphs.

There are many parameters in a large-scale TPMS, of which some should be sequentially selected for adjustment. However, the complex interconnections among models, especially in recent advanced ones (e.g. activity-based and agent-based models) means there are a large number of parameters, where selecting the right ones for adjustment can be complicated. Even supposing that the proper parameters for adjustment are selected, choosing the direction (increase or decrease) and the increments with which the adjustments should take place is challenging. In an unstructured calibration approach, with the choice of the parameters, the direction of adjustments and steps by which they should be adjusted depend exclusively on the modeller's opinion.

Furthermore, the TPMS calibration process is not simple. Since their demand-side and assignment models/parameters are intrinsically interconnected, they should ideally be calibrated together. Since considering both demand-side and traffic assignment models in large-scale TPMSs requires an extensive number of operations to investigate the influences of various adjustments on the parameters, the TPMS calibration process is computationally burdensome and problematic. Notably, traffic assignment models usually involve long computational runtimes, such that including them in the calibration process can significantly increase the calibration time. Therefore, to make the process much faster, the standard practice is to perform the calibration sequentially/independently, with the primary emphasis on calibrating demand-side model parameters according to calibrated network conditions (see Figure 4-1). However, a problem arises when assignment models are introduced to the calibrated demand-side models. Since the assignment models (creating a feedback loop in simulations) change the values of variables within the demand-side models, the gap between the simulated and observed statistics will be greater than the gap encountered during the calibration. Inadequately addressing the linkages between the demand and traffic assignment models in the calibration process can result in significant issues of stability, error propagation and transferability of the model system.

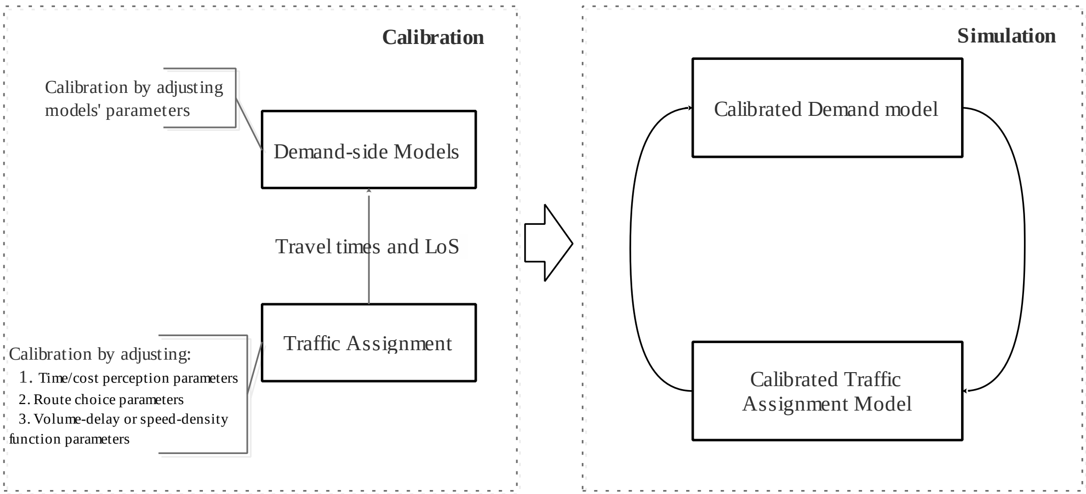



Figure 4-1 Conventional TPMS estimation, calibration and simulation processes

Another problem arises where the calibration process involves many iterations and where very few parameters are considered. Consideration of only a few parameters in each iteration of an unstructured calibration process prevents investigation of the interactions among the model parameters. In other words, a priori selection of parameters for adjustment may result in no improvement, because the effective adjustment of a parameter in one iteration may have adverse impacts in subsequent iterations where adjustments of other parameters are given effect. As a result, sequential calibration (with many iterations) without considering the interactions among parameters may result in inconsistent parameter adjustments that not only do not affect the model system but, also, cause the adjusted parameters to lose their best-estimated values. An alternative approach is taking into consideration many parameters in each iteration of the calibration process.

Furthermore, calibration of TPMSs is a multi-objective procedure. That is, various objectives must be considered during the calibration process. Often, the adjustments may improve one or more of the objectives while negatively affecting others. For example, while OD-matrix estimation methods minimise the difference between estimated and observed traffic count data, they may have the opposite effect on vehicle miles travelled (Cools et al. 2010). Given the multi-objective nature of the calibration process, there are numerous solutions for adjusting parameters which necessitates having a procedure for selecting the best solution.

Also, in practice, the focus of model calibration efforts is usually on reproducing the base year conditions (Donnelly et al. 2010) so that the validation, which is typically done for some other years, of the model is either neglected or totally ignored. Focusing on only the base-year statistics may affect the forecasting capabilities which are the ultimate purpose of TPMS development.

The above problems are common to all generations of TPMSs but may be more critical for more advanced ones due to their higher number of parameters. Therefore, the necessity of using effective calibration techniques that are comparable to their classic counterparts is apparent. In this chapter, an alternative calibration approach is sought which is applicable in all types of TPMSs. To improve the calibration process of model systems, an alternative RSM-based model is proposed. RSM utilises the experimental design methods to determine which parameters influence the response of interest (reproducing the observed statistics). After designing the experiment, a response surface can be fitted to quantify the relationships between the response and parameters. As a result, this method can guide the gradual adjustment of the parameters that significantly influence improvement of the response measures.

## 4.4 Optimal design for experiments and response surface methodology

The RSM consists of a set of mathematical and statistical techniques used to develop, improve and optimise processes in which a response of interest is influenced by several factors, with the eventual objective of optimising the response (Box and Draper 2007). To do the analysis, RSM quantifies the functional relationship between a response of interest, $y$, and the explanatory factors, $x$ (See Equation (4-1)). This mathematical representation can correspond to different models depending on the order of polynomial chosen. The technique is useful where reliable mathematical models between dependents and independents factors are not available. Furthermore, these techniques are useful in cases where obtaining experimental data is time-consuming or costly.

$$y = f(x_1, x_2, \dots, x_m) \tag{4-1}$$

Usually, the relationship between the response and the explanatory factors is unknown; however, it can be approximated by a low-degree polynomial model. For a complete review of RSM techniques, the reader is referred to Khuri and Mukhopadhyay (2010). It should be emphasised that the interaction of the parameters can also be estimated mathematically. In the current research, the order of polynomial of each equation is selected according to the fitness function value of the estimated equations.

Central composite designs were first introduced in Box and Wilson (1951) and, together with Box-Behnken designs (Box and Behnken 1960), are two common quadratic modelling approaches. As shown in Figure 4-2 for three factors, to fit the functional relationship in Equation (4-1), CCD uses three groups of design points: 1) corners which represent the factorial design points and coded by $\pm 1$, 2) centre point where the value of each factor is the median of the values used in the factorial portion, codes by zero, and 3) axial points where all parameters are held constant as (coded) zero except for one with the value of $+\alpha$ or $-\alpha$, well-known as *design parameter* (Marget 2015). Centre point is often replicated in order to improve the precision of the experiment.

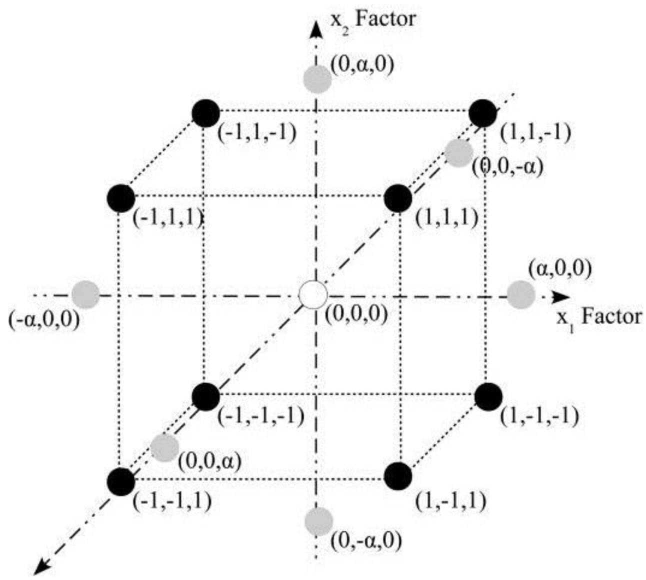



Figure 4-2 Schematic diagram of a three factor central composite design (CCD)

To illustrate how the experiments are implemented, a seven-factor CCD design is described in Table 4-1. The columns in the table represent the parameters and their corresponding deviation limits, while each row constitutes an experimental run which is performed at the given parameter settings. For example, Experimental Trial #2 uses Parameters 1, 2, 4 and 6 at their positive deviation limits, and Factors 3, 5, and 7 at their negative deviation limits. The last column in Table 4-1 represents the performance of the experiments in terms of different objective functions. For example, an objective function can be defined as the absolute difference between simulated and observed screenline counts in a network. For more information, the interested reader is recommended to consult existing books or commercial software (such as Design Expert, R and Minitab) available in the field.

Table 4-1 A central composite design with seven parameters

| Experiment | Parameter 1 | Parameter 2 | Parameter 3 | Parameter 4 | Parameter 5 | Parameter 6 | Parameter 7 | Response values |
|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 1 | 1 | -1 | 1 | 1 | 1 | $r_1^1, r_2^1, \ldots, r_n^1$ |
| 2 | 1 | 1 | -1 | 1 | -1 | 1 | -1 | $r_1^2, r_2^2, \ldots, r_n^2$ |
| 3 | 1 | 1 | -1 | 1 | 1 | -1 | 1 | $r_1^3, r_2^3, \ldots, r_n^3$ |
| 4 | 1 | -1 | 1 | -1 | -1 | -1 | 1 | $r_1^4, r_2^4, \ldots, r_n^4$ |
| | | | | | ⋮ | | | |
| 34 | 0 | 0 | 0 | 0 | 0 | $-\alpha$ | 0 | $r_1^{34}, r_2^{34}, \ldots, r_n^{34}$ |
| 35 | 0 | 0 | 0 | 0 | 0 | $\alpha$ | 0 | $r_1^{35}, r_2^{35}, \ldots, r_n^{35}$ |
| 36 | 0 | 0 | 0 | 0 | 0 | 0 | $-\alpha$ | $r_1^{36}, r_2^{36}, \ldots, r_n^{36}$ |
| 37 | 0 | 0 | 0 | 0 | 0 | 0 | $\alpha$ | $r_1^{37}, r_2^{37}, \ldots, r_n^{37}$ |

Applied to the TPMS calibration, the factors are the parameters that should be considered for adjustment and responses are the values that should be calibrated. Therefore, RSM shows how the parameters of different models in a TPMS affect its output, and allows determination of the independent parameters that optimise the output for calibration purposes. To conduct an RSM analysis, in the current study, a central composite design (CCD) is used to design the experiments and analyse the results to obtain the optimal parameter values. For more information about different experimental designs and the required number of experiments to be run, the reader is referred to Myers et al. (2009) and Ranade and Thiagarajan (2017).

## 4.5 Proposed calibration model

In this section, a calibration model is proposed to overcome the problems of unstructured calibration processes (discussed in Section 4.3). The proposed calibration model has four main advantages. First, interactions among the models and their parameters are considered. Second, the number of iterations, in comparison to the classic calibration process, is significantly reduced and, instead, the number of candidate parameters under consideration in each iteration is increased. Third, the estimated values of the parameters remain unchanged unless their adjustments significantly improve the TPMS's performance. Fourth, calibration and validation efforts are systematically performed.

Despite the proposed model being structured and developed to amend the critical problems in unstructured calibration processes, it does not fully automate the calibration process. Thus, the model is not completely a replacement for modeller' judgement. Instead, it is a tool that can provide more information to modellers. The tool significantly enhances the capacity and understanding of modellers about the very complex system of models in TPMSs. As a result, the tool and the modellers work together to develop better TPMSs. Furthermore, the model cannot affect the model specification and its scope is limited to the adjustment of the parameters for given model specifications. Addressing the shortcomings in model specifications is out of the scope of the research in this chapter.

### 4.5.1 An alternative calibration approach

RSMs allow determination of the optimum combination of parameters by conducting a small number of experiments, which makes finding the optimal solution conceivable in terms of time and cost. Furthermore, fractional designs can be used to reduce the number of experiments. This helps avoid individual calibration of demand-side and network models (explained in Section 4.3) and helps to include the feedback loop between demand-side and network models in the calibration process and, as a result, calibrate TPMSs in consideration of the interactions between the demand-side and network models.

RSM can consider many parameters at the same time, so that investigating their interactions is possible. Taking into account the interactions among the parameters of the TPMS structure, RSM is expected to produce more consistent and accurate results. Therefore, the selection of parameters is less complicated than in unstructured calibration, where few parameters are selected over many iterations. Furthermore, choosing the direction and increment of adjustment is no longer required. Regarding the multi-objective nature of the calibration process, different equations (Equation (4-1)) can be developed for each of the objectives. Knowing the functional relationships among the objective values (as the response of interest) and the parameters (as explanatory factors), the optimal values for each parameter can be calculated.

In the proposed structure, RSM methods are used to adjust parameters iteratively. Figure 4-3 shows a model that systematically calibrates TPMSs using a statistics-based approach. The model has two main stages in each iteration of the calibration process: 1) TPMS calibration, and 2) TPMS validation. TPMS calibration includes parameter evaluation and adjustment. The TPMS calibration stage obtains several non-dominated solutions, while TPMS validation selects the best one (fittest combination of values to scenarios). A *solution* is a combination of values used to adjust the selected parameters. The model allows selection of the best solution so that the adjusted parameters fit better in the TPMS structure. Furthermore, a solution is called non-dominated if none of the objective functions can be improved in value without degrading at least one of the other objective values (Miettinen 1999). A set of non-dominated solutions forms a Pareto front.

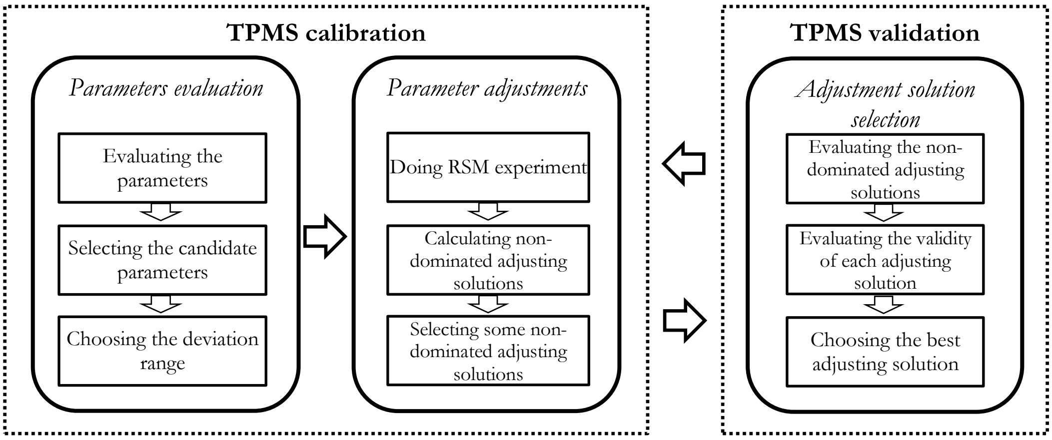



Figure 4-3 Proposed model structure for the calibration process

Detailed descriptions of different stages of the proposed model's structure are discussed in the following subsections.

### 4.5.2 TPMS calibration

In the TPMS calibration stage, the objective is to find a set of non-dominated solutions that can improve reproduction of the base-year statistics.

#### 4.5.2.1 Parameter evaluation

Usually, adjustment of all the parameters is not necessary, because not all the parameter adjustments can significantly affect the model system performance. Usually, the important parameters for calibration are determined by modeller's knowledge and expertise. Furthermore, the parameters may have different priorities; e.g., the modeller may prefer to adjust the model's constants rather than their coefficients and elasticities. In the current study, for the sake of brevity, the term "constant" is used to refer to alternative-specific constants and location-specific constants in the models. The alternative-specific constants are applicable to all the choice models in a TPMS, while the location-specific constants are usually applicable for the mode choice models and can be defined by mode, origin planning district (super zone), destination planning district, trip purpose, and time of day. The other parameters such as time and cost parameters are referred to as "coefficients". In addition, considering all the parameters within a single iteration is problematic, since a higher number of parameters requires a higher number of experiments. Therefore, in each iteration of the calibration process, a subset of parameters is selected and analysed for possible adjustment. These parameters are those suspected to have considerable impact on reducing the discrepancy between the simulated and observed statistics.

Selection of the parameters and their acceptable adjustment ranges has to be determined based on the modeller's experience and the discrepancy between the TPMS's output and the observed statistics. Generally, the parameters can be categorised into groups based on their behaviour and sensitivity in the model system. For example, the alternative specific constant of the mode choice model for people with professional and sales occupations (according to the Travel/Activity Scheduler for Household Agents categorisation; TASHA) may have similar effects on trip generation rates. Hence, to reduce the number of parameters that are candidates to adjustment, the constants can be grouped to lower the model's dimensionality. For each parameter group, a deviation range is defined, as allowing unlimited deviation risks over-calibration of the model. Given the groups and deviations, each group is assigned an auxiliary factor that is applied to all of the parameters of the group for experimentation. For example, two lists of parameters, which are selected among the full list of Greater Toronto-Hamilton Area Model (GTAModel) parameters, are provided in Table B1 and Table B2 in Appendix *B* which will be discussed in Section 4.6. The parameters in the second column of the tables are categorised into groups, each of which is equivalent to one factor (see first column of the tables). Also, the acceptable adjustment ranges for the parameters are provided in the "deviation bounds" columns.

Parameters of a TPMS may have different levels of importance. Generally, the alternative-specific constants, location-specific constants and weights to account for different agents are subject to adjustment. Adjusting other parameters (coefficients), such as time and cost parameters in the calibration process is generally avoided in the literature. To the best of author's knowledge, there are no guidelines or research on this issue. The possible reasons may be that 1) predicting the behaviour of the constant parameters is simple; hence, so is their adjustment, 2) constants capture "all else being equal" systematic effects and hence are arguably more likely to require adjustment, relative to coefficients which capture trade-offs among explanatory variables and are often "trusted" to have been estimated appropriately, and 3) adjusting the constant parameters may have become a culture. Since the model used in this chapter considers the interaction among the parameters and optimises their values, it is a good opportunity to use model coefficients in the calibration process.

#### 4.5.2.2 Parameter adjustment

In this step, RSM-based experiments are conducted in accordance with a predefined experimental design, an example of which is presented in Table 4-1. Then, RSM formulations are used to determine the relationships between the objective functions and each of the candidate parameters selected for calibration. The output is a number of equations, one for each objective function (according to Equation (4-1)). This, of course, leads to the challenging problem of multi-objective optimisation. Two main approaches for multi-objective optimisation are *a priori* and *a posteriori* (Dhiman and Kumar 2018). In the a priori approach, a multi-objective problem is converted to a single-objective problem with a set of weights that are defined based on the significance of each objective. In the a posteriori approach, it is permissible to explore the results and select one of the obtained solutions based on their performance (Deb 2012).

A TPMS's model components are estimated using different objective functions and a wide variety of data sources. This leads to the objective functions having different scales, which complicates their integration. Furthermore, the objective functions themselves are usually aggregated measures. Therefore, aggregating some aggregated objective functions may be misleading. As a result, in the TPMS calibration, a set of non-dominated solutions can be selected (using a posteriori approaches), each of which is a potential solution for the calibration process. Although each of the solutions is optimal to the multi-objective problem, their performance can be completely different. For instance, a solution may correctly estimate the mode share of trips while underestimating trip generation rates. Reviewing multi-objective optimisation methods is beyond the scope of this thesis. For more information about the methods, the reader is referred to Al-Dujaili and Suresh (2018) and Dhiman and Kumar (2018).

Therefore, the output of this step is a set of non-dominated solutions. Obviously, choosing a set of non-dominated solutions that can well approximate the entire Pareto front, and cover a wide range of solution possibilities, can increase the quality of the results for the next stage—TPMS validation. Some concepts, such as the crowding distance measures, are discussed in many studies and can be used for obtaining diverse non-dominated solutions. Since investigating non-dominated solutions is well-discussed in the literature and is beyond the scope of this study, the readers are referred to Shao and Ehrgott (2016) and Zhang et al. (2016) for a complete review. The elements in the non-dominated solution set should be selected so they are reasonably uniformly distributed on the Pareto front, allowing them to cover a wide range of possible solutions.

### 4.5.3 Optimisation formulation for parameter adjustments

In the calibration process, this study seeks to minimise the discrepancies between the observed and simulated statistics while having the minimum deviation from the estimated parameter values and preventing over-calibration of the models. To achieve this, this study uses simultaneous optimisation using desirability functions, as popularised by Derringer and Suich (1980). In this technique, each parameter $x_i$ and response $y_j$ is converted into a desirability function ($d_i$ and $d_j$ respectively) that varies between 0 and 1. If a response $y_j$ is outside its acceptable range, then $d_j = 0$. If a response is at its target $t_j$ then $d_j = 1$. Each of the responses can deviate between its lower $l_j$ and upper $u_j$ limits. The same definition applies for parameters and their desirability functions. After that, the design parameters are chosen so that the overall desirability is maximised, as in Equation (4-2) (Gunst et al. 2006).

$$\max\left(\prod_m d_i\right)^{\frac{1}{m}}\left(\prod_n d_j\right)^{\frac{1}{n}} \tag{4-2}$$

In this equation, $m$ and $n$ are the total number of parameters and the total number of responses, respectively. Depending on the target of each response, different desirability functions can be defined. For the sake of brevity, as the desirability formulations for parameters and responses are similar, the formulations are not indexed. If the goal is the minimisation of a response, Equation (4-3) is used for defining the desirability.

$$d = \begin{cases} 1 & y < t \\ \left(\frac{u-y}{u-t}\right)^w & t \le y \le u \\ 0 & y > u \end{cases} \tag{4-3}$$

where $w$ is the weight to give more/less emphasis to the goal. Weights more/less than 1 give more/less weight to the goal values. In Equation (4-4), the desirability function for maximisation-based goals for responses is given.

$$d = \begin{cases} 0 & y < l \\ \left(\frac{y-l}{t-l}\right)^w & l \le y \le t \\ 1 & y > t \end{cases} \tag{4-4}$$

In cases where the goal is located between the lower $l_j$ and upper $u_j$ limits, Equation (4-5) should be used.

$$d = \begin{cases} 0 & y < l \\ \left(\frac{y-l}{t-l}\right)^w & l \leq y \leq t \\ \left(\frac{u-y}{u-t}\right)^w & t \leq y \leq u \\ 0 & y > u \end{cases} \tag{4-5}$$

Formulating the calibration process using the desirability functions can be an effective solution for reproducing the observed statistics with minimal deviation from the estimated parameter values. Furthermore, the initially estimated values for the parameters are the target values for those parameters unless their deviation (losing desirability) improves the objective function's desirability. Therefore, Equation (4-5) is the applicable desirability function for the parameters.

In cases where the above-mentioned desirability functions collapse to a uniform distribution, as in Equation (4-6), a structured, calibrated, model system with similar performance to an unstructured, well-calibrated, model system can be obtained, since reproducing the observed statistics (and not restricting the deviation of the parameters using desirability functions) is usually important in the unstructured calibration.

$$d = \begin{cases} 1 & l \leq y \leq u \\ 0 & otherwise \end{cases} \tag{4-6}$$

### 4.5.4 TPMS Validation

The output of the TPMS calibration is a non-dominated solution set where each of its elements can suitably reproduce the base year's observed statistics. Although each of the solutions is potentially suitable for the TPMS structure (according to their fit to the objective functions) and can reproduce the base year's statistics, they may have different effects on the model system's prediction capabilities. Therefore, each of the non-dominated solutions can be used in the simulation for running different scenarios (refer to the definition of validity in Section 4.1) to investigate the predictive power of the resulting TPMSs. On the other hand, ultimately, usually one solution should be selected to form a calibrated model. Thus, in the validation stage, the modeller selects the most suitable solution which can generate a behaviourally better TPMS. For example, in the case study of this study, the most suitable solutions in each iteration of the proposed calibration model are shown in the "Solution" columns in Table B1 and Table B2 in Appendix *B*. Each of the solutions is selected among 10 candidates.

## 4.6 Case study

In this section, the performance of the proposed calibration model is demonstrated via a case study: GTAModel V4.0 model system for the Greater Toronto-Hamilton Area (GTHA) which, in addition to the Cities of Toronto and Hamilton (located at the west end of the region) includes the regional municipalities of Halton (immediately east of Hamilton), Peel (west of Toronto), York (north of Toronto) and Durham (east of Toronto). GTAModel is the first fully activity-based travel demand model in Canada, within which the Travel/Activity Scheduler for Household Agents (TASHA) has been implemented. TASHA is an activity-based, household-based and agent-based microsimulation model that is designed to operate either as a stand-alone model or embedded within the Integrated Land Use Transportation Environment (ILUTE) modelling framework, which forecasts the long- and short-term decisions of households (Roorda et al. 2008). For a detailed description of the TASHA, see Miller and Roorda (2003) and Roorda et al. (2008).

To illustrate the application of the proposed model, variants of model systems built on GTAModel are used. The goal of the case study is to 1) analyse the performance of the classic unstructured calibration process, 2) structurally calibrate the initially-estimated version of GTAModel, 3) determine the optimal values of the parameters in the TPMS structure, and 4) compare the performance of the variants and investigate the capabilities and defects of the unstructured and structured calibration methods. These variants are abbreviated as follows: IET (initially-estimated TPMS), UCT (unstructured calibrated TPMS), SCTR-C (structured calibrated TPMS with relaxed deviation, as in Equation (4-6), in constants), SCTR-C&C (structured calibrated TPMS with relaxed deviation, as in Equation (4-6), in constants and coefficients) and SCT (structured calibrated TPMS with restricted deviation, as in Equation (4-5)). In the IET, the initial version of the GTAModel model is used so that the initially estimated parameters are kept unchanged. In the UCT, the final currently operational version of the GTAModel model system, which is already calibrated using classic techniques and is widely used in practice, is used for simulation. In the SCTR-C and SCTR-C&C, the proposed algorithm is implemented on the IET variant with adjustment of some constants, and some constants and coefficients, respectively. Here, the parameters can only be adjusted within their ranges without losing desirability. Finally, in the SCT, the proposed model is applied to the IET variant and loss of desirability by adjustment is considered. It should be mentioned that as minimising the discrepancies between the observed and simulated statistics matters; therefore, Equation (4-3) is used for the responses (calibration criteria) in all the variants.

To be able to compare the performance of the new variants with UCT, the same performance criteria and observed statistics that were used in the UCT calibration are used to generate the new variants (see Table 4-2). In the table, the passenger mode refers to a person whose travel is being facilitated by another household member who is driving. Furthermore, reproducing the observed statistics for trips from/to Toronto is the main focus of calibration. According to the last calibration criterion, the observed statistics are categorised as *Toronto-based* and *non-Toronto-based* so that the variants can be evaluated in term of over-calibration. Toronto-based refers to the trips from/to the City of Toronto while non-Toronto-based refers to the trips with both origin and destination outside Toronto. Further, against the UCT calibration process, where the interaction between demand-side and network models is not considered, a feedback loop from the network model to the demand-side models is included in the calibration process of the new GTAModel variants.

Furthermore, to build the variants of SCTR-C&C and SCT, only two iterations of the proposed model are performed. In the first iteration, and in line with popular implemented TPMSs (e.g. MORPC: Parsons Brinckerhoff 2005, ALBATROSS: Arentze and Timmermans 2004a, NYMTC: Parsons Brinckerhoff 2014), only the candidate parameters are chosen among the constants in the initially-estimated TPMS. With the optimal values for the constants included in the first iteration, a selection of coefficients is adjusted for further improvement of the TPMS. The results show that these two iterations are enough for building competitive TPMSs with UCT. It should be noted that the resulting variant after implementing the first iteration of SCTR-C&C calibration is SCTR-C.

Table 4-2 Calibration criteria for calibration of TPMSs

| Row | Calibration criteria |
|---|---|
| 1 | Reproducing the observed departure time for work purpuses |
| 2 | Reproducing the observed departure time for market purposes |
| 3 | Reproducing the observed departure time for other purposes |
| 4 | Reproducing the observed mode share of automobile (city level) |
| 5 | Reproducing the observed mode share of bicycle (city level) |
| 6 | Reproducing the observed mode share of carpool (city level) |
| 7 | Reproducing the sum of the observed mode shares of drive access transit (DAT) and walk access transit (WAT) (city level) |
| 8 | Reproducing the observed mode share of passenger (city level) |
| 9 | Reproducing the observed observed mode share of schoolbus (city level) |
| 10 | Reproducing the observed mode share walk (city level) |
| 11 | Reproducing the observed mode Share of automobile (district level) |
| 12 | Reproducing the observed share of carpool (district level) |
| 13 | Reproducing the sum of the observed shares of DAT and WAT (district level) |
| 14 | Reproducing the observed share of passenger (district level) |
| 15 | Reproducing the observed share of schoolbus (district level) |
| 16 | Reproducing the observed share of walk (district level) |
| 17 | Reproducing the observed screenlines statistics for AM |
| 18 | Reproducing the observed screenlines statistics for PM |

To determine the factors of the experimental design, as discussed in Section 4.5.2.1, it is not necessary to choose a single factor for adjustment of each candidate parameter. Instead, the parameters can be categorised into different groups and then an auxiliary factor can be selected for each group so that the optimisation method adjusts all the parameters in a particular group by that factor. In the first iteration, 75 parameters in 28 groups are selected for calibration (see Table B1). Indeed, there are 28 auxiliary factors that should be adjusted where their values affect the parameters of the IET (as the first building block). An auxiliary factor can be one of the calibration techniques that have been extensively used in practice. For example, in the case study, the K-factor technique can be used as an auxiliary factor to adjust the constant of *planning district of Toronto CBD for market purposes* (location choice) at different times of the day (e.g. factor code R in Table B1, Appendix *B*).

Since computation time is one of the main hurdles in the calibration processes of many TPMSs, for each of the iterations, the experimental design with the least required experiments is chosen intentionally to show the effectiveness of the model with a worst-case experimental design. Accordingly, the least number of experiments for conducting the CCD-analysis in iteration 1 (with 28 factors) is 465. Nonetheless, for more accurate analysis and better results, a different experimental design with a higher number of experiments can be used. Increasing the number of experiments produces more accurate and powerful TPMSs. It should be emphasised that the full GTAModel (including both demand-side and network models) is run in each trial of CCD model which helps to include the interactions (feedback loop) between the conventionally disjoint models in the calibration process. Furthermore, in this chapter, the network parameters are not considered for possible adjustment, instead, their interconnections with the candidate demand-side parameters for adjustment affect the optimal adjustment values for these parameters. The CCD tool of Design Expert software is selected to design and analyse the experiments.

Modellers' expertise is the main source for choosing the candidate calibration parameters and the corresponding auxiliary factors. The selected parameters and auxiliary factors for consideration in the first iteration are provided in Table B1 of the Appendix *B*. Furthermore, the initially-estimated values for the selected parameters and their adjusted values using the classic calibration process (UCT) are provided in the 3rd and 4th columns of the table. The lower- and upper-bounds of the deviation from the estimated values are given in the 5th and 6th columns.

Using these settings, the first iterations of the proposed model for SCTR-C&C and SCT variants produce a set of non-dominated solutions. To build each of the variants, 30 non-dominated solutions are produced, and 10 of the 30 solutions that can well reproduce the base-year observed statistics (these are selected based on modellers' experience) are selected for investigation in the next stage—TPMS validation. These solutions are all used to run forecasts enabling the selection of the most fitted solution for each variant. The best values of deviation from the estimated values, as well as the calibrated values for the parameters in the first iterations of creating the SCTR-C&C and SCT variants, are shown in 7th to 10th columns of Table B1. In the table, the "calibrated values" column is obtained by adding the initially-estimated and the optimum deviation columns. Comparing the calibrated columns for SCTR-C&C, SCT and UCT show the extent to which the solutions differ from each other.

Before proceeding to explain the second iteration, it is worth explaining a technical issue in finding the optimal solution. A large amount of observed data is used in calibration. The data as well as the corresponding outputs of the experiments should be processed to be prepared for use as response values in CCD analysis. Accordingly, the performance indicator of mean Euclidean distance (MED) using the 1-norm distance measure is used, as per Eq. (4-7).

$$MED_{ij} = \frac{\sum_k \left|\Delta v_{ijk}\right|}{n_j} \qquad \forall\, i \in I \quad and \quad \forall\, j \in J \tag{4-7}$$

where $i$ is the experiment number, $j$ is the response measure, $k$ is the observed statistic number, $n_j$ is the total number of records for response measure $j$, and $\Delta v$ represents the difference between the observed and simulated values. To illustrate this further, consider an observed screenline dataset with 500 records. In this example, reproducing screenline counts is one of the response measures. Each of the records is an observed statistic, and the total number of records in the dataset is 500.

Since the MED values are often of different units and scales (depending on the scales of $n$ and $\Delta v$), it could significantly affect the output of Eq. (4-2). Therefore, the performance indicators of the experiments should be scaled before importing them into the optimisation formula. As a result, the performance indicators are replaced with the normalised indicators as in Eq. (4-8).

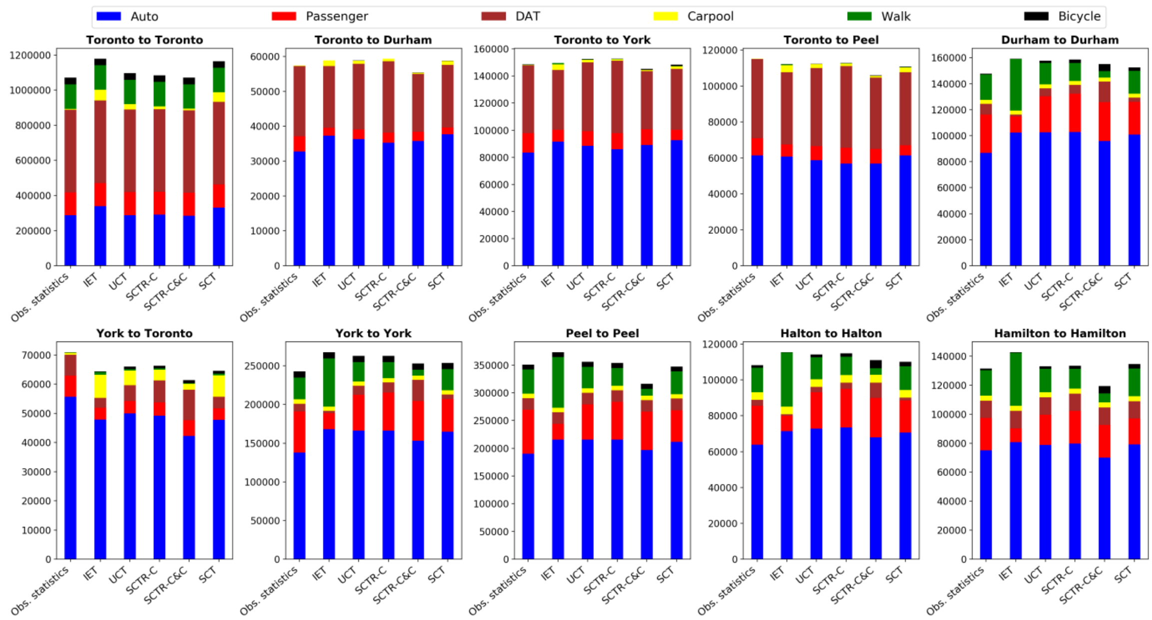
$$NMED_{ij} = \frac{MED_{ij} - \mu_j}{\sigma_j} \qquad \forall\, i \in I \quad and \quad \forall\, j \in J \tag{4-8}$$

where $\mu_j$ and $\sigma_j$ are the mean and standard deviation of the performance indicators (*MED*) for response $j$ over all the experiments. The smaller *NMED* means a lower difference between the simulated and observed statistics and, therefore, better performance.

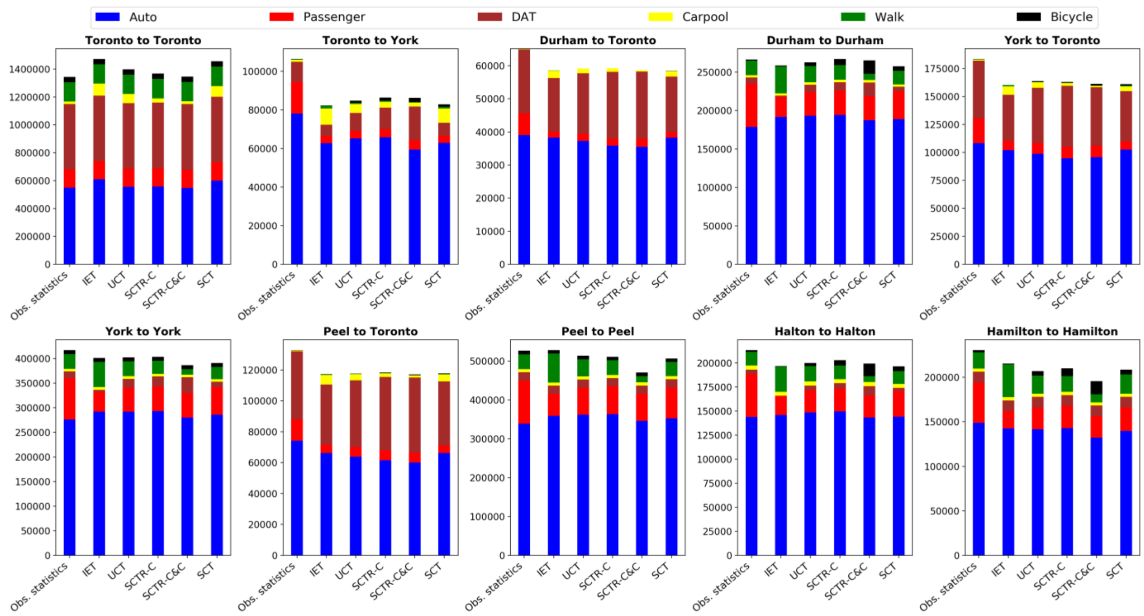
In the second iteration, a similar calibration process for selected parameters (chosen from the coefficients in the demand-side models) is performed, the output of which (including the optimum solutions) is shown in Table B1 (Appendix *B*). It should be noted that other than the setting in the table, the selected parameters in iteration 1 are fixed on their adjusted values. In iteration 2, different deviation ranges are defined for SCTR-C&C and SCT so that the factors for SCT can move within a tighter range. The reason for the tight range for SCT is that adjusting the coefficients is not common practice. Additionally, we are not interested in significantly deviating from the initially-estimated parameters for this variant.

Next, the performance of different variants of the GTAModel model system is compared. Before elaborating the results, it should be emphasised that it is not in the scope of the study to develop a perfect model to be used for forecasting instead, it intends more to explain what analysis can be done. Figure 4-4 depicts their performance in terms of trip generation and mode split for the origins and destinations with more than 50,000 trips. While UCT, SCTR-C and SCT can reproduce the trip generation and mode split rates relatively well, the SCTR-C&C results are not satisfactory. A closer inspection reveals that SCTR-C&C can reproduce Toronto-based trips well but is relatively inadequate for non-Toronto-based trips. On the other hand, in spite of the mediocre performance of SCT for Toronto-based trips, it has superior performance over the other variants for non-Toronto-based trips. Considering these behaviours as well as the relaxed deviations condition in the calibration processes of UCT, SCTR-C and SCTR-C&C, the relaxation condition is suspected to cause the UCT, SCTR-C and SCTR-C&C variants to fall into an over-calibration trap.

To evaluate the over-calibration problem, the statistics for non-Toronto-based trips are considered as out-of-sample statistics, as the focus of calibration was on reproducing the observed statistics for Toronto-based trips. To investigate the performance of the variants in reproducing the observed statistics and avoiding over-calibration traps, the Toronto-based and non-Toronto-based trips are separately plotted for each mode. As shown in Figure 4-5a for Toronto-based trips (trips for AM and PM are plotted on the same graph), UCT, SCTR-C and SCTR-C&C can reproduce the observed values for auto, walk, DAT and WAT, and have acceptable performance with other modes. A closer inspection of the figure shows that SCTR-C and SCTR-C&C slightly outperform UCT (except in DAT + WAT). This means that, in practice, the classic calibration method can be replaced with SCTR-C and SCTR-C&C if the modeller is only looking to reproduce observed statistics.




a) AM peak hour

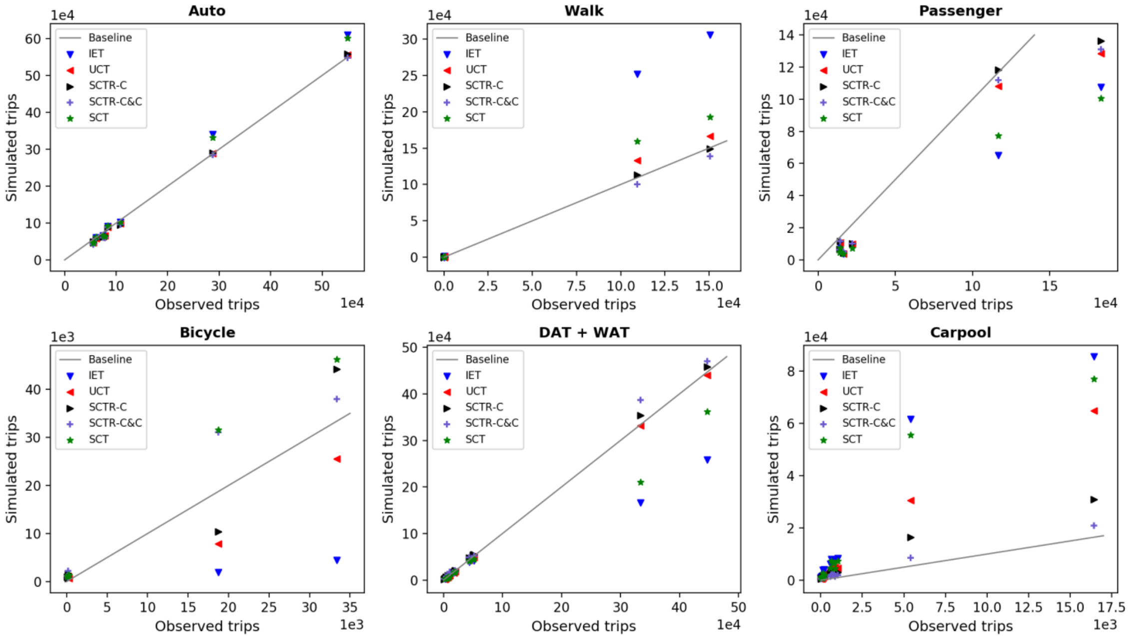



b) PM peak hour

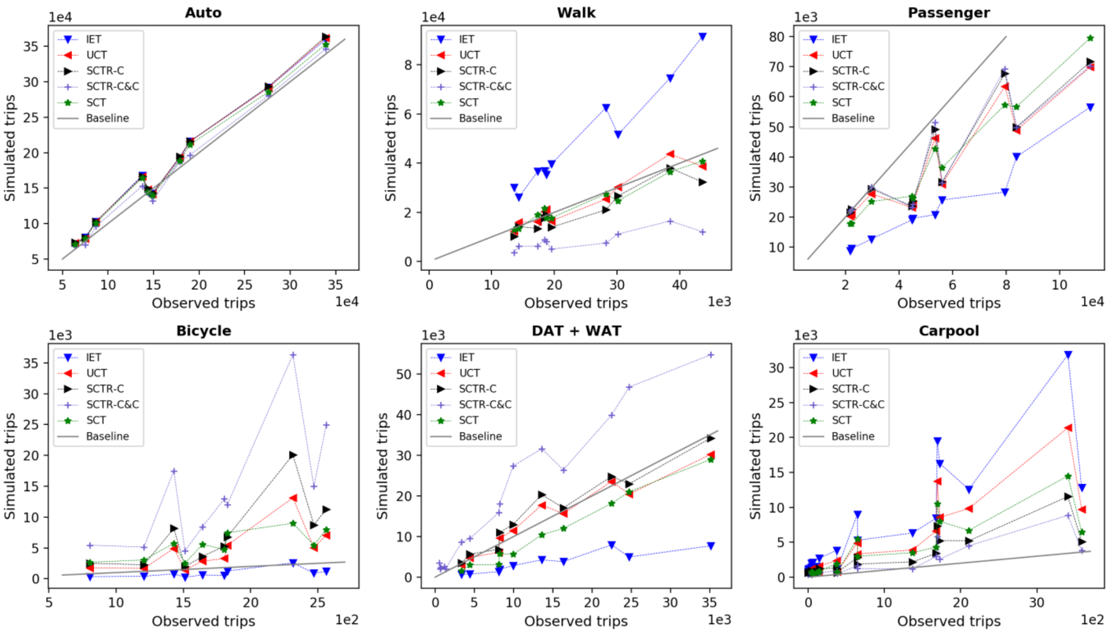
Figure 4-4 Number of trips and mode splits performance

Plotting the non-Toronto-based trips (Figure 4-5b) reveals that UCT, SCTR-C and SCTR-C&C affect the trip rates with inconsistent and significantly different trip generation rates. The plotted fluctuations in the figure clarify the inconsistencies which appear due to over-calibration. The worst case is for SCTR-C&C, where the constants and coefficients freely deviate. The most interesting behaviour in Figure 4-5b is for SCT, where it not only competes with UCT and SCTR-C, but also has more consistent simulation behaviour.

Therefore, it can be seen that the SCT variant is not in the over-calibration trap and, therefore, it can compete with the other variants.




a) Toronto-based trips




b) Non-Toronto-based trips

Figure 4-5 Trip generation performance according to mode of transport

To further investigate over-calibration, the performance of the variants in reproducing traffic counts are analysed. As mentioned in Table 4-2, screenline data for the AM and PM peak periods have been used for creating the variants. The screenlines do not cover all the count posts, so the out-of-sample count posts can be used for investigation of over-calibration. Further, the mid-day (MD) time period data has not been used in the calibration process for any of the variants. Therefore, plotting the out-of-sample count posts can be used for the over-calibration investigation. The performance of reproducing the observed traffic counts is plotted in Figure 4-6. The figure for AM and PM does not show dominant behaviour for any of the variants which are foreseeable, because these data have been used in the calibration processes of all the variants. However, for MD, the SCT is slightly dominant over the others which shows the over-calibration problem that exists for UCT and SCTR-C. Therefore, the classic calibration method can be replaced with the SCT if forecasting capability of TPMS has higher priority than reproducing the observed statistics.

The results reveal that if the proposed calibration model uses relaxed parameters, the resulting TPMS can generate competitive TPMSs which have the potential to replace the unstructured calibrated TPMS. It means that simultaneous use of the modeller's expertise and structured models can result in better calibrated TPMS in comparison to when solely the modeller's expertise is applied, even when reproducing the base-year statistics is the main goal. Furthermore, it is shown that relaxing the parameters can cause over-calibration problems, which threatens the ultimate purpose of a TPMS—that of forecasting. Therefore, SCT variant could be a suitable substitution for UCT.

Another important benefit of using the proposed calibration method, which makes it a viable alternative to the classic calibration process, is that it requires less knowledge about the structure of the estimated TMPS. Also, the modellers are not required to prioritise the parameters for calibration. They can choose many parameters simultaneously. Furthermore, instead of determining adjustment values, they determine the acceptable adjustment ranges for the parameters. Therefore, the proposed model may make the TPMS calibration process easier.

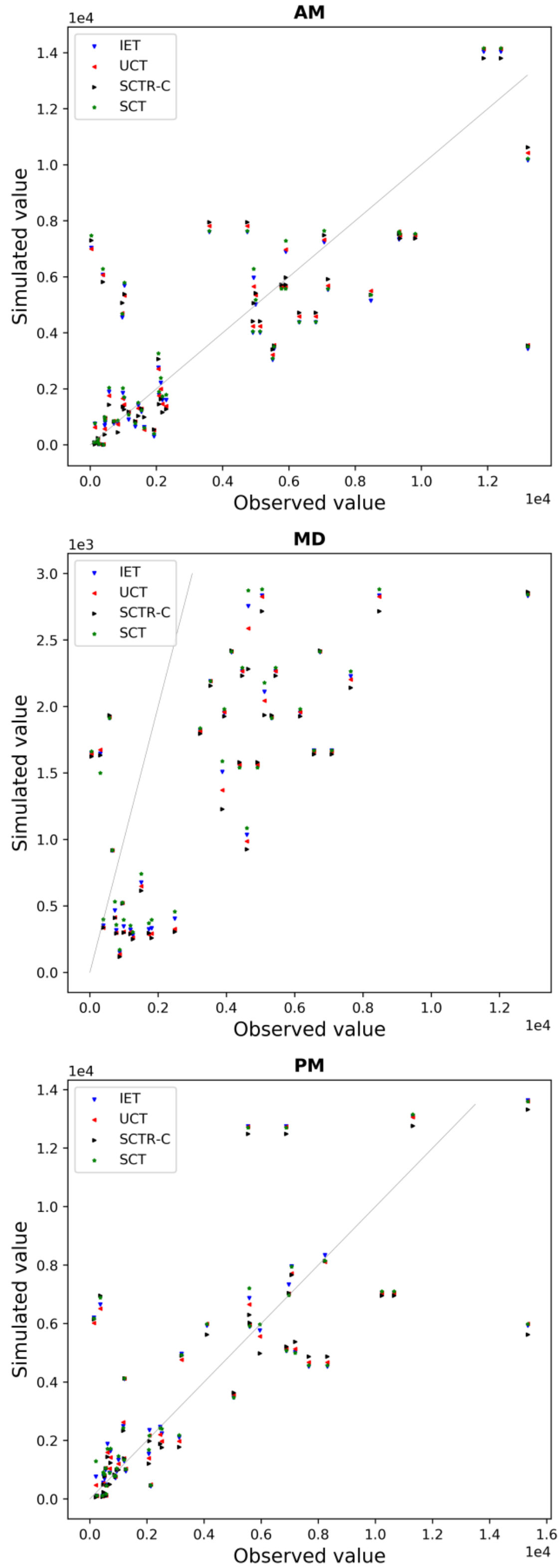



Figure 4-6 Traffic count performance of GTAModel variants

Discussing the time it took to implement the calibration model can be helpful for interested readers and practitioners. Having the experiments outputs in an iteration, the computation of the optimum values for the parameters does not take much time; instead, the computation time in each iteration of the proposed calibration model highly depends on the implementation speed of the model under study (the GTAModel in this case study). Iterations 1 and 2 include 465 and 326 experiments, respectively. Furthermore, each run of GTAModel takes around 1.5 hours on a server with an i9-7900X with 32GB of RAM. Thus, conducting the experiments in iterations 1 and 2 takes about 698 and 489 hours to be implemented. The experiments in iteration 2 depend on the output of the calibration model in iteration 1; however, as there is no direct relationship between different experiments in each of the iterations, the experiment runs can be parallelised.

The model proposed in this chapter is built on the exploration and optimisation of response surfaces where the relationship between the response variable of interest and a set of predictor variables might in some cases be known exactly, based on the underlying engineering, chemical, or physical principles. In cases where the underlying mechanism is not fully understood (which is a common problem faced by experimenters in many technical fields) and the experimenter must approximate an unknown function with an appropriate empirical model, the response surface model can be used effectively. The proposed calibration framework of this chapter is applicable for models (not limited to the transport model systems) where the impacts of the model parameters on the model outputs cannot be explained by a mechanistic model. This is usually the case in the transport models that are formed by joining at least two individually estimated models (demand and network models). Furthermore, calibration of a transport system is a multi-objective problem where the existence of a Pareto-front is its inherent feature. The proposed model assists the modellers to extract the Pareto-front systematically.

## 4.7 Conclusions

Calibration can have crucial impacts on the efficiency and effectiveness of transport models. Non-convex solution spaces, along with the multi-objective nature of TPMS calibration, make this process complicated. Interconnections among the models and parameters in a TPMS increase this complexity. Despite the intrinsic characteristics of the model systems, sequential calibration which relies on the modeller's expertise is still the standard practice in the TPMS calibration process. This may result in ineffective parameter adjustments which then may affect the accuracy of the TPMSs in reproducing base-year statistics and forecasting scenarios. Further, the TPMS calibration process is as much an art as a science and, actually, there is no substitute for modellers' expertise. As a result, an analytical procedure is needed to structure the calibration process, to direct the modellers' expertise, and to address the intrinsic characteristics of TPMSs.

In this chapter, a calibration model was proposed to systematically and structurally calibrate and validate TPMSs. Different variants of the GTAModel were created by changing the settings of the proposed calibration model. They were then compared against a particular variant of GTAModel that was calibrated using the classic technique, UCT. The results reveal that the structured calibrated variants of GTAModel, SCTR-C and SCT, are non-dominant variants of UCT in reproducing observed statistics. This means that quality calibrated TPMSs are achievable even if access to the modellers' expertise or knowledge is limited. However, the results show that SCTR-C and UCT variants were subject to over-calibration and their forecasting capabilities were affected. In term of prediction power, the SCT variant dominated the others as it circumvented the over-calibration trap.

The application of the proposed model is not limited to the transport domain and transport systems. It is applicable in many cases where there is complicated and *unknown* relationship (e.g. in decision tree-based models) between the model outputs and model parameters. Thus, as a future direction of research, the model could be implemented and evaluated on other areas of research which are conceptually or methodologically different.

# Chapter 5

# Robustness in Calibration

***This chapter is in line with Aim 2. Focusing on reducing the impact of error terms in the TPMSs, a systematic approach is proposed to enhance TPMSs calibration process considering both demand-side and traffic assignment models in a unified structure.***

*Calibration of a transport planning model system is a complex process. While trial-and-error methods and modelling expertise are still the backbone of calibration of transport models, analytical approaches automating the calibration process can improve the accuracy of the models. Introducing a model to guide modellers in the calibration process of large-scale transport planning model systems is the core of this study, where a systematic model for choosing the most appropriate models and parameters is discussed. The effectiveness of the proposed model is investigated by comparing three scenarios which are built on the Travel/Activity Scheduler for Household Agents (TASHA) model as a large-scale agent-based model system.*

## 5.1 Introduction

In the past decades, different generations of *Transport Planning Model Systems (TPMSs)* have emerged, including four-step models and activity-based models. Each TPMS consists of a number of models that interact with each other within the overall model system. The models can be categorised into demand-side and network-side models. The *demand-side* models reflect travel decisions of agents in the transport system. The *network-side* models deal with the interaction of the travel demand with the supply of infrastructure and transport services (Bliemer et al. 2013). The models include, among others, trip generation, destination choice, departure time, mode choice and traffic assignment models, each of which might be referring to a group of sub-models.

*Estimation* usually involves maximisation of some functions, such as a likelihood function, a simulated likelihood function, or squared moment conditions (Train 2003) over the observed data. Generally, linkage of some estimated models forms the initial structure of TPMSs. Since, the observed data is usually collected from multiple sources or in different years, it may negatively affect the performance of TPMSs when used for simulation purposes. Therefore, some process should be employed to calibrate and validate the whole structure of TPMS. According to NYMTC (2014), *calibration* refers to the process by which models (with estimated parameters) of each TPMS are adjusted to best approximate the observed data from the base timeframe (Parsons Brinckerhoff 2014). The base timeframe is ideally defined as the year all data has been collected (WisDOT 2018). However, in some cases, such as Capelle et al. (2015), the calibration has been performed using data from multiple base years. *Validation* refers to assessing the effectiveness of a TPMS in reflecting the travel market characteristics and traveller choice behaviours which are typically assessable using data for other than the base timeframe. In practice, calibration and validation efforts are usually iterative, with model validation revealing issues that require further calibration to overcome (Donnelly et al. 2010). Henceforth, the iterative process of calibration and validation is called the *calibration process*.

Although a TPMS comprises some travel demand and network models, its performance is highly dependent on the quality of both the estimation of the models and the calibration process of the model system. An ideally calibrated TPMS should reproduce base year conditions, be sensitive to the policies being tested, and respond logically to changes in input (Donnelly et al. 2010). However, unfortunately, little attention has been paid to the calibration process of TPMSs. For example, the focus of model calibration efforts in practice is usually on reproducing the base year conditions (Donnelly et al. 2010) which can result in overfitting and consequently biased predictions.

Trial-and-error efforts and using the classic techniques including OD-k-factors, alternative-specific constants adjustments, and weighting agent and activities are still the backbone of the transport models calibration. The non-systematic use of the techniques can be problematic. Further, the calibration process of TPMSs is not simple since the models/parameters included in the model systems are intrinsically interconnected, and thus should be ideally calibrated together. However, in the standard practice, the calibration process includes sequentially adjustment of parameters, with primary emphasis usually going to calibrating the traffic assignment parameters based on network conditions. Inadequately addressing the linkages among the models/parameters of TPMSs can result in significant issues in terms of stability, error propagation, and transferability of the model system.

In addition to the problems in the TPMS calibration process in practice, the simulation process which is the main target of development of TPMSs is dependent on random numbers used to simulate choices (or other source of variation) which are varied in each run. This can be disturbing for someone looking for the source of these changes in the inputs (Castiglione et al. 2003). To overcome this problem, two approaches are commonly employed: 1) fixing the random seeds at some arbitrary values and running the model system once per scenario, 2) running the model system several times with different random seeds and then averaging the results from the runs. Examples for the first and the second approaches are TASHA (Miller and Roorda 2003) and SFCTA (Castiglione et al. 2003), respectively. While the results of the second approach are more stable, the number of times the model systems need to be run to achieve high precision with stability is questionable. Addressing this challenge is one of the contributions of the proposed algorithm of this chapter.

This chapter addresses the following questions: 1) is there any analytical approach to systematically guide transport modellers in the calibration process of large-scale TPMSs? and 2) is there a solution for reducing the stochasticity of TMPSs without any generality loss? Another shortcoming of the existing calibration methods pertains to their inability coming from losing critical information contained in demand-side models at the cost of over-calibrating the network models resulting in loss of forecasting capabilities.

Therefore, the contributions of the current chapter are summarised as follows:

- A meta-analysis of the extant calibration techniques that are used in TPMSs development;
- Proposing a model, based on the Taguchi method, to systematically calibrate large-scale TMPSs;
- Examining the capacity of the proposed model for minimising the effects of uncertainty in the TPMS; and
- Demonstrating the effectiveness of the proposed calibration model on a realistic TPMS for the city of Toronto, Canada.

The rest of the chapter is structured as follows. The literature on two different approaches for calibration and the extant calibration techniques is reviewed in Section 5.2. Section 5.3 elaborates the problem statement, which includes the significant drawbacks of using the current calibration techniques in practice. In Section 5.4, the Taguchi experimental design is introduced as a statistical method for stablishing a robust calibration approach. In Section 5.5, the proposed model for structuring TPMSs is elaborated, which is then followed by discussion on the application of the modelling structure on the case study of the City of Toronto in Section 5.6. Finally, a brief overview of findings and possible extensions is presented in Section 5.7.

## 5.2 Literature review

Many different TPMSs have been developed over the past decades. In contrast to the well discussed research works on calibration of demand-side and network models separate from each other, calibration of TPMSs has received relatively limited attention. There are two usual approaches for calibrating TPMSs. In the first approach, different models, which form TPMSs, are individually estimated using available disaggregate data. Then, after linking the models and forming an initial TPMS, the parameters of the individually developed models are iteratively and manually adjusted to minimise the discrepancy between the simulated and observed statistics. *Observed statistics* refer to information that is obtained from surveys, traffic volume data, etc. which can include mode share, traffic counts, and transit ridership. In contrast, in the second approach, knowing some observed statistics, modellers try to jointly calibrate TPMS parameters.

### 5.2.1 Demand Models

The first approach has been extensively applied in practice by demand modellers. A comprehensive example of such a calibration method for a four-step model system is provided in NYMTC (2014). In this report, the calibration process focuses on adjusting the inputs, network and demand-side models' parameters, with a focus on utility constants to reproduce the base year travel statistics. In the model system, the journey production and attraction models are calibrated using scaling factors, applied to the zone of residence grouped by the purpose of trip. Further, the county-to-county K-factors and utility constant adjustments are used to shape the OD distribution and daily journey mode shares, respectively. Parsons Brinckerhoff (2005) calibrates the MORPC model system to reproduce OD flows and mode shares using OD K-factors and scaling factors, respectively. It also introduces a number of general rules for calibrating TPMSs. The rules include small adjustments in each iteration of calibration process, spreading minimal adjustments over maximum possible number of segments, and selecting the alternative-specific factors for adjustment.

The more disaggregated model systems, such as activity-based models (i.e. the Sacramento activity-based travel demand model) are discussed by Bowman et al. (2006). According to their calibration process, some constant terms in the utility function of the demand-side models are adjusted to reproduce screenline counts, transit boarding counts, and transit trip observations. In recent years, Cools et al. (2010) also highlight a framework to link demand-side models in general, and activity-based models in particular, with traffic counts. In their study, activity-based model parameters are adjusted by weighting chosen activity patterns and agents to reproduce the observed OD matrix. Availability of an observed full OD table is a unique feature of their modelling context. To review the experiences in development and application of TPMSs in practice, the readers are referred to Davidson et al. (2007). The authors point out the general technical issues appearing when developing and implementing such model systems. As can be understood, transport modellers have used a handful of calibration techniques (discussed in detail in Section 2.3.5) for TPMS calibration. However, no systematic framework is reported in the literature for the calibration process.

### 5.2.2 Network Models

The second approach is applied by network modellers when modelling the dynamics and real-time state of the transport system. Although researchers in this area claim that the demand and network models are jointly calibrated, their definition of demand models are limited to OD matrices. Omrani and Kattan (2013) develop a multi-criteria optimisation framework for jointly calibration of demand and network parameters. The framework estimates the OD matrix and calibrates the driver behavioural parameters, including mean headway, mean reaction time, and route choice parameters. They employ a Genetic Algorithm to reduce the computation time of the calibration process. Balakrishna (2006) and Balakrishna et al. (2007) focus on drivers' pre-trip route choice behaviour and implicitly captured their departure time preferences through the dynamic OD flows. Appiah and Rilett (2010) propose an optimisation framework for joint OD estimation and calibration of microscopic models with vehicle trajectories from aggregate intersection turning-movement counts. The authors treat OD flows as unknown and then jointly calibrate the unknown OD flows using the driver behaviour parameters (i.e., car following and lane changing). For a comprehensive review of these so-called joint calibration efforts, the readers are referred to Balakrishna (2006) and Omrani and Kattan (2012).

To conclude, the research on the calibration of TPMSs mostly focuses either on individual estimation and then iterative calibration of models or jointly estimation/calibration of network parameters and the OD trip table as the output of demand models. Extension of the second approach and replacing the OD matrices with demand-side models themselves for a full calibration of network and demand-side parameters are quite challenging due to intense computation complexities. The current chapter intends to address the calibration process for large-scale TPMSs, as explained in the first approach, where many individually calibrated models and an extensive number of parameters need to be considered for adjustment in the calibration process. Despite the widespread use of this approach in practice, the modellers' expertise still plays an important role in the calibration process where unstructured and non-coherent decisions can affect the quality of the TPMSs.

## 5.3 Problem statement

As discussed in Section 5.2, the focus of calibration efforts has been mainly on adjusting the network parameters and applying some popular calibration techniques to the demand-side models (for large-scale TPMSs). In practice, a calibration process is not a predefined process or a pure mathematical exercise to adjust the parameters based on observed statistics. It is generally an unstructured process with an objective of reproducing the observed statistics. *Unstructured/classic* calibration is defined as the unsystematic calibration process where adjustments are sequentially made, mainly based on modellers' knowledge and expertise. *Sequential calibration* is defined as the process of adjusting the parameters of a model system iteratively and sequentially hoping to reproduce the observed statistics. Coupling the unstructured calibration process with the calibration techniques discussed in Section 2.3.5 may result in several problems that are discussed in the following paragraphs.

There are many parameters in a large-scale TPMS from which, sequentially, some parameters should be selected for adjustment. However, selecting parameters among a large number of parameters for adjustment, in each iteration of the sequentially calibration of the TPMS, is not an easy task considering the complex interconnection among the models, especially in the recent advanced models. For a comprehensive review of the sequentially calibration process of TPMSs in practice, the readers are referred to (Najmi et al. 2018).

Considering a priori selection of parameters for adjustment can result in no improvement because an effective adjustment of a parameter in an iteration may result in adverse impacts in the next iterations, where adjustments of other parameters take effect. As a result, a sequential calibration (with many iterations) may result in inconsistent adjustments in the parameters where they not only do not affect the model system but also the adjusted parameters lose their best-estimated values.

Further, there are two main sources of errors and randomness in transport demand-side models namely model specification error and input variable measurement error, where these error sources can result in error propagation (Rezaeestakhruie 2017). Due to the effects of the randomness in the developed TPMSs in the literature, running the model systems several times can generate different outputs. It should be noted that there are other sources of uncertainty, including uncertain parameters/rules and microsimulation error which can make the variations in the outputs more intense. A common approach to overcome this variation is to run the TPMS multiple times and then use the average value of the results (Bao et al. 2015). The larger the variation, the more the runs of the TPMSs may be required. If a TPMS is calibrated in such a way that the effects of the errors are minimised, the robustness of the model system is enhanced and, therefore, fewer model system runs are needed.

In addition to the above issues, calibration of TPMSs is a multi-objective procedure where different objectives have to be considered in the calibration process. Often adjustments help improving one objective, while they may negatively affect the other objective functions. As an example, while OD-matrix estimation methods optimise the correspondence between estimated and observed traffic counts, they can negatively affect the correspondence to vehicle miles travelled (Cools et al. 2010). Usually, the multi-objective evaluation of calibration processes has not been properly performed. Therefore, a systematic approach is required to evaluate the impacts of different adjustments on various considered objectives.

The above problems are common to all generations of TPMSs. Nonetheless, they can be more critical for the more advanced TPMSs. Further, the larger number of parameters in such models results in higher the number of ways for adjusting the model system during the calibration processes (Donnelly et al. 2010). Therefore, the necessity for using effective calibration techniques than the classic counterparts appears to be quite apparent. In the study covered in this chapter, the Taguchi experimental design is used to improve the calibration process of transport model systems.

## 5.4 Taguchi experimental design

The Taguchi method is a statistical method developed by Taguchi (1986) and is recognised as an important Design of Experiments (DOE) method. Initially, the Taguchi method was developed to improve manufacturing processes. Later, it was applied extensively in many other fields in Engineering, such as Biotechnology (Rao et al. 2008), operations research (Zandieh et al. 2009), etc.

The Taguchi method uses orthogonal arrays to systematically vary and test different levels of each control factor, minimise the number of experiments, and analyse the specific interactions between control factors and noise factors (Peace 1993). The control factors are those processes and design parameters which can easily be controlled. The noise factors refer to the external factors (uncontrollable parameters) that affect the outcome of the quality characteristics (Roy 1990). *Quality characteristics* are the metrics that are used for evaluation.

Figure 5-1, shows an $L_8$ orthogonal array as an instance of the structure of orthogonal arrays where 7 factors, each of which containing 2 different levels, are considered. The columns in the orthogonal array represent the factors and their corresponding levels, while each row in the orthogonal array constitutes an experimental run which is performed at the given factor settings. For example, in Table 5-1, experimental trial #5 has Factors 1, 3, 5, and 7 at their corresponding Level 2, and Factors 2, 4, and 6 at their corresponding Level 1. A complete list of orthogonal arrays including the commonly used orthogonal arrays e.g. $L_4$, $L_8$, $L_9$, $L_{12}$, and $L_{27}$ can be found in texts such as (Phadke 1989). The appropriate factor levels for each control factor depend on the experimental designer; however, either 2 or 3 levels are typically chosen for each factor (Wysk et al. 2000).

Table 5-1 Orthogonal array $L_8(2^7)$ of Taguchi

| Experiment | Factor 1 | Factor 2 | Factor 3 | Factor 4 | Factor 5 | Factor 6 | Factor 7 | Response value |
|---|---|---|---|---|---|---|---|---|
| 1 | Level 1 | Level 1 | Level 1 | Level 1 | Level 1 | Level 1 | Level 1 | $r_1$ |
| 2 | Level 1 | Level 1 | Level 1 | Level 2 | Level 2 | Level 2 | Level 2 | $r_2$ |
| 3 | Level 1 | Level 2 | Level 2 | Level 1 | Level 1 | Level 2 | Level 2 | $r_3$ |
| 4 | Level 1 | Level 2 | Level 2 | Level 2 | Level 2 | Level 1 | Level 1 | $r_4$ |
| 5 | Level 2 | Level 1 | Level 2 | Level 1 | Level 2 | Level 1 | Level 2 | $r_5$ |
| 6 | Level 2 | Level 1 | Level 2 | Level 2 | Level 1 | Level 2 | Level 1 | $r_6$ |
| 7 | Level 2 | Level 2 | Level 1 | Level 1 | Level 2 | Level 2 | Level 1 | $r_7$ |
| 8 | Level 2 | Level 2 | Level 1 | Level 2 | Level 1 | Level 1 | Level 2 | $r_8$ |

The results of doing the experiment, which are measured according to quality characteristics, are transformed into a signal-to-noise ratio (S/N) as the performance statistic (Kackar 1989). Signal refers to the change in quality characteristics of a process under investigation in response to a factor introduced into the experimental design; while, noise refers to the effects of external factors (Roy 1990). The signal-to-noise (S/N) ratio considers desirable and undesirable states of the performance simultaneously. In the context of the study, one source of noise can be the error terms while all the estimated parameters can be considered as the signal factors since they can affect the results systematically. Depending on the desired performance response ($r$), there are three standard types of (S/N) ratios 1) smaller the better, 2) nominal the best, and 3) larger the better. The formulations for calculating (S/N) ratios are provided in Equation (A-2) to (A-4) in Appendix *A*.

Taguchi defined the optimal operator combinations such that they minimise variances of quality characteristics resulting from ($S/N$) ratios, which explains the reason why this parameter design is also called a robust design.

After computing the (S/N) ratios for each experiment, the Taguchi method applies a graphical approach to analyse the data. The plotted (S/N) ratios and average responses for each factor against each of its levels is used to locate the optimal parameters level combinations. Examining the graphs, the best factor level for each factor is selected. The best level for a factor 1) best maximises the (S/N) ratio and 2) brings the mean on target of quality characteristics. Based on the (S/N) ratio and mean value (discussed below), the control factors can also be grouped as follows: 1) Factors that have significant effects on both the (S/N) ratio and the mean value, 2) Factors affecting the (S/N) ratios only, 3) Factors affecting the mean value only, and 4) Factors affecting neither (S/N) ratio nor the mean value (Wysk et al. 2000). To reduce variations in the system characteristics (output of the system) and as a result make a more robust system, factors in the first and second groups are the best candidates to be considered. Factors in the third group are recognised as adjustment factors and are used to adjust the output toward the target value. Finally, factors in the fourth group are recognised as neutral factors so that their unstructured estimated values should be kept unchanged.

## 5.5 Proposed calibration model

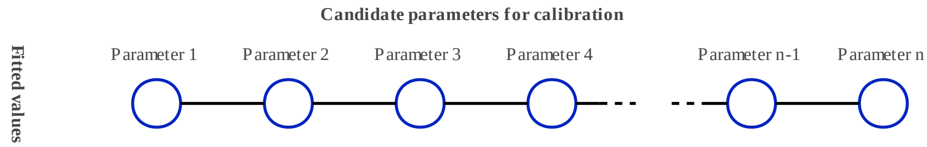
The proposed calibration process of in this section intends to overcome the disadvantages of the current calibration process (discussed in Section 5.3) in practice. Backbones of the proposed calibration model are 1) reduction in variation of simulated results, 2) reduction in number of iterations, in comparison to the classic calibration process and instead increase in the number of candidate parameters under consideration in each iteration, and

3) selection of the best adjustments from a pool of alternative adjustments. It should be noted that in the proposed calibration model, similar to the unstructured/classic calibration process, the modeller's expertise plays a key role. Nonetheless, the model systematically steers the modeller's decisions within the calibration process.

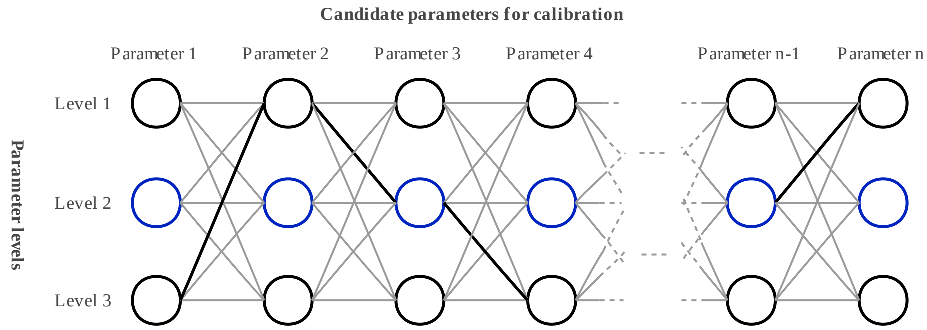
### 5.5.1 An alternative calibration approach

In the process of TPMS development, selection of the modelling specification and estimation of their parameters are based on optimising some objective functions among which the most popular one is the likelihood function. In this regard, separate estimation of each model using disaggregate data from a household survey is typically performed (Davidson et al. 2007). Then, the individually estimated models bring together the initial TPMS. Therefore, there is only one combination of the selected models or model parameters based on the estimation methods (see Figure 5-1a). It should be highlighted that, after selecting the models, their parameters are subject to change in the calibration process. However, in the process of TPMS development, if the modeller can compare different combinations of model alternatives and model parameters, and then systematically select the best combination, the performance of the TPMSs may improve significantly (Figure 5-1b). In the example provided in the Figure 5-1b, the bold lines show the best hypothetical combination.

Therefore, investigating different combinations of models/parameters and then selecting the best combination in the structure of TPMS can be an alternative approach in TPMS calibration. If the modeller is unsure which combination of models and parameters should be chosen, all the combinations could be tested to find the models and parameters which result in the best fit to observed statistics (NCHRP 2012). However, if the modeller runs the full factorial experiment, the huge computational efforts will prevent this process from being feasible. Considering time and cost, the full experimental design is not economical. Fortunately, statistical theories facilitate doing just a small number of experiments using fractional replicated designs. Therefore, as it is necessary to conduct experiments and execute the calibration process by reasonable computational efforts, the emphasis of this study is the use of a Taguchi plan, by which the appropriate levels of parameters that have the most effective impacts on the overall structure can be determined. The Taguchi method (Taguchi 1986) has the advantage of conducting much fewer experiments as well as establishing robustness by minimising variation of outputs (Al-Aomar 2006). The Taguchi method considers the interaction between the models/parameters and the noise factors and enables achieving a robust TPMS by reducing the variances in the system.




a) The only combination based on the most fitted values for the parameters




b) Selection of the best combination

Figure 5-1 An alternative structure for calibration

As already discussed, the main structure of the proposed model for calibration is based on iteratively examining different combinations and then choosing the best combination. In Appendix *A*, the methodology for choosing the best combination of the adjusting candidates is introduced which is a combination of Taguchi and ANOVA methods. To keep consistency with the concepts used in Taguchi method in all the statistics textbooks, in the current chapter both the models that are subject to replacement and the parameters that are subject to adjustment are called *factors*.

Figure 5-2 shows a model that systematically calibrates TPMSs using a statistics-based approach. The model has four steps including 1) models evaluation, 2) models selection, 3) parameters evaluation, and finally 4) parameters adjustment. The first two steps select the most appropriate combination of modelling specifications. At stages 3 and 4, the parameters are adjusted iteratively or simultaneously. It is worth mentioning that the application of the proposed calibration process is not limited to TPMSs and the transport domain. It could be an asset for calibration of any complex models where the modellers' expertise alone is not sufficient.

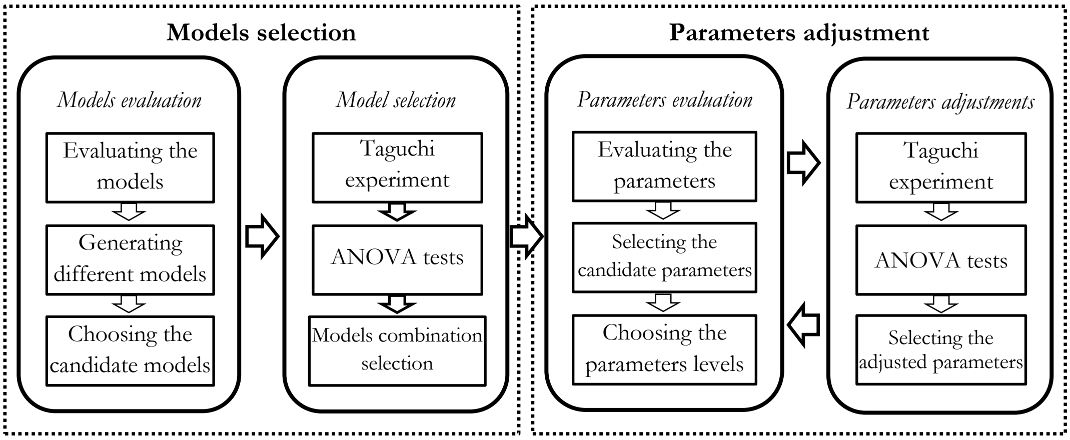



Figure 5-2 The proposed model structure for calibration

The detailed descriptions of different stages of the proposed model structure are discussed in the following subsections.

### 5.5.2 Models selection

When travel demand models are developed, the models with the highest likelihood are selected as the best model in the literature, while their combination may not form the best structure of TPMS. There are a number of reasons that the combination of models, all individually the best, is not the best in a TPMS framework. These reasons include different assumptions of the models, unobserved variables, and the differences in time scale between the observed demand statistics and the observed traffic statistics. Therefore, a systematic procedure for simultaneous selection of models in TPMS structure is expected to produce more consistent and accurate results.

There are many ways for selecting the candidate models for a position in the structure of a TPMS. These include selection of different models of the same type with acceptable log-likelihood values, selection of different nesting structures for one model, and whether to include household interaction in the model system. Then, the proposed model can be used to choose the candidate options that increase the robustness of TPMS and better reproduce the observed statistics.

#### 5.5.2.1 Model evaluation

A number of candidate models for each of the model positions of the TPMS should be estimated. Then, the most interpretable candidates should be chosen for further considerations. The nominated models are the inputs of the next step where the best combination of the nominated models must be selected.

#### 5.5.2.2 Model selection

In this step, the nominated models should be evaluated using Algorithm. In the algorithm, each of the model positions and nominated models are considered as a factor $f$ and a factor level $l \in L^f$, respectively.

### 5.5.3 Parameter adjustment

In the previous step, the most suitable estimated models in the structure of TPMS are selected where their parameters have not been adjusted yet. Whichever models are in the structure of TPMS, reproducing the observed statistics without adjusting their parameters is usually impossible. The initially estimated parameters are not necessarily the best fitted parameters in the body of TPMSs. Therefore, the parameters should be adjusted iteratively. A similar solution to selecting the models can be prescribed for parameters of each model. The parameters can include both alternative specific constants and variable coefficients.

#### 5.5.3.1 Candidate parameters evaluation

In each iteration of the calibration process, a set of parameters $P$, is selected to be analysed for possible adjustments. These parameters might have some impacts on the TPMS output. Each parameter $p \in P$ has different levels $l \in L^p$. Selection of the levels for the parameters is based on the modeller's experience, the current solution of the TPMS and its difference to observed statistics. Further, a key decision in model calibration is which parameters to be selected and in which direction the adjustments should take place. The selected levels in an iteration provide a guideline for selecting the parameters in subsequent iterations. For instance, if $p \notin (P^s \cup P^r)$ or if $p_t^* = p_{t-1}^*$, where $t$ is the iteration number for stage 2 in the proposed calibration model, the parameter can be removed from the list of candidate parameters for adjustment. Further, choosing the lower level or the upper level of a parameter can be a guide for choosing the levels of the parameters in the subsequent iterations because the levels determine suitable direction of the values for that parameters. Therefore, the algorithm can also be an asset for the modeller to find the direction of the changes in parameters adjustment.

#### 5.5.3.2 Parameters adjustment

Similar to model selection step, the candidate parameters should be evaluated using Algorithm. Therefore, each of the selected parameters is a factor in the Algorithm. It should be stressed that each alternative value for each parameter has to be determined by experts and therefore it is a valid and meaningful value for that parameter. One of the main strength of the proposed calibration model is that it provides a systematic structure to adjust many parameters simultaneously.

## 5.6 Case Study

In this section, the performance of the proposed calibration model is shown via a case study of Travel/Activity Scheduler for Household Agents (TASHA) model system for the Greater Toronto Area (GTA) (TMG, 2015). Since, this study intends to show the capability and effectiveness of the proposed model in calibrating the large-scale TPMS and not to conduct 100% of calibration process of a large-scale TPMS, it uses an already built TPMS and only focus on the second stage (parameters adjustment) of the proposed model. TASHA is an activity based model that was designed to mainly improve the behavioural representation of human decision-making, the spatial and temporal precision of outputs, and the sensitivity to demand-oriented policies of the traditional TPMS used in the Toronto Area. It is an activity-based, household-based, and agent-based microsimulation model that is designed either to operate as a stand-alone model or to be embedded within the Integrated Land Use Transportation Environment (ILUTE) modelling framework for forecasting long-term and short-term decisions of households (Roorda et al. 2008). For detailed description of the TASHA model system, the readers are referred to Miller and Roorda (2003) and Roorda et al. (2008).

This latest version of TASHA which is already calibrated and implemented in the Greater Toronto Area (GTA) is intentionally used in order to show the breadth of the proposed model capabilities by comparing the calibrated parameters of the proposed model and the existing unstructured calibration process of TASHA. Henceforth, the latest version of TASHA model system is denoted as unstructured calibrated TASHA. This comparison helps identifying problems that may originate from solely applying the usual techniques. Clearly, the proposed model cannot dramatically improve the model fit since it is applied to an already calibrated TASHA model system. Using the case study, it is tried to 1) recognise parameters that have been unnecessarily adjusted using traditional techniques, 2) minimise the noise in the system, and 3) improve reproduction of the observed statistics.

To indicate whether any adjustment in a particular model is necessary for building the latest version of the TASHA model or not, and also to have an idea of the extent of the effects of adjusting the parameters, the proposed method is applied to the mode choice model. For this purpose, the calibrated mode choice parameters are substituted with the initially estimated mode choice parameters in the TASHA model system to be then iteratively improved (calibrated) using Algorithm. It should be noted that the model does not examine all the mode choice parameters. Instead a subset of all parameters is selected for improvement.

The mode choice model of TASHA is built according to different types of modes and occupations. The modes are auto, carpool, drive-access-transit (DAT), walk-access-transit (WAT), walk, bike, and (car) passenger. Further, there are six person categories: four worker categories (professional, general, manufacturing and sales) and two non-worker categories (students, and unemployed non-students) in the mode choice model. For more details, the readers are referred to TMG (2015). In total, the mode choice model in TASHA includes 282 parameters. 155 of 282 parameters are adjusted in the unstructured calibration phase. Therefore, two different scenarios (here called TPMSs) are built by substituting the initially estimated mode choice parameters and the calibrated mode choice parameters in the structure of TASHA model system.

The third TPMS is built by running two iterations of steps 3 and 4 of the proposed model, with the initially estimated mode choice models. These TPMSs are abbreviated as follows: UCT (unstructured calibrated TPMS), BCT (base case TPMS) and TCT (Taguchi calibrated TPMS). UCT includes the latest version of TASHA which is based on calibrated results using classic techniques. In the BCT, unstructured calibrated TASHA model is used except, its calibrated mode choice model is replaced with the initially estimated mode choice model. BCT is applicable as a reference for comparing various settings. And lastly, in the TCT, the proposed algorithm is implemented on the base case TPMS (BCT) to improve the model system.

As mentioned, two iterations of the second stage of the proposed algorithm (parameters adjustment) are implemented to form the TCT because two iterations are enough for building a TMPS that outperforms the UCT and BCT. In a real situation within which a benchmark like UCT is not available, the model can be run until no further improvement is achievable. However, modellers should pay attention to avoid falling into the over-calibration trap that may happen by applying significant adjustments/deviations in the parameters. Accordingly, the orthogonal array $L_{36}$ with just 36 trials (Table 5-2) is used instead of doing an immense number of experiments in full factorial design. In the table, let A-X denote the controllable factors. To use the terminologies of the Taguchi method, let denote different levels with integer values, i.e.: 1, 2 and 3. In each iteration, according to $L_{36}$, there are 23 independent control factors (parameters) to be tested. Twelve of the parameters have 3 levels and the others have 2 levels. The intention is to select the best combination of parameters so that best placed in the TPMS structure. The other columns in Table 5-2 will be discussed later.

Table 5-2 Orthogonal array for the control factors

| Trial | Factors | | | | | | | | | | | | | | | | | | | | | | | $r_{i1}$ | $r_{i2}$ | $r_{i3}$ | $\bar{r}_i$ | $(S/N)_i$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | A | B | C | D | E | F | G | H | J | K | L | M | N | O | P | Q | R | S | T | U | V | W | X | | | | | |
| 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 865.46 | 865.17 | 865.11 | 865.24 | -58.743 |
| 2 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 867.31 | 866.97 | 866.93 | 867.07 | -58.761 |
| 3 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 869.11 | 869.85 | 869.59 | 869.52 | -58.786 |
| 4 | 1 | 1 | 1 | 1 | 1 | 2 | 2 | 2 | 2 | 2 | 2 | 1 | 1 | 1 | 1 | 2 | 2 | 2 | 2 | 3 | 3 | 3 | 3 | 867.30 | 867.09 | 867.07 | 867.15 | -58.762 |
| 5 | 1 | 1 | 1 | 1 | 1 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 3 | 3 | 3 | 3 | 1 | 1 | 1 | 1 | 867.96 | 867.07 | 868.45 | 867.83 | -58.769 |
| 6 | 1 | 1 | 1 | 1 | 1 | 2 | 2 | 2 | 2 | 2 | 2 | 3 | 3 | 3 | 3 | 1 | 1 | 1 | 1 | 2 | 2 | 2 | 2 | 868.27 | 868.29 | 867.91 | 868.16 | -58.772 |
| 7 | 1 | 1 | 2 | 2 | 2 | 1 | 1 | 1 | 2 | 2 | 2 | 1 | 1 | 2 | 3 | 1 | 2 | 3 | 3 | 1 | 2 | 2 | 3 | 868.49 | 867.40 | 867.13 | 867.67 | -58.767 |
| 8 | 1 | 1 | 2 | 2 | 2 | 1 | 1 | 1 | 2 | 2 | 2 | 2 | 2 | 3 | 1 | 2 | 3 | 1 | 1 | 2 | 3 | 3 | 1 | 866.60 | 867.74 | 867.30 | 867.21 | -58.763 |
| 9 | 1 | 1 | 2 | 2 | 2 | 1 | 1 | 1 | 2 | 2 | 2 | 3 | 3 | 1 | 2 | 3 | 1 | 2 | 2 | 3 | 1 | 1 | 2 | 868.99 | 867.70 | 868.17 | 868.29 | -58.773 |
| 10 | 1 | 2 | 1 | 2 | 2 | 1 | 2 | 2 | 1 | 1 | 2 | 1 | 1 | 3 | 2 | 1 | 3 | 2 | 3 | 2 | 1 | 3 | 2 | 869.65 | 869.96 | 870.36 | 869.99 | -58.790 |
| 11 | 1 | 2 | 1 | 2 | 2 | 1 | 2 | 2 | 1 | 1 | 2 | 2 | 2 | 1 | 3 | 2 | 1 | 3 | 1 | 3 | 2 | 1 | 3 | 868.85 | 868.44 | 869.45 | 868.91 | -58.780 |
| 12 | 1 | 2 | 1 | 2 | 2 | 1 | 2 | 2 | 1 | 1 | 2 | 3 | 3 | 2 | 1 | 3 | 2 | 1 | 2 | 1 | 3 | 2 | 1 | 870.74 | 870.61 | 870.30 | 870.55 | -58.796 |
| 13 | 1 | 2 | 2 | 1 | 2 | 2 | 1 | 2 | 1 | 2 | 1 | 1 | 2 | 3 | 1 | 3 | 2 | 1 | 3 | 3 | 2 | 1 | 2 | 870.01 | 870.66 | 869.48 | 870.05 | -58.791 |
| 14 | 1 | 2 | 2 | 1 | 2 | 2 | 1 | 2 | 1 | 2 | 1 | 2 | 3 | 1 | 2 | 1 | 3 | 2 | 1 | 1 | 3 | 2 | 3 | 870.23 | 870.49 | 871.57 | 870.76 | -58.798 |
| 15 | 1 | 2 | 2 | 1 | 2 | 2 | 1 | 2 | 1 | 2 | 1 | 3 | 1 | 2 | 3 | 2 | 1 | 3 | 2 | 2 | 1 | 3 | 1 | 871.18 | 870.84 | 870.86 | 870.96 | -58.800 |
| 16 | 1 | 2 | 2 | 2 | 1 | 2 | 2 | 1 | 2 | 1 | 1 | 1 | 2 | 3 | 2 | 1 | 1 | 3 | 2 | 3 | 3 | 2 | 1 | 870.38 | 869.40 | 870.42 | 870.07 | -58.791 |
| 17 | 1 | 2 | 2 | 2 | 1 | 2 | 2 | 1 | 2 | 1 | 1 | 2 | 3 | 1 | 3 | 2 | 2 | 1 | 3 | 1 | 1 | 3 | 2 | 872.85 | 872.84 | 872.19 | 872.63 | -58.817 |
| 18 | 1 | 2 | 2 | 2 | 1 | 2 | 2 | 1 | 2 | 1 | 1 | 3 | 1 | 2 | 1 | 3 | 3 | 2 | 1 | 2 | 2 | 1 | 3 | 867.65 | 868.04 | 867.98 | 867.89 | -58.769 |
| 19 | 2 | 1 | 2 | 2 | 1 | 1 | 2 | 2 | 1 | 2 | 1 | 1 | 2 | 1 | 3 | 3 | 3 | 1 | 2 | 2 | 1 | 2 | 3 | 868.29 | 868.08 | 868.53 | 868.30 | -58.773 |
| 20 | 2 | 1 | 2 | 2 | 1 | 1 | 2 | 2 | 1 | 2 | 1 | 2 | 3 | 2 | 1 | 1 | 1 | 2 | 3 | 3 | 2 | 3 | 1 | 870.42 | 870.67 | 871.77 | 870.95 | -58.800 |
| 21 | 2 | 1 | 2 | 2 | 1 | 1 | 2 | 2 | 1 | 2 | 1 | 3 | 1 | 3 | 2 | 2 | 2 | 3 | 1 | 1 | 3 | 1 | 2 | 866.08 | 866.31 | 865.60 | 866.00 | -58.750 |
| 22 | 2 | 1 | 2 | 1 | 2 | 2 | 2 | 1 | 1 | 1 | 2 | 1 | 2 | 2 | 3 | 3 | 1 | 2 | 1 | 1 | 3 | 3 | 2 | 867.49 | 867.53 | 867.33 | 867.45 | -58.765 |
| 23 | 2 | 1 | 2 | 1 | 2 | 2 | 2 | 1 | 1 | 1 | 2 | 2 | 3 | 3 | 1 | 1 | 2 | 3 | 2 | 2 | 1 | 1 | 3 | 867.85 | 867.62 | 867.01 | 867.50 | -58.765 |
| 24 | 2 | 1 | 2 | 1 | 2 | 2 | 2 | 1 | 1 | 1 | 2 | 3 | 1 | 1 | 2 | 2 | 3 | 1 | 3 | 3 | 2 | 2 | 1 | 867.48 | 867.07 | 867.10 | 867.22 | -58.763 |

Table 5-2 Orthogonal array for the control factors

| Trial | Factors | | | | | | | | | | | | | | | | | | | | | | | $r_{i1}$ | $r_{i2}$ | $r_{i3}$ | $\bar{r}_i$ | $(S/N)_i$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | A | B | C | D | E | F | G | H | J | K | L | M | N | O | P | Q | R | S | T | U | V | W | X | | | | | |
| 25 | 2 | 1 | 1 | 2 | 2 | 2 | 1 | 2 | 2 | 1 | 1 | 1 | 3 | 2 | 1 | 2 | 3 | 3 | 1 | 3 | 1 | 2 | 2 | 867.83 | 866.92 | 867.13 | 867.29 | -58.763 |
| 26 | 2 | 1 | 1 | 2 | 2 | 2 | 1 | 2 | 2 | 1 | 1 | 2 | 1 | 3 | 2 | 3 | 1 | 1 | 2 | 1 | 2 | 3 | 3 | 865.34 | 865.77 | 866.42 | 865.85 | -58.749 |
| 27 | 2 | 1 | 1 | 2 | 2 | 2 | 1 | 2 | 2 | 1 | 1 | 3 | 2 | 1 | 3 | 1 | 2 | 2 | 3 | 2 | 3 | 1 | 1 | 867.48 | 866.96 | 867.83 | 867.42 | -58.765 |
| 28 | 2 | 2 | 2 | 1 | 1 | 1 | 1 | 2 | 2 | 1 | 2 | 1 | 3 | 2 | 2 | 2 | 1 | 1 | 3 | 2 | 3 | 1 | 3 | 871.58 | 870.31 | 871.72 | 871.20 | -58.802 |
| 29 | 2 | 2 | 2 | 1 | 1 | 1 | 1 | 2 | 2 | 1 | 2 | 2 | 1 | 3 | 3 | 3 | 2 | 2 | 1 | 3 | 1 | 2 | 1 | 869.80 | 870.09 | 869.35 | 869.75 | -58.788 |
| 30 | 2 | 2 | 2 | 1 | 1 | 1 | 1 | 2 | 2 | 1 | 2 | 3 | 2 | 1 | 1 | 1 | 3 | 3 | 2 | 1 | 2 | 3 | 2 | 872.49 | 872.42 | 871.87 | 872.26 | -58.813 |
| 31 | 2 | 2 | 1 | 2 | 1 | 2 | 1 | 1 | 1 | 2 | 2 | 1 | 3 | 3 | 3 | 2 | 3 | 2 | 2 | 1 | 2 | 1 | 1 | 868.82 | 868.10 | 869.74 | 868.89 | -58.779 |
| 32 | 2 | 2 | 1 | 2 | 1 | 2 | 1 | 1 | 1 | 2 | 2 | 2 | 1 | 1 | 1 | 3 | 1 | 3 | 3 | 2 | 3 | 2 | 2 | 868.32 | 869.64 | 868.15 | 868.70 | -58.777 |
| 33 | 2 | 2 | 1 | 2 | 1 | 2 | 1 | 1 | 1 | 2 | 2 | 3 | 2 | 2 | 2 | 1 | 2 | 1 | 1 | 3 | 1 | 3 | 3 | 869.57 | 869.85 | 869.69 | 869.70 | -58.787 |
| 34 | 2 | 2 | 1 | 1 | 2 | 1 | 2 | 1 | 2 | 2 | 1 | 1 | 3 | 1 | 2 | 3 | 2 | 3 | 1 | 2 | 2 | 3 | 1 | 869.96 | 870.26 | 870.46 | 870.23 | -58.793 |
| 35 | 2 | 2 | 1 | 1 | 2 | 1 | 2 | 1 | 2 | 2 | 1 | 2 | 1 | 2 | 3 | 1 | 3 | 1 | 2 | 3 | 3 | 1 | 2 | 866.70 | 867.08 | 866.79 | 866.85 | -58.759 |
| 36 | 2 | 2 | 1 | 1 | 2 | 1 | 2 | 1 | 2 | 2 | 1 | 3 | 2 | 3 | 1 | 2 | 1 | 2 | 3 | 1 | 1 | 2 | 3 | 870.23 | 869.54 | 869.41 | 869.73 | -58.788 |

This study focuses on the parameters of the mode choice, location choice, and access station choice models of the TASHA model for calibration. The selected parameters for consideration in the first iteration are provided in Table 5-2. For determining the levels of each parameter, this study first compares the initially estimated values and the calibrated values used in UCT. If the initially estimated and calibrated values are different, then both the estimated and calibrated values are intentionally included in the levels of those parameters. Comparing the impact of these values in conjunction with other parameters in the TPMS helps evaluating the performance of classic calibration techniques. If the selected parameters are not adjusted (where usually happens for coefficients of the variables) in UCT, the initially estimated value and two proportions of it (usually 1 ± 10%) are considered as the parameters' levels. It is not necessary to choose a single parameter as a factor. A factor can be any of the calibration techniques that have been extensively used in practice. For example, in this case study, some of parameters for different specific modes or occupations are adjusted by a constant value using classic calibrated techniques (e.g. parameter code B in Table 5-3). In these cases, the adjustment constant for those parameters is selected as one auxiliary factor so that Algorithm either adjusts all those parameters by that constant or keep them unchanged. Therefore, these parameters are placed under the same auxiliary factor. The estimated and adjusted values for the selected parameters using the classic calibration process are provided in the 3rd and 4th columns of Table 5-3. The chosen values for different levels of the parameters (to be used in TCT) are given in the 5th, 6th, and 7th columns. Further, the best value for each of the parameters is considered in the 8th column which will be discussed later.

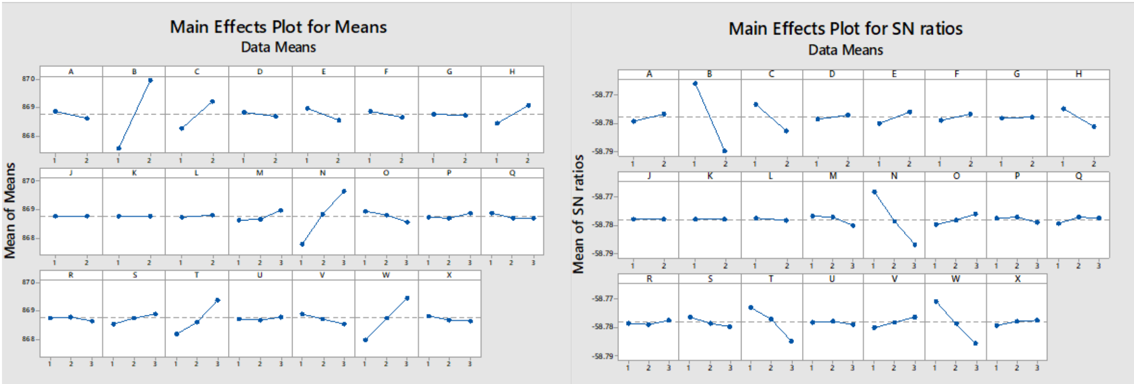
According to Rasouli and Timmermans (2012), travel demand is uncertain because of multiple sources of uncertainty including uncertain input, the inherent probabilistic nature of the models involved, uncertain parameters/rules and microsimulation error. In the current case study, uncertainties are due to uncertain input and probabilistic nature of the models in the TPMS. To consider uncertainty in the models (error term components), the random seed parameters of different models are not fixed when running the case scenarios. Further, 3 random samples are drawn from the synthetic population. To further illustrate, 10% fraction of the synthetic population was randomly selected 3 times and thereby, the expansion factors for each of the selected agents are changed to 10. This helps to account for the errors in the input data. Next, each of the trials is performed 3 times with the drawn random samples and variable random seeds. Note that the more replications results in higher accuracy.

In practice, different criteria such as reproduction of traffic counts, reproduction of origin-destination matrix, mode shares, etc. are considered in the calibration exercise, however, to evaluate the proposed algorithm in this chapter, only one single objective (quality characteristic) is used, that is the minimisation of root mean square deviation (RMSD) as in Equation (5-1):

$$RMSD = \sqrt{\frac{\sum_n (\Delta v)^2}{n}} \tag{5-1}$$

where $\Delta v$ represents the difference between observed traffic counts and simulated traffic counts. The quality characteristic shows the extent to which the TPMS result is different from the observed counts. The smaller RMSD are interpreted as the better model, "the lower is better" principle in Taguchi method (Equation (A-2) in Appendix *A*) is chosen for conducting the analysis. Afterwards, the responses of the case scenarios for each trial are transformed into (S/N) ratios. It should be noted that this study has considered the observed and simulated flows for 1,753 links for four different time periods within the day. Therefore, there is totally 7,012 link flows observation for this case study.

To illustrate the calculations of Taguchi method using an example, discussing the detailed calculations (as in Algorithm) for factor B is helpful. The response value for three experiments ($r_{in}\ for\ n = \{1,2,3\}$) performed in iteration 1 are depicted in Table 5-2. In the table, column $\bar{r}_i$ includes the average of the responses for each trial and the values in column $(S/N)_i$ are calculated using Equation (A-2). The values in column B determine the level of factor B that is used in each trial. Therefore, to calculate the effect of each of the two levels of this parameter, the average effects of factor B at level 1 ($\bar{r}_1^B$ and $(S/N)_1^B$) and level 2 ($\bar{r}_2^B$ and $(S/N)_2^B$) need to be calculated. For example, the average of the values in column $\bar{r}_i$ that correspond to the trials with level 1 and level 2 in column B are 867.562 and 869.952, respectively. With the same calculations, the effects of different levels of all the factors are calculated and plotted in Figure 5-3. Then, according to the rules in Section 0, the best level for each of the selected factors is extracted (they are provided in the 8th column of Table B3 in the Appendix *B*).

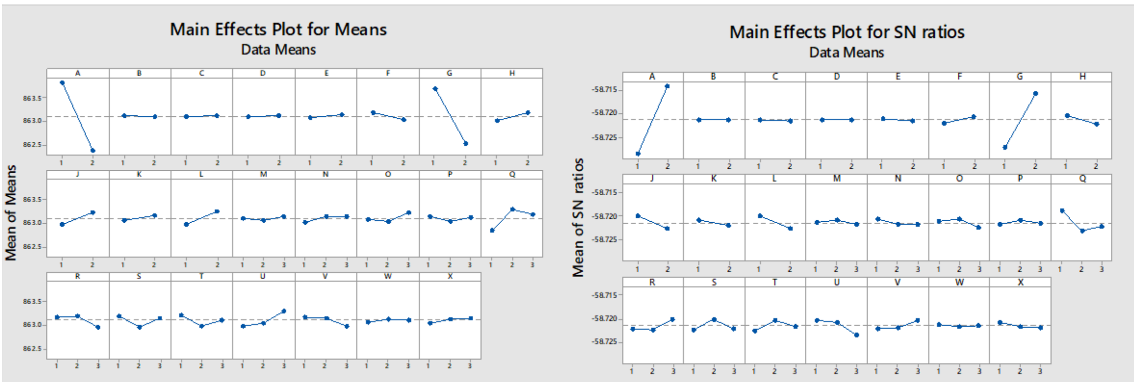



a) Mean of Means ($\bar{r}_l^f$) for different levels  b) Mean of signal-to-noise $(S/N)_l^f$ for different levels

Figure 5-3 Taguchi plots of the first iteration for different factors

After assigning the best values of the factors obtained in the first round, another set of factors and parameters is chosen for the second iteration of algorithm. It should be noted that the parameters with significant impacts on the (S/N) ratio and mean of RMSD in the first iteration of the algorithm are chosen again in the second iteration. The new set of factors and parameters is provided in Table B4 in Appendix *B*.

Similar to the first iteration, the results of the calculations for the second iteration are visualised in Figure 5-4. Further, the best levels for the parameters are provided in the 8$^{th}$ column of Table B4. Knowing the best levels for the selected parameters in the first and second iterations, the third TPMS (TCT) is built by replacing the best values for the parameters with the corresponding values in BCT.




a) Mean of Means ($\bar{r}_l^f$) for different levels  b) Mean of signal-to-noise $(S/N)_l^f$ for different levels

Figure 5-4 Taguchi plots of the second iteration for different factors

Next, to compare the performance of the classic calibration process and the proposed model, the three TPMSs are run with different synthesised data. For this purpose, each of the three case scenarios is run with 30 random samples that are drawn from synthetic population.

The absolute difference between the simulated and observed traffic counts ($|\Delta v|$) are used to form the following performance measures:

1. Number of links with significant reduction in $|\Delta v|$ (LR): the average total number of links for which the $|\Delta v|$ is significantly reduced when comparing two different scenarios;
2. Number of links with significant reduction in the standard deviation of $|\Delta v|$ (LRSD): the average total number of links for which the standard deviation of $|\Delta v|$ is significantly reduced.

When comparing UCT and TCT, it has to be noted that in the UCT calibration process, several criteria have already been considered by the expert; while, reducing the RMSD is the only criterion for calibration of TCT. However, it is assumed in this chapter that UCT can be evaluated based on RMSD meaning that UCT and TCT are comparable.

Table 5-3 and Table 5-4 break down the number of links that have significant differences among different case scenarios. As shown in these tables, TCT dominates BCT and UCT scenarios in terms of both LR and LRSD. For instance, in 4,849 link values, the TCT significantly ($\Delta d > 5$) outperform BCT and UCT; while, in 2,830 link values, TCT is significantly outperformed by the BCT and UCT. Comparing UCT and BCT reveals that while UCT produces closer simulated counts to observed counts (smaller LR), BCT has a better performance in term of LRSD. Therefore, TCT has the most robust structure followed by BCT and UCT. Also, TCT can reproduce the observed traffic counts better followed by UCT and BCT. According to the rules discussed earlier in Section 0, higher robustness is achieved when the values of the best level of each parameter ($8^{th}$ column of Table B3 and Table B4) are selected for those parameters.

Table 5-3 Comparing different scenarios in term of LR

| | TCT | | | BCT | | | UCT | | | Sum |
|---|---|---|---|---|---|---|---|---|---|---|
| | 5≤Δd≤20 | 20<Δd≤50 | Δd >50 | 5≤Δd≤20 | 20<Δd≤50 | Δd >50 | 5≤Δd≤20 | 20<Δd≤50 | Δd >50 | |
| TCT | 0 | 0 | 0 | 1379 | 783 | 412 | 1240 | 695 | 340 | 4849 |
| BCT | 635 | 411 | 283 | 0 | 0 | 0 | 610 | 407 | 355 | 2701 |
| UCT | 718 | 469 | 314 | 987 | 541 | 412 | 0 | 0 | 0 | 3441 |
| Sum | | 2830 | | | 4514 | | | 3647 | | |

Table 5-4 Comparing different scenarios in term of LRSD

| | TCT | | | BCT | | | UCT | | | Sum |
|---|---|---|---|---|---|---|---|---|---|---|
| | 1<Δσ≤5 | 5<Δσ ≤10 | Δσ >10 | 1<Δσ≤5 | 5<Δσ ≤10 | Δσ >10 | 1<Δσ≤5 | 5<Δσ ≤10 | Δσ >10 | |
| TCT | 0 | 0 | 0 | 1332 | 495 | 372 | 1257 | 274 | 181 | 3911 |
| BCT | 717 | 111 | 58 | 0 | 0 | 0 | 1202 | 377 | 331 | 2796 |
| UCT | 1003 | 164 | 72 | 805 | 172 | 117 | 0 | 0 | 0 | 2333 |
| Sum | | 2125 | | | 3293 | | | 3622 | | |

Regarding the calibrated parameters of UCT, it is found that some of the values that were chosen for some parameters do not have significant impact neither on reproducing the observed counts nor on reducing the standard deviation of the simulated values. For example, adjusting the estimated constants of passenger models (code H in Table B4) by adding +1 (as is done in UCT) does not have influence on the performance of TASHA. Further, in TCT, the candidate parameters for adjustment are not limited to only the constants of the models as the coefficients are also selected for calibration. As can be seen in the tables, some of them can significantly affect TASHA outputs; therefore, adjusting the coefficients is a great opportunity for large-scale TPMS adjustments.

In forming two iterations of Algorithm in this case study, as can be seen in Table 5-5, 91, 17, and 3 parameters are respectively chosen from mode choice, location choice, and access station choice for model calibration. Among these, the calibrated values in UCT are recognised suitable only for 47 mode choice parameters and 7 location choice parameters. Further, for 25, 7 and 1 of the parameters respectively for mode choice, location choice, and access station model, values other than estimated and adjusted in UCT are recognised as the calibrated parameter.

Table 5-5 Calibrated parameters in different models

| Parameter type | # of parameters | # of adjusted parameters in UCT | # of considered parameters in TCT | # of parameters with similar adjustment in both UCT and TCT | # of adjusted parameters only in TCT | # of adjusted parameters in TCT |
|---|---|---|---|---|---|---|
| Mode choice parameters | 282 | 155 | 91 | 47 | 25 | 72 |
| Location choice parameters | 84 | 68 | 17 | 7 | 7 | 65 |
| Access station model | 28 | 0 | 3 | 0 | 1 | 1 |

## 5.7 Conclusion

Appropriate selection of models and properly adjustment of their parameters have a crucial impact on the efficiency and effectiveness of any model (not limited to transport models). Despite the interactions among the components of TPMS, they are often calibrated separately. It may result in ineffective and unnecessary adjustments in the parameters. Certainly the accuracy of the TPMSs in forecasting scenarios is highly affected by the procedures taken in linking different models and the calibration afterward. Moreover, the TPMS calibration process is as much art as science and actually, there is no substitute for modellers' expertise. Nonetheless, guidelines are needed to recognise proper adjustments that will result in well-calibrated TPMSs.

In this chapter a calibration model is proposed for systematic calibration of TPMSs. Using the TASHA model system, the capability of the model in the calibration of large-scale TPMS model is shown. The advantages of the model along with its simple calculations can make the model as an effective decision support system that complements the modellers' expertise. The drawback of the proposed model is that manual interventions by the modellers (in selecting the candidates for model components and parameters) still play a considerable role in the calibration process.

# Chapter 6

# Integrated Formulation for TPMSs

***This chapter is in line with Aim 3 and formulates an integrated TPMS. In contrast to chapters 4 and 5 which develop calibration models to enhance the performance of conventional TPMSs, this chapter proposes an alternative formulation for the conventional TPMSs.***

*In this chapter, a novel transport planning model system (TPMS) is formulated built on the concepts of network, multi-modality, integrity and instant calibration. In the proposed formulation, activity-travel pattern (ATP) choice elements including the choices of activity, activity sequence, mode, departure time, and parking location, are all unified into a time-dependent ATPs generator. The proposed model accounts for the dynamicity of the network, including time-of-day and congestion effects in a joint structure for transport supply and demand. Moreover, the proposed TPMS explicitly formulates an operating capacitated public transport system. To allow visiting locations multiple times and to alleviate the complexity of the proposed model, a novel multi-visit vehicle routing problem is proposed which does not enumerate the node and link visits. In order to calibrate the model based on the major travel attributes of the travel survey data, a set of splitting ratios are introduced to distribute trips on the network. The model uses the splitting ratios to integrate the ATPs generator and the traffic assignment (TA) model in a unified TPMS structure. The effectiveness of the proposed structure is demonstrated through numerical examples provided.*

## 6.1 Introduction

Research on Transport Planning Model Systems (TPMSs) such as activity-based models (ABMs) has recently attracted a lot of attention. TPMSs include a number of sub-models such as trip generation, destination choice, mode choice, activity choice, activity chains, route choice, and traffic assignment models which are linked together. In the standard practice, the sub-models are partly developed individually, usually based on maximising an objective function which can be total travel time, or log-likelihood function. They are then connected in a sequential and ad-hoc manner so that the outputs of one or some models are fed into the other models. The fundamental limitations of such sequential approaches are well-discussed in Boyce (2002) and Najmi et al. (2019a,b).

Capturing the synchronisations among the sub-model outputs in the sequential structure could be problematic because of two main limitations. First, due to the absence of spatiotemporal constraints in a physical network in the unconstrained econometric (dis-)utility minimisation/maximisation modelling approaches, the interactions between the models and the interdependencies among the choice dimensions are lost (Recker, 2001; Jara-Díaz, 2003). Second, the optimisation formulation resulting from the combination of traffic assignment models and demand-side models is non-convex in general, which makes the convergence of the integrated TPMSs slow and sometimes impractical.

Asynchronisation among model components in conventional TPMSs such as trip-based models and ABMs may unrealistically affect the activity-travel patterns (ATPs) generation process of travellers. This is a limitation of conventional models which cannot fully capture the temporal and spatial dimensions of the entire problem. Specifically, the appropriate treatment of the temporal and spatial dimensions is perhaps the most important prerequisite to generate precise ATPs (Pinjari and Bhat, 2011). Therefore, the asynchronisation in addition to the needs of having detailed ATPs of travellers has triggered researchers to develop different unified demand-side models (or so-called ATPs generators) (e.g. Ouyang et al., 2011; Liao et al., 2010, 2013; Fu and Lam, 2014; Liu et al., 2015; Chow and Djavadian, 2015a; Västberg et al., 2019). Thus, *ATPs generator*s are unified formulations that can generate all the demand-side choice facets of travellers simultaneously and usually for a whole day. As in conventional models, spatiotemporal constraints have not sufficiently received attention in the ATPs generators, possibly due to their complexity. Nonetheless, there are some studies in which spatiotemporal constraints play a key role in model development (e.g. Chow, 2014; Chow and Djavadian, 2015a). Owing to the importance of synchronisation in the precision of the TPMSs, we try to develop an integrated model which not only incorporates a unified ATPs generator at the presence of spatiotemporal constraints, but also attempts to synchronise the ATPs generator and traffic assignment model.

Furthermore, to obtain optimal ATPs, proper modelling of the interactions among different travel modes in the transport systems is helpful. Usually, the analytical equilibrium models of multimodal systems are based on trip-based demand (Chow and Djavadian, 2015b). The trip-based structure disjoints the inter-modal connections among the models. This is also in contrast with the reality that demand for multimodal transport systems has a high correlation with activity schedules of travellers so that the availability or accessibility of a mode can remarkably change the activity agenda. This necessitates modelling the multimodal transport systems and activity schedules of travellers in a unified structure. Modelling the inter-modal interactions allows representing the multimodal dynamicity of the system and compromising between cost and time in the multimodal structure (Resat and Turkay, 2015). Specifically, the public transport timetable is another parameter that may affect ATPs for travellers. Many studies address the capacitated time-dependent public transport problem which is usually implemented on discrete space-time networks (Lu et al., 2016; Liu and Zhou, 2016; Liu et al., 2018). The models are usually network design problems which seek the answer of strategic decisions such as constructing new transit lines and adding or optimising train or bus schedules through a static origin-destination (OD) demand input (Martínez et al., 2014; Liu and Zhou, 2016). Nonetheless, at the microscopic level, studies on the interactions between the public transport time tables and routes, private transport and demand are limited. Thus, we attempt to address the multi-modality of the transport systems as well as the interaction of public transport and private vehicle modes.

The output of activity scheduling, whether having temporal and spatial dimensions or not, usually includes Origin-Destination (OD) matrices that should be loaded to a traffic assignment model. Nonetheless, the aggregate trips are not stable because if the resulted ODs are imported to the traffic assignment model, the resulted travel times and dis-utilities may be significantly different from the ones that were used for activity scheduling (Cools et al., 2010). The mismatch in interaction between demand-side and traffic assignment models is very common (Najmi et al., 2019b) which usually leads to the most inordinate asynchronisation in TPMSs. This is mainly due to the non-convex solution space of the interacting models which is resulted from the existence of non-linearities as well as the lack of closed form formulations. The problem is more common for multimodal and dynamic TPMSs. To alleviate the discrepancy in the literature, demand-side and traffic assignment models are iteratively solved (at the presence of feedback loops) until convergence minimising the discrepancy between travel time estimations of consecutive iterations (e.g. MORPC: Parsons Brinckerhoff, 2005; NYMTC: Parsons Brinckerhoff, 2014). However, the feedback loops are present only at the simulation step and their impacts on the calibration parameters (in the calibration step) are not properly addressed in the literature (Najmi et al., 2019c). As a main contribution of this study, we attempt to address the interaction not only within the simulation step but also within the calibration step of TPMSs.

Regardless of whether the feedback loops are considered in the calibration step or not, the calibration of the unified ATPs generators itself is challenging. Since the expanded network concept is usually used in unified ATPs generators, and the choices of nodes in the networks are not exclusive, the calibration of the unified ATPs generator to household travel survey data is very challenging and the conventional calibration approaches are not applicable in the models (see Chow and Recker, 2012). However, there are some efforts to calibrate parameters of the unified models. In Recker et al. (2008) and Chow and Recker (2012), a genetic algorithm and an inverse optimisation approach have, respectively, been proposed to calibrate some parameters limited to the ATPs of households (household-level properties). However, the main difference between their work and the current study is that the collective behaviour of travellers (system-level properties) is not investigated in their work while it is a main contribution of our approach. System-level properties are of utmost importance in the structure of TPMS because it is the system-level travelling behaviour that forms the traffic assignment model (Najmi et al., 2018).

Furthermore, using the ATPs generators in the body of TPMSs, in the presence of multiple traffic assignment models, is an interesting topic that has not received enough attention (Najmi et al., 2019b). The inconsistency in the scheduling period of ATPs generators, usually a whole day, and in the time period of traffic assignment models, each of which is usually for few hours, makes the formation of a TPMS complicated. One of the main reasons is that congestions in different time periods concurrently affect the daily ATPs of all travellers and vice versa. We attempt to address this complexity in this research.

In this study, we formulate a novel integrated TPMS structure in which a unified ATPs generator and multiple traffic assignment models are integrated. We make multiple theoretical contributions, each of which having specific practical implications. First, we provide a comprehensive formulation for a unified ATPs generator in which we attempt to incorporate the above-mentioned aspects of demand-side model such as spatiotemporal constraints, multi-modality, as well as private and public transport all together. The ATPs generator is integrated with a number of traffic assignment models corresponding to specific time periods of the entire planning period (typically a day) to capture transport demand-supply dynamics. Second, to simplify using expanded, discrete space-time networks, we embed a new multi-visit vehicle routing formulation in the proposed integrated TPMS which allows visiting nodes and edges of the network multiple-times throughout the planning period. Third, using a number of feedback loops, the proposed model iteratively and dynamically updates travellers' daily itinerary while accounting for dynamic travel times (i.e. congestion effects) at different time periods of the planning period until convergence. Fourth, a new calibration solution, using splitting ratios, is proposed to effectively calibrate the proposed TPMS as a whole. Not only do the splitting ratios control system-level properties of the transport system, they also take into account the interaction among travellers. Lastly, we provide ample numerical examples to illustrate the insights of the proposed approach, as well as numerical results. The analysis conducted reveals the critical role of splitting ratios for reproducing the observed travel patterns as well as in speeding up the convergence of the TPMS. The outcomes also highlight the critical role of feedback loops in the proposed model and in integrated ATPs generators in general.

## 6.2 Literature review

In this section, parallel research on the ATP generation is presented. Section 6.2.1 presents the standard practice of ATPs generation approaches that are widely used in commercial transport packages. Sections 6.2.2 and 6.2.3 illustrate the novel approaches in ATPs generation which are developed to circumvent problems in the conventional ATPs generators by unifying different model components. Lastly, Section 6.2.4 explores two approaches for linking demand and traffic assignment models.

### 6.2.1 Conventional ATPs generators

TPMSs, in practice, usually cannot guarantee seeking the optimum ATP for each traveller as it is a computationally challenging task. Therefore, modellers are more inclined to estimate the feasible space–time region for travellers. Accordingly, ABMs usually deploy a series of models including 1) utility maximisation-based models (i.e., multinomial logit and nested logit models)(CEMDAP: Bhat et al., 2004; FAMOS: Pendyala et al., 2005; Sacramento: Bowman et al., 2006) and 2) rule-based models (such as ALBATROSS: Arentze and Timmermans, 2004a; TASHA: Roorda et al., 2008) to circumvent the feasible space–time complexity. Nonetheless, these models have been extensively used in practice and in developing large-scale models with their focus being on simulation of activity patterns which opposes the spatiotemporal constrained scheduling behaviour (Chow and Nurumbetova, 2015). Using these models, some travelling decisions (such as trip purpose and activity sequence) are initially made for each traveller and then, using the space-time constraints for fixed activities (such as work and school), the ATPs of travellers are heuristically scheduled. There is a rich body of research under this category; however, we do not further illustrate the technical issues of these efforts because our focus is not on this category. Interested reader is referred to Pinjari and Bhat (2011).

### 6.2.2 Supernetwork-based ATPs generators

In line with the efforts to develop unified ATPs generators, a stream of expanded network-based (also known as supernetwork) models has been introduced in which the ATP for a traveller can be obtained by running classic shortest path algorithms onto an expanded network. The concept of supernetwork was first introduced by Daganzo and Sheffi (1977) to represent a multi-modal transport network. Their proposed representation has been the main building block of the supernetwork research. In the representation, to interconnect different single-modal networks, transfer links which connect the modal networks at the same physical locations were added. Following this idea, a supernetwork can be constructed with connecting many independent networks each of which for an individual mode-time period. Later, Nagurney and Dong (2002) introduced transaction links to model activity implementation. In their representation, location choice and route choice can be modelled simultaneously. Although any path through their proposed expanded network represents route choice, multi-modal networks were not taken into account. Later, several multimodal travel choice models in an integrated framework were emerged in the supernetwork literature (e.g., Carlier et al., 2003; Nagurney et al., 2003).

In the last 15 years, the so-called supernetwork models have been developed to address the integrated structure of transport systems. Arentze and Timmermans (2004b) suggested multi-state supernetworks, which unified activity programs of travellers, multi-modal transport networks and locations of activities. Their supernetworks were constructed for each traveller separately and are composed of as many copies of physical networks as different modes and activity states in an activity program execution. In their approach, while the travel mode state determines which particular mode is used, if any, the activity states determine which activities have been conducted. Later, this formulation is extended by a stream of research at the Eindhoven University of Technology. As the developed supernetworks in Arentze and Timmermans (2004b) became very large and possibly intractable even for a small activity program, Liao et al. (2010) used separate sets of private vehicle networks, public transport network and transition and transaction links to scale down the size of the supernetwork. To further reduce the size of the network, Liao et al. (2011) proposed a heuristic approach to select small set of locations for each traveller. Later, they added a temporal dimension to their suggested supernetwork by incorporating time-space constraint in their formulation (Liao et al., 2013). Recently, more advance versions of the supernetwork-based model is proposed by incorporation of travel time uncertainty (Liao et al., 2014), day-to-day ATPs (Liu et al., 2019), individual bounded rationality (Wang et al., 2019), joint traveling (Liao, 2019), free-floating car-sharing (Li et al., 2018) each of which focuses on a particular facet of the shortest path-based stream of supernetworks. Ramadurai and Ukkusuri (2010) proposed another unified framework, referred to as activity-travel networks, to model activity location, route choices, and activity duration, simultaneously using a supernetwork representation of the problem subject to a dynamic user equilibrium condition. The authors assumed an aggregate traffic assignment to measure congestion; however, they omitted the details of the scheduling constraints that are specific to each decision maker (Chow, 2014).

While the literature on supernetwork-based representation of a physical network and activities is rich, the time-dependent activity-travel assignment models of supernetworks are limited and not well developed (Liu et al., 2015), because time dimension significantly increases the size of supernetwork. Ouyang et al. (2011) proposed a model for solving the daily ATP scheduling problem by constructing an expanded time–space network which is extended by Fu and Lam (2014) to include uncertainty in the network. Liu et al. (2015) proposed a formulation, so-called dynamic activity-travel assignment (DATA), that is a discrete-time dynamic user equilibrium (DUE) model, in which any path through a personalised supernetwork represents an activity-travel pattern at a high level of spatial and temporal detail. In Liao et al. (2013), space-time considerations are incorporated in the supernetwork formulation, however, it is limited to space-time considerations in selection (filtration) of location sets to be included in the expanded network.

There are some critical problems with the reviewed models. In contrast to econometric-based models, the temporal dimension has been used in supernetworks; however, it is limited to time-discretised supernetworks which remarkably increase the network size. Furthermore, the structure of the developed models in the literature is a concatenation of selected locations and connections distributed at different activity-vehicle states. This structure comes with an explosion of the network scale and as a result, the optimisation on the network is intractable even for a small number of activity nodes (Liao et al., 2013). Despite the fact that some heuristics have been used to scale down the size of the personalised network by choosing a small set of locations, it is not an easy task as the (dis-) utility of choosing a location not only does depend on the (dis-) utility of that location, but also depends on the sequence of activities, the activity duration, departure time, and most importantly the network condition. Thus, scaling down the expanded network may affect the validity of the model.

### 6.2.3 HAPP-based ATPs generators

To optimally schedule the activity-travel pattern of travellers, activity routing problem (ARP) formulations have been widely used in the literature. It should be mentioned that ARP and vehicle routing problem (VRP) are identical; therefore, for the sake of simplicity, we use the ARP term to explain the concepts throughout the chapter. Recker (1995) for the first time mathematically formulated an ARP, named Household Activity Pattern

Problem (HAPP) by proposing a pickup and delivery optimisation models for the scheduling the household activity patterns in which the space-time constraint is incorporated; nonetheless, it suffers from restrictions on the choice dimensions covered such as route, mode and parking. After that, to embed a destination choice model into the routing and scheduling considerations of daily activities, the generalised ARP was introduced which allowed selection of a single location for conducting an activity among a number of candidate locations (Chow and Liu, 2012; Kang and Recker, 2013). Built on the HAPP model, Gan and Recker (2013) developed new models to model human dynamics in uncertain environments. Later, in Chow and Djavadian (2015a), the multimodality was added to the original version of HAPP to improve its functionality. It should be noted that while any point-to-point paths through supernetworks express an activity-travel pattern, the formulation in HAPP family seeks the optimal path of travellers through time and space as they complete a prescribed agenda of out-of-home activities.

Distinct from the majority of activity-based travel demand modelling techniques pointed out in the previous section, ARP-based models can offer spatiotemporal constraints as the space–time prism is associated with each activity and each traveller. Continuity of time in these models results in a relatively smaller expanded network time; nonetheless, the solution algorithms for the models are much more computationally demanding than those for the time-discretised supernetworks-based models (VRP versus shortest path algorithms).

### 6.2.4 Linkage of demand (ATPs) and traffic assignment model

The interaction between travel demand and traffic assignment models has been the backbone of the contention among researchers (Lin et al., 2008; Najmi et al., 2018) mainly due to the inconsistency between the outputs of the models. Demand outputs that are consequences of loading travel times into demand models, if loaded into the traffic assignment model, may produce updated travel times that are different from the initially loaded travel times to produce the demand outputs. This inconsistency has triggered three main research approaches for dealing with the interaction between the demand-side and traffic assignment models.

In the first category, the main purpose is running microscopic and mesoscopic analysis on the transport network. Therefore, the OD matrices, as the representatives of demand models, are linked to traffic assignment models. As loading the OD matrices usually does not result in observed traffic counts statistics, it is very common to update the OD matrices using OD calibration methods (e.g. Spiess, 1987; Cascetta and Nguyen, 1988; Lundgren and Peterson, 2008). Although the updated OD matrices are usually fully compatible with the traffic assignment model, there is actually no linkage between the original demand-side models and traffic assignment model. Neither the demand-side models are available to update the OD matrices, nor is feedback loop to transfer the network congestion to the demand-side models. This category is not under the scope of this study so the interested reader is referred to Najmi et al. (2018) for further information.

In the second category, some researchers have tried to develop combined models to fully remove the inconsistency in the models. In this regard, behavioural assumptions are translated into mathematical conditions, and then seek approximate solutions that satisfy these conditions (Bar-Gera and Boyce, 2003). In these models, travellers are often divided into some classes, either by socio-economic attributes or the purpose of their travel, assuming that travel-decision characteristics are the same within each class (e.g. same value of time and similar sensitivity to travel times in choosing their origin, destination and mode of travel) but differ among classes (Boyce and Bar-gera, 2004). Thus, the combined models are aggregates in all the perspectives which are applicable in macro and meso-level forecasting of travel demand. For a comprehensive review of the combined models, the interested reader is referred to Boyce (2002). The major problem with the combined models is that they suffer from lack of detailed ATP for each traveller.

In the third category, the focus is on simulating the travel demand and detailed ATPs. Also, there are some efforts to consider the impact of the network congestion in the scheduling process (e.g. Miller and Roorda, 2003; Kang et al., 2013; Xiong et al. 2018). Accordingly, after scheduling the travel demand over time, the scheduled trips are usually imported into the traffic assignment models (in form of ODs) for network-side analysis. Using feedback loops, the updated travel times (congestion) are fed back to the demand-side models to update travel demands and ATPs based on the measured congestion of the network. The usage of a feedback loop is indispensable in large-scale models mainly due to the non-convexity and complexity of the joint modelling structure. The standard practice is to run the joint structure iteratively until convergence. Despite the fact that these efforts connect demand-side models to traffic assignment models (Lin et al., 2008; Hao et al., 2010; Konduri et al., 2011), the linkage has some critical problems. First, within the domain of unconstrained econometric or rule-based models, the congestion effect does not optimally change the ATPs; instead, it affects some integrated attributes such as trip generation rate and OD pair values (Miller and Roorda, 2003; Lin et al., 2008b; Konduri et al., 2012). Second, as discussed by (Najmi et al., 2019a), the feedback loop is limited to simulation of TPMSs; thus, any error at the estimation of the models may result in a mismatch between the models at the initial stage of simulation which can be problematic in the subsequent iterations. The feedback loop between the models propagates the errors in the TPMSs while the iterations proceed. To rectify the second problem, a possible solution can be calibrating the whole TPMS in the presence of the feedback loop hoping to minimise the mismatch between the demand-side and traffic assignment models. Then, the calibrated model can be used in simulation. This approach is implemented in the current study as well as in Najmi et al. (2019a,b). It should be mentioned that the Multi-Agent Transport Simulation (MATSim), which is a well-known TPMS, attempts to integrate traffic assignment model and travellers' behaviours (Horni et al., 2016). MATSim runs iteratively while travellers adapt. The model starts with a pre-determined share of the travellers, normally 10%, and generates new plans by searching for new shortest-path or by optimizing the starting times and durations (Nagel and Barrett, 1997). Then MATSim selects, randomly proportional to logit-transformed scores, and executes the next plan for the remaining travellers. Thus, while MATSim generate ATPs of travellers, they are not optimal. In other word, MATSim is primarily used to search for a steady-state approximating a dynamic Nash-equilibrium (Balmer et al., 2008).

An overview of the literature as well as our contribution is presented in Table 6-1. As can be seen, all the supernetwork- and HAPP-based ATPs generators are activity-based models that have space-time considerations. While some of them (under supernetwork stream) consider traffic congestion effects on the ATPs generation, these effects are not remarkably discussed in HAPP-based models. The models typically suffer from poor/expensive/computationally intense calibration procedures. The proposed model in the this chapter is an extension of HAPP model where an ATPs generator is linked to multiple traffic assignment models. The linkage is not limited to simulation; rather, the interaction of the ATPs generator and traffic assignment models are considered in the calibration of parameters. Also, the public transport formulation is included in the model to better generalise the formulation. Furthermore, a novel calibration solution is applied to the proposed ATPs generator to better reproduce observed statistics.

Table 6-1 Overview of the literature

| ATPs generators | Spatiotemporal constraints | Model type | | | Activity-based model | Public transport included | Presence of TA model | Demand-side models calibration | | Simultaneous TA and demand calibration |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Conventional | Supernetwork-based | HAPP-based | | | | Sequential | Simultaneous | |
| TASHA: Roorda et al. (2008) | | ✓ | | | ✓ | ✓ | ✓ | ✓ | | |
| ALBATROSS: Arentze and Timmermans (2004a) | | ✓ | | | ✓ | ✓ | ✓ | ✓ | | |
| Sacramento: Bowman et al. (2006) | | ✓ | | | ✓ | ✓ | ✓ | ✓ | | |
| NYMTC: Parsons Brinckerhoff (2014) | | ✓ | | | ✓ | ✓ | ✓ | ✓ | | |
| FAMOS: Pendyala et al. (2005) | | ✓ | | | ✓ | ✓ | ✓ | ✓ | | |
| Liao (2016) | ✓ | | ✓ | | ✓ | ✓ | | | | |
| Liu et al. (2015) | ✓ | | ✓ | | ✓ | | ✓ | | | |
| Liu and Zhou (2016) | ✓ | | ✓ | | ✓ | ✓ | | | | |
| Liu et al. (2019) | ✓ | | ✓ | | ✓ | ✓ | ✓ | | | |

Table 6-1 Overview of the literature

| ATPs generators | Spatiotemporal constraints | Model type | | | Activity-based model | Public transport included | Presence of TA model | Demand-side models calibration | | Simultaneous TA and demand calibration |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Conventional | Supernetwork-based | HAPP-based | | | | Sequential | Simultaneous | |
| Li et al. (2018) | ✓ | | ✓ | | ✓ | ✓ | ✓ | | | |
| Liao (2019) | ✓ | | ✓ | | ✓ | | | | | |
| HAPP: Recker (1995) | ✓ | | | ✓ | ✓ | | | | | |
| Chow and Djavadian (2015a,b) | ✓ | | | ✓ | ✓ | | | | | |
| Chow and Recker (2012) | ✓ | | | ✓ | ✓ | | | | ✓ | |
| Xu et al. (2018) | ✓ | | | ✓ | ✓ | | | | ✓ | |
| Liu et al. (2018) | ✓ | | | ✓ | ✓ | | ✓ | | | |
| The proposed model | ✓ | | | ✓ | ✓ | ✓ | ✓ | | ✓ | ✓ |

## 6.3 Proposed TPMS

The model attempts to determine the activity-pattern of the entire day for individuals. This is helpful in TPMSs where the activity scheduling is an important component of the models. Suppose there is a list of individuals where we intend to schedule their daily trips and activity participations. The proposed model of this study primarily tries to find the optimal path of each traveller (schedule his/her activity visits in terms of sequence and duration) through time and space as they complete a prescribed agenda of activities. Furthermore, the model determines transport modes between activity locations while network properties are simultaneously updated

We make the following assumption:

1- Each traveller has a list of activity types to pursue within the spatiotemporal constraints.
2- To meet each of the traveller-specific activity types, there is a list of candidate activity nodes specific to each traveller to visit.
3- All ATPs are home-based in which home is both the origin and the destination of any feasible daily ATP which may include some sub-tours.
4- All travellers are heterogeneous so that they should be considered individually; however, they impact each other through congestion happening on the network which depends on their ATPs.
5- Public transport vehicles punctually operate based on pre-specified timetables.

To explain the general structure of the model, we use the simple example in Figure 6-1. In the proposed model, nodes are either physical nodes, which are real locations in space (physical network nodes), or activity nodes (e.g., working, shopping and parking), which are never visited for moving on the physical network but represents candidate activities that may be conducted in a physical node. Further, any link is either a travel link, on which a movement can happen on a physical network (e.g., private vehicle road, public transport links), or a virtual link, which never changes the location of a traveller but allows transition between different modes or an activity conduction (e.g., links adjacent to parking and activity nodes).

The ATP in Figure 6-1 shows that a traveller leaves home (by private car) to conduct an activity at node 8 for 2 hours, then drives to node 4 to park his/her car and switches to public transport to conduct another activity (for 4 hours) at node 14. Using public transport, the traveller goes back to node 4 to pick up his/her car, and finally to return home. In the figure, the blue links interconnecting home, activity and parking locations represent virtual links.

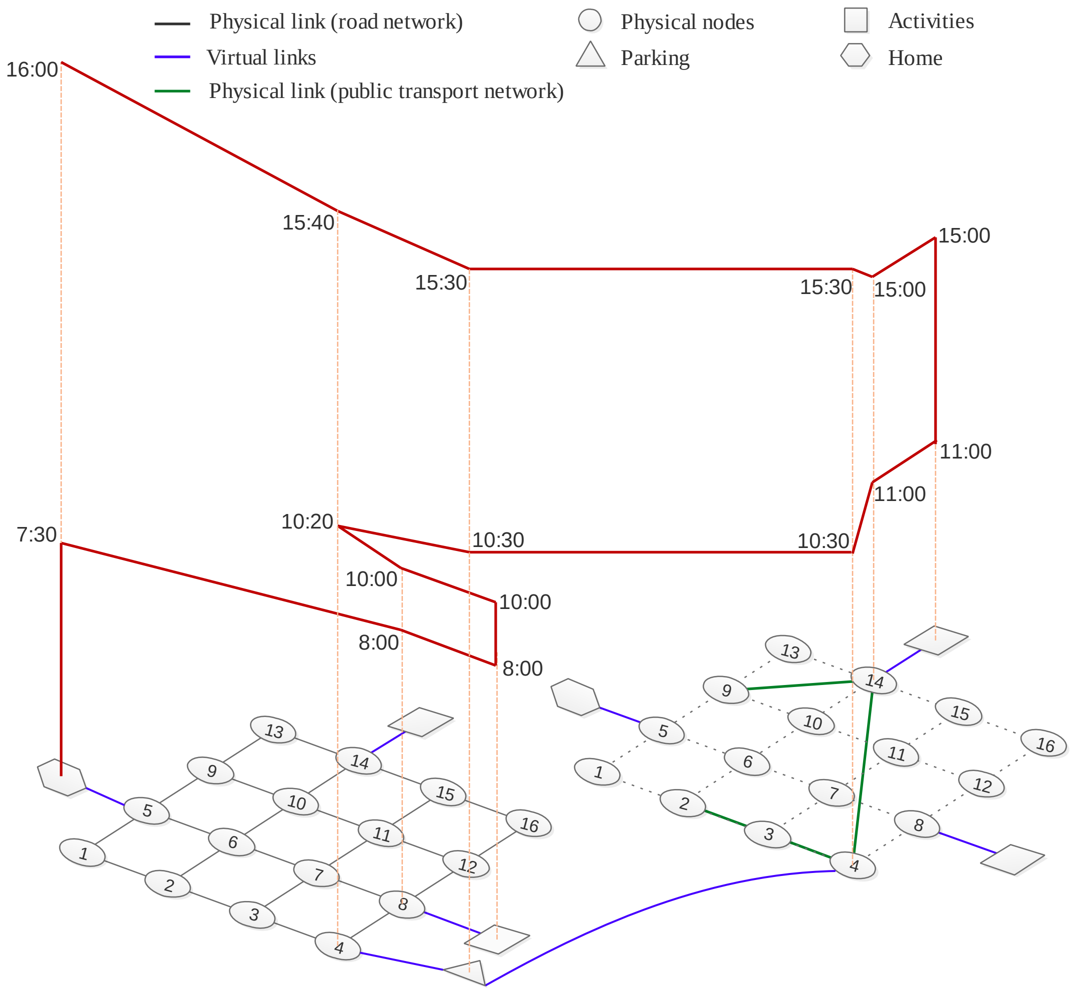



Figure 6-1 Network representation

The problem of visiting a set of activities on a network is an ARP which forms the main structure of the scheduling part of this model. As it was mentioned earlier, the proposed model is a generalised ARP with spatiotemporal constraints in which the interaction among travellers is taken into account. The pure ARP is NP-hard in complexity (Lenstra and Rinnooy Kan, 1981), whose extensions make the problem computationally burdensome. Thus, to solve the problem, we propose a pre-processing step, to prepare and scale down the solution space, and a post-processing step to map the solution to the physical network. The whole structure of the proposed model is shown in Figure 6-2.

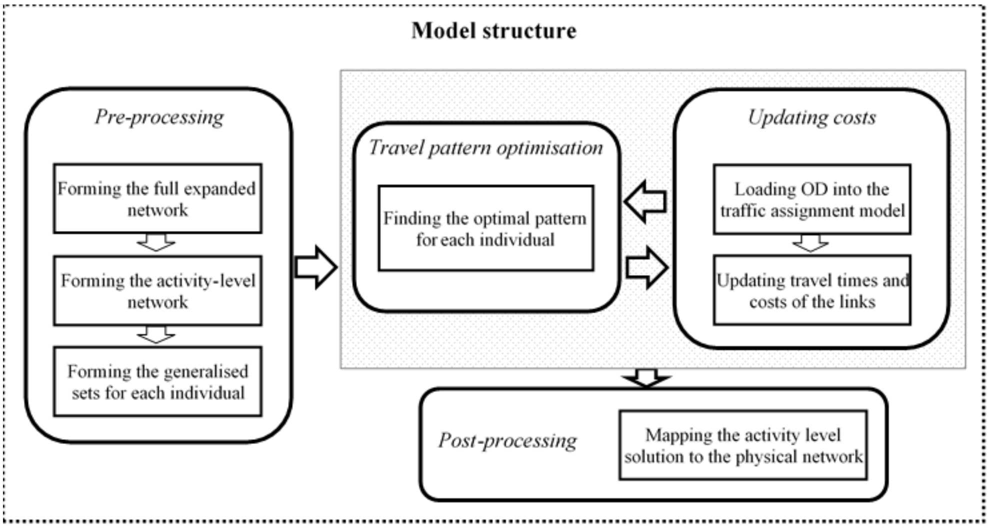



Figure 6-2 The main steps of the proposes ATP generation

### 6.3.1 Pre-processing

Optimising the original connected networks (as in Figure 6-1) is quite challenging because 1) while the individual networks (road, transit, and activity networks) within the initial connected networks are spatially connected, there are a number of logical rules and requirements that cannot be addressed by the original network, and 2) the large number of nodes and links within and between the networks represent a substantial computational challenge in solving the problem. To circumvent these obstacles, the steps that should be performed in the pre-processing include: 1) filtering the activity locations, 2) expanding the original connected networks, and 3) forming its mapped network in the activity level.

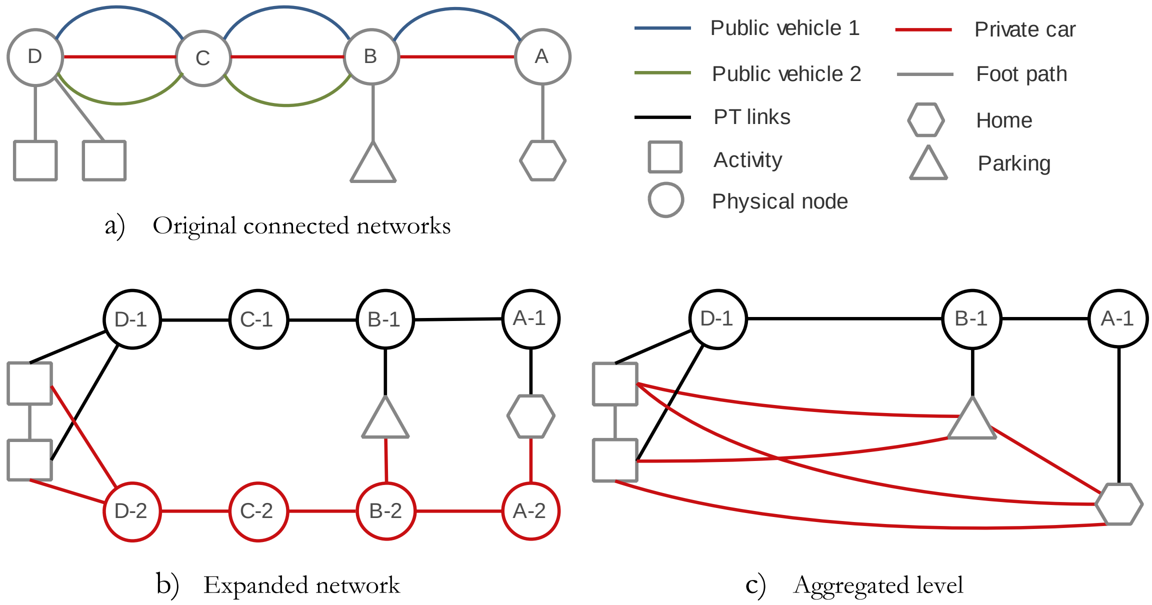
The ATP of a traveller should reflect where the traveller engages in activities, how and when to get there, and where to park private vehicles (if any) (Liao et al., 2013). The interwoven factors are optimised concurrently when solving the proposed ARP-based optimisation model (see Section 6.3.2.3) for the scheduling part of the proposed structured. The ideal case is to use all the physical and activity nodes of the network in the optimisation; however, the model is ARP-based and it is computationally burdensome to solve the model with a large number of nodes. Selection of a few activity nodes for each traveller and ignoring low-influence physical nodes (those that are less likely to be used en-route) in the network (forming activity-level network) is an alternative solution to reduce the complexity; however, it may result in undesired ATPs. While considering the trade-off between the size of network and precision of the ATP, designing a location filtering approach is a critical task. One way for tackling the problem of filtering the activity locations is to firstly determine the activity locations (for example based on some logit models) and then to opt for landmark physical nodes such as those parking nodes and transit stations that can be used to get the activity locations. An interesting filtering approach is provided in (Liao et al., 2013). The landmark physical nodes in activity-level network have a key role in modal changes. The nodes are used for intermodal changes among private car and public transit and walk.

Then, to form expanded activity-level network, additional nodes and links should be added to the original connected networks to address the necessary rules in the proposed model. The rules are as follows:

1- A traveller can leave home with a private car, bicycle, public transport, or on foot to conduct out-of-home activities.
2- If a traveller leaves home by a private car/bicycle, he/she needs to return to his/her home with the same mode of private car/bicycle at the end of their tour.
3- A traveller cannot switch from the road network to the public transport network unless he/she parks his/her private vehicle in a parking lot at a parking node.
4- If a traveller parks his/her private vehicle in a parking space to use other travelling modes, he/she must return to the parking space to remove the car before the end of the day.
5- If a traveller uses a private vehicle to get to activity locations, he/she either goes to these locations directly or park the vehicle at parking nodes to change his/her modes to get there.
6- A traveller cannot switch to the private vehicle network if he/she has left his/her home by public transport.

It should be mentioned that omitting low-influence physical nodes and connecting filtered activity nodes and landmark physical nodes does not affect the solution space because what is important in activity-level is the link type and its associated costs among the activities (which can be obtained by shortest path algorithm) and not the physical nodes that are visited en-route. Nonetheless, this reduction does not affect the solution space including the sequences of modes and switching points of the modes as the ATP on expanded the supernetwork could be easily retrieved in a post-processing step to map the activity layer to a physical network. It should be noted that in the activity level, there is a single network for all the modes, but the links are tagged by modal types.

Figure 6-3 shows how a physical network can be converted to an activity-level expanded network. In this example, there are two activities that are accessible by public vehicles 1 and 2 and a private car (see Figure 6-3a). A traveller can leave home by public vehicle 1 or private car. After reaching to the physical node B, he/she may change mode or continue with the same mode. He/She can move to public transport from the private car network only after parking the private vehicle (see Figure 6-3b). As the public transport vehicles have the same rules, all of the corresponding nodes and links for different vehicles are combined and relabelled by PT. An activity should be left with the same mode (PT or private vehicle) as is visited. Then, the expanded network can be formed by replacing low-influence physical nodes (or sequences of nodes) with the links. In the private car network (set of links), the physical nodes are only useful to make the connections among the activity and landmark nodes (here parking node); however, the accessibility and distances among the nodes are the important features of our model. Therefore, to simplify the model, all physical nodes of the private car network can be removed and replaced with links. For public transport network, the abstraction is to some extent different. Due to having parking nodes and public transport in the formulation, some of the physical nodes (landmark nodes) should be kept in the final network that the model is going to be built on. For example, in the case of public transport, the boarding stations (in this example, they are adjacent to home and parking) should be kept in the final network but keeping the other stations en-routes are not necessary. So, after deciding the nodes that should be kept in the final network, the links among them should be stablished. The cost of the new links can be obtained using shortest path algorithms on the expanded network. The boarding stations are kept as the travel times on the public transport links not only do depend on the link cost, but also on the waiting time of the nodes (see Fig 3c). Due to existence of both activity and physical nodes in the final network, we call it the aggregated level in the figure. Thus, pre-processing allows incorporating the logic rules in the solution space by expanding the network and simplifying the network by neglecting unnecessary information in the network.




a) Original connected networks

b) Expanded network

c) Aggregated level

Figure 6-3 Expanding network in Pre-processing

### 6.3.2 Travel pattern optimisation

Generalisation of the ARP and revisiting the nodes are two main concepts that are applied in the model formulation. Thus, before presenting the main body of the model, the concepts are illustrated in the following sections.

#### 6.3.2.1 Generalised activity routing problem

The Generalised ARP (GARP), equivalent to Generalised VRP (GVRP), is an extension of the VRP and was firstly introduced by Ghiani and Improta (2000). The GVRP looks for the optimal delivery or collection routes, subject to capacity restrictions, from a given depot to a number of predefined, mutually exclusive and exhaustive node-sets (clusters) (Pop et al., 2012). The concept of GVRP could be extended to daily activity destination selection where a location should be selected from a set of locations for conducting a specific activity (Kang and Recker, 2013).

Without loss of generality, we assume that each traveller has a set of activity types that needs to be conducted within the spatiotemporal constraints. Some activity types, such as school and work may have only a single candidate destination, whereas each flexible activity such as shopping can be conducted in one of multiple candidate locations. Therefore, no more than one of the candidate locations can be visited. Therefore, the problem is under the category of GARP in which the node set $V$ is partitioned into a number of clusters and the goal is to determine the best cycle, starting and ending at home, and visiting no more than one node in each cluster. Different candidate locations for each activity, assuming the same activity duration, offer the same satisfaction. Figure 6-4 depicts the network generalisation on a sample network.

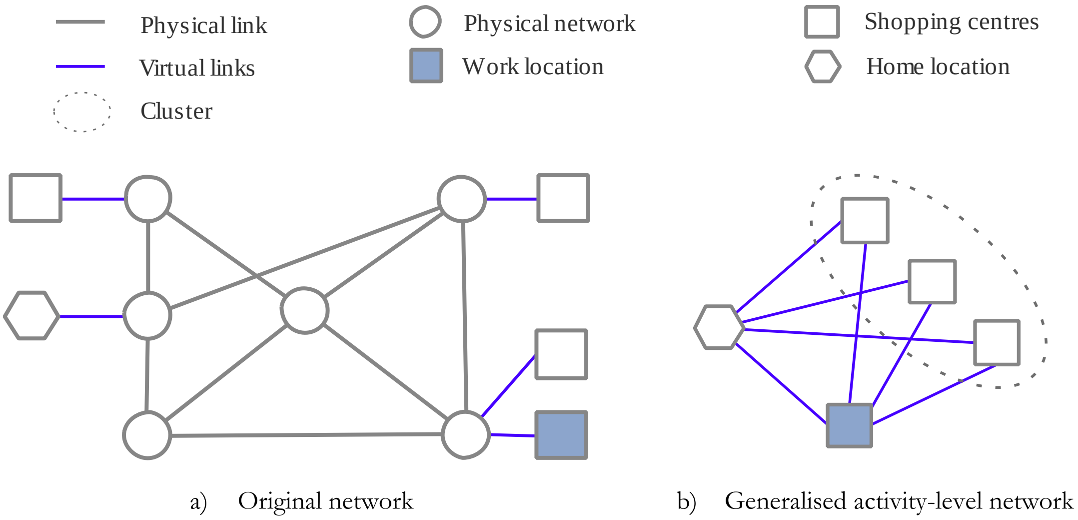



Figure 6-4 Network generalization

#### 6.3.2.2 Multi-visit vehicle routing model

Each traveller leaves home to conduct a number of activities and then returns home again by the end of the day. Such home-based tours may happen several times in a day for each traveller. In addition, parking locations and work places are other nodes that may be visited multiple times over a scheduling period. Therefore, the problem falls under the category of Split Delivery Vehicle Routing Problem (SDVRP). In the SDVRP, a fleet of capacitated vehicles serve a set of nodes (customers), with known demand, each of which is required to be visited by at least one vehicle (Archetti and Speranza, 2008). In other words, the demand and depot nodes are allowed to be served in more than one visit, thus allowing routes with smaller travel cost.

In the SDVRP literature, to formulate the multi-visit feature, scholars have enumerated either the deliveries to a specific node or the links connected to the nodes. Enumerating deliveries is commonly applied in scheduling problems (see e.g. Asbach et al., 2009;

Berghman et al., 2014; Maghrebi et al., 2014; Narayanan et al., 2015). Although both options allow revisiting nodes more than once, enumerating the nodes and link may be costly in the context of supernetworks and ARP-based models where they can significantly increase the solution space. Furthermore, while the traditional revisiting formulations can easily distinguish the routes, they do not provide all scheduling features namely departure time and visiting duration for each revisit. More precisely, expressing the scheduling constraints in the traditional revisit formulations is difficult (Kinable et al., 2014). This is in contrast with the supernetwork and ARP contexts where generating the ATPs for travellers is its main purpose. Thus, a new formulation for the SDVRP is presented in the next section which not only does not enumerate the nodes and links, but even allows tracing the optimal tours, departure time and activity duration in each node revisit.

#### 6.3.2.3 Model formulation

Visiting activities in the space-time prism with the least cost is the main factor that determines the ATP for each traveller. To achieve the optimum ATPs for the travellers, in this section, a mixed integer linear programming problem is presented.

Consider an activity-based network composed of a set of nodes, $V$, and a set of directed links, $E$. Let $(i,j) \in E$ denotes a directed link in the network which connects node $i$ to $j$ and allows the traveller/passenger $p \in P$ to traverse the links to conduct some activities. In addition, the set of home locations of the travellers is represented by $H(p) \in V$. It should be noted that a traveller may visit its home more than once in an ATP.

The time period [0,T] is chosen such that all possible daily activity-travel patterns are covered. Each node is associated with a departure time window constraint $[\underline{t}_i^p, \bar{t}_i^p]$, where $\underline{t}_i^p$ and $\bar{t}_i^p$ are the earliest and latest time to departure from node $i \in V$ by traveller $p \in P$; and an activity duration $[\underline{d}_i^p, \bar{d}_i^p]$ constraint, where $\underline{d}_i^p$ and $\bar{d}_i^p$ are the minimum and maximum durations that traveller $p \in P$ can spend at node $i \in V$. A traveller may depart a node at different time slots $n \in N$. The departure may happen by different modes of transport $k \in K$. We denote link selection variable $x_{ijll'}^{p,k,n}$, which takes the value of 1 if node $j \in V$ is visited for visit $l' \in L$ immediately after visiting node $i \in V$ for visit $l \in L$ by traveller $p \in P$ and mode $k \in K$ and at time period $n \in N$, and 0 otherwise. The variable determines the type and the sequence of visits to the nodes. Note that each node can be visited more than once each of which is called a visit.

Parameters

| | |
|---|---|
| $i \in V$ | nodes in the network |
| $k \in K$ | mode of transport which can be categorised into $PT$, $PV$, and $W$ |
| $v \in K(PT)$ | public transport vehicles |
| $S \subset V$ | subset of nodes representing parking locations |
| $i \in V(S)$ | parking nodes in the network |
| $i \in V(PT)$ | public transport nodes in the network |
| $i \in V(v)$ | nodes in the network where public vehicle $v$ has station |
| $i \in B$ | nodes in the subtour |
| $y \in Y$ | activity types |
| $i \in y$ | nodes in activity type $y \in Y$ |
| $p \in P$ | traveller $p$ in the network |
| $\bar{P} \subset P$ | subset of travellers to be used for calibration purposes |
| $H(p)$ | home location of traveller $p \in P$ |
| $n \in N$ | time slots for traffic assignment model |
| $M$ | big constant |
| $l \in L$ | visits |
| $\xi \in C^p$ | set of clusters for traveller $p \in P$ |
| $i \in \xi$ | nodes in cluster $\xi$ |
| $(i,j) \in E(k)$ | links of type $k \in K$ in the network |
| $u \in U(v)$ | counter of scheduled departure time for public vehicle $v$ |
| $h_{iu}^{v}$ | $u$th departure time of public transport $v \in K(PT)$ at node $i \in V$ |
| $\tau_{ij}^{n}$ | travel time on link $(i,j) \in E$ at time slot $n \in N$ |
| $[l_n, u_n]$ | time slot limits for time slot $n \in N$ |
| $[\underline{d}_i^p, \bar{d}_i^p]$ | limits of the spent time on node $i$ by traveller $p \in P$ |
| $[\underline{t}_i^p, \bar{t}_i^p]$ | limits of the departure time from node $i$ by traveller $p \in P$ |
| $\epsilon$ | numerical tolerance parameter |
| $\beta_{yy'}^{PV,n}$ | proportion of trips, as parameter, that select activity type $y' \in Y$ at time slot $n \in N$ (on the private vehicle network) immediately after conducting activity type $y \in Y$ |
| $\alpha_{y}^{PT,n}$ | proportion of trips, as parameter, that choose public transport (including walking) at time slot $n \in N$ immediately after conducting activity type $y \in Y$ |
| $\delta^{n}$ | proportion of trips, as parameter, that are generated at time slot $n \in N$ |

| | |
|---|---|
| $\hat{X}_{yy'}^{PV,n}$ | observed number of trips from activity type $y \in Y$ toward activity type $y' \in Y$ in time slot $n \in N$ by private vehicles |
| $\hat{X}_{y}^{PT,n}$ | observed number of trips that are originated from activity type $y \in Y$ in time slot $n \in N$ by public transport |
| $\hat{X}^{n}$ | observed number of trips that are generated in time slot $n \in N$ |

Variables:

| | |
|---|---|
| $x_{ijll'}^{p,k,n}$ | 1 if node $j \in V$ is visited for visit $l' \in L$ by mode $k \in K$ immediately after visiting node $i \in V$ for visit $l \in L$ by traveller $p \in P$ and at time slot $n \in N$ and 0 otherwise |
| $t_{il}^{p}$ | departure time from node $i \in V$ after visit $l \in L$ by traveller $p \in P$ |
| $d_{il}^{p}$ | time spent at node $i \in V$ by traveller $p \in P$ when visiting the node for visit $l \in L$ |
| $\lambda_{i}^{p}$ | 1 if traveller $p \in P$ visit node $i \in V$ and 0 otherwise |
| $\gamma_{ilu}^{p,v}$ | 1 if traveller $p \in P$ leaves node $i \in V$ after visit $l \in L$ by vehicle $v \in K(PT)$ at its $u$th departure time and 0 otherwise |

From here on, the model constraints are discussed. Constraint (6-1) states that all the activity clusters for each traveller must be visited at least once. This constraint will be discussed further together with equations (6-7)-(6-9).

$$\sum_{\substack{i\in\xi,k\in K,n\in N\\ j:(i,j)\in E(k);\, l,l'\in L}} x_{ijll'}^{p,k,n} \geq 1 \qquad \forall\, p \in P\,, \forall \xi \in C^{p} \tag{6-1}$$

Constraints (6-2)-(6-4) are the flow conservation constraints and indicate that, in an ATP, if a node is visited, it must also be left. Specifically, Constraint (6-2) enforces travellers to eventually remove their private vehicles from nodes that are used to be visit by the vehicles, before going home. Constraint (6-3) captures the transition between all modes in the system. Constraint (6-4) ensures that home is the start and end of the ATPs.

$$\sum_{\substack{i:(i,j)\in E(PV)\\ n\in N,l'\in L}} x_{ijl'l}^{p,PV,n} - \sum_{\substack{i:(j,i)\in E(PV)\\ n\in N,l'\in L}} x_{jill'}^{p,PV,n} = 0 \qquad \forall\, p \in P,\ \ \forall\, j \in V\backslash H(p),\ \ \forall l \in L \tag{6-2}$$

$$\sum_{\substack{i:(i,j)\in E(k)\\ k\in K,n\in N,l'\in L}} x_{ijl'l}^{p,k,n} - \sum_{\substack{i:(j,i)\in E(k)\\ k\in K,n\in N,l'\in L}} x_{jill'}^{p,k,n} = 0 \qquad \forall\, p \in P,\ \ \forall\, j \in V\backslash H(p),\ \ \forall l \in L \tag{6-3}$$

$$\sum_{\substack{i=H(p),j:(i,j)\in E(k)\\ k\in K,n\in N;\, l\in L}} x_{ij1l}^{p,k,n} - \sum_{\substack{j=H(p),i:(i,j)\in E(k)\\ k\in K,n\in N;\, l\in L}} x_{jil2}^{p,k,n} = 0 \qquad \forall\, p \in P \tag{6-4}$$

Private vehicle park locations play a key role in the model. They have a transition role to connect the private car and bicycle networks to public transport and pedestrian networks. If people use private vehicles to get to activity locations, either they go to the locations directly, or they park the vehicles at parking nodes to change their modes to get there. The parking nodes are usually at train stations and park-and-ride centres which allow switching to other modes to avoid urban traffic congestion. If a traveller parks their private vehicle in a parking lot, he/she must return to the parking lot to remove the car from it. Since the flow conservation constraint distinguishes between road and non-road links, the parking constraint is already covered by the constraint.

Constraint (6-5) is a time-window constraint and ensures that a feasible route (sequence of nodes) in the space-time prism will be selected. We denote the travel time on the link $(i,j)$ and time period $n \in N$ by $\tau_{ij}^{n}$.

$$t_{il}^{p} + \tau_{ij}^{n} + d_{jl'}^{p} - t_{jl'}^{p} - M\left(1 - x_{ijll'}^{p,k,n}\right) \le 0 \qquad \forall\, p \in P, \forall\, k \in K, \\ \forall (i,j) \in E(k),\ \ \forall\, l, l' \in L,\ \ \forall\, n \in N \tag{6-5}$$

Constraint (6-6) is the connectivity constraint (sub-tour elimination).

$$\sum_{\substack{k\in K,n\in N,(i,j)\in E(k)\\ i\in B, j\notin B,\ \ l,l'\in L}} x_{ijl'l}^{p,k,n} \ge 1 \qquad \forall\, p \in P,\ \ \forall B \subset V\backslash\{H(p)\} \tag{6-6}$$

where $B$ is a sub-tour formed in the ARP solution. The provided connectivity constraint is an extension of the traditional sub-tour elimination constraint originally developed by Dantzig et al. (1954). In every ARP solution, the constraint forces at least one edge pointing from $B$ to its complement. This means $B$ cannot be disconnected. In this constraint, every node $i \in B$ must be the origin of one edge to another node of $j \in B$ or to a node $j \notin B$.

Equations (6-6)-(6-8), together with equation (6-1), form an extension of the generalised vehicle routing problem that not only look for the optimal ATPs to visit a number of predefined, mutually exclusive and exhaustive activity node-sets (clusters), but also do allow visiting each of the clusters multiple times. To illustrate more, while only one node in each cluster can be visited, the node may be visited more than once (as discussed in section 6.3.2.2). Furthermore, the travellers do not necessarily visit all clusters. In this regard, for each participant $p$, $V$ is partitioned into a number of clusters $\xi$. We denote $C^p$ the set of activity clusters for traveller $p$. Thus, constraints (6-7)-(6-9) guarantee that although a node in a cluster can be visited more than once, at most one of the nodes in a cluster is visited. Constraint (6-7) ensures that at most one link in each cluster is visited. Constraint (6-8) allows outgoing links of a node to be visited only if the node is determined for at least one visit.

$$\sum_{i\in\xi}\lambda_i^p \leq 1 \qquad \forall\, p\in P, \forall\xi\in C^p \tag{6-7}$$

$$\sum_{\substack{k\in K,(i,j)\in E(k)\\ n\in N;l,l'\in L,j\in V}} x_{ijll'}^{p,k,n} - |L|\lambda_i^p \leq 0 \qquad \forall\, p\in P, \forall i\in V \tag{6-8}$$

$$\lambda_i^p \in \{0,1\} \qquad \forall\, p\in P, \forall i\in V \tag{6-9}$$

where $L$ is the set of visit numbers.

Constraints (6-10) and (6-11) ensure that departure times and activity durations are properly handled. As each of the activities and facility locations may be revisited several times (an example of which is leaving work place for eating lunch and revisiting the work activity later), the sum of the participation in an activity is accounted as the activity duration which is an important attribute that the travellers are seeking. It should be noted that the time window for departure time and minimum duration of the non-activity nodes are $[0, \mathrm{T}]$ and 0, respectively. Constraint (6-12) ensures that arrival time to each node satisfies the time restrictions of visiting the node. In the constraints, we denote $\underline{t}_i^p$ the earliest start time of conducting the activity at node $i$ by traveller $p$.

$$\underline{t}_i^p \leq t_{il}^p \leq \bar{t}_i^p \qquad \forall\, p\in P, \forall\, i\in V, \forall l\in L \tag{6-10}$$

$$\underline{d}_i^p \leq \sum_{l\in L} d_{il}^p \leq \bar{d}_i^p \qquad \forall\, p\in P, \forall\, i\in V \tag{6-11}$$

$$\underline{t}_i^p \leq t_{il}^p - d_{il}^p \qquad \forall\, p \in P, \forall\, i \in V, \forall l \in L \tag{6-12}$$

Constraints (6-13) and (6-14) specify the domain of the decision variables.

$$x_{ijll'}^{p,k,n} \in \{0,1\} \qquad \forall\, p \in P, \forall\, k \in K, \forall\, n \in N, \forall\, (i,j) \in E(k),\ \ l, l' \in L \tag{6-13}$$

$$t_{il}^p, d_{il}^p \in \mathbb{R}_{\geq 0} \qquad \forall\, p \in P, \forall\, i \in V, \quad \forall l \in L \tag{6-14}$$

**Public transport links**

Choosing the best route highly depends on the time schedule of public transport vehicles in a transport system. In this section, we abuse the notation by replacing mode $k$ with public transport vehicle $v \in K(PT)$. Each public vehicle $v \in K(PT)$ departs node $i \in V(v)$ for the $u$th visit at time $h_{iu}^v$. Furthermore, the binary variable $\gamma_{ilu}^{p,v}$ determines the time when traveller $p \in P$ leaves node $i \in V(v)$ by public vehicle $v \in K(PT)$ at its $u$th visit. Accordingly, constraint (6-15) determines the $u$th scheduled departure time of vehicle $v \in K(PT)$ that traveller $p \in P$ can get on the vehicle. Specifically, the constraint ensures that a traveller can use a public transport vehicle only if a public transport node is visited.

$$\sum_{u \in U} \gamma_{ilu}^{p,v} - \sum_{\substack{j:(i,j) \in E(v) \\ l' \in L, n \in N}} x_{ijll'}^{p,v,n} = 0 \qquad \forall\, p \in P, \forall\, v \in K(PT), \forall\, i \in V(v), \forall\, l \in L \tag{6-15}$$

Constraint (6-16) states that the departure time from a public transport node must be equal to a departure time of public transport vehicle. In the equations, the multiplication of scheduled vehicle departure time parameter $h_{iu}^v$ to vehicle departure time variable $\gamma_{ilu}^v$ determines the time when traveller $p \in P$ departs node $\in V(v)$ .

$$\sum_{u \in U, v \in K(PT)} \gamma_{ilu}^{p,v} \left(t_{il}^p - h_{iu}^v\right) = 0 \qquad \forall\, p \in P, \forall\, i \in V(v), \forall\, l \in L \tag{6-16}$$

Inequality (6-17) is the tight vehicle capacity constraint, and constraint (6-18) defines the public transport usage as an integer variable.

$$\sum_{p \in P, l \in L} \gamma_{ilu}^{p,v} - C_i^v \leq 0 \qquad \forall\, v \in K(PT), \forall\, u \in U(v), \forall\, i \in V(v) \tag{6-17}$$

$$\gamma_{ilu}^{p,v} \in \{0,1\} \qquad \forall\, p \in P, \forall\, i \in V(PT), \forall\, v \in K, \forall\, l \in L, \forall\, u \in U(v) \tag{6-18}$$

**Integration of activity-based and traffic assignment models**

Much of the literature on strategic transport models and traffic equilibrium models explore the congestion effects in peak period (e.g. de Cea et al., 2005; Gonzales and Daganzo, 2012; Wahba and Shalaby, 2014) which results in ignoring the trip chains and user scheduling behaviour throughout the scheduling period (usually a day) (Chow and Djavadian, 2015b). Entering the trip chains into the model has magnified the necessity of having multi-slots (e.g. AM, MD, PM, and EV) in TPMSs with multiple traffic assignment models. It should be mentioned that it is a common practice in TPMSs to divide a day into 4-5 time slots based on the peak hours and periods falling in between the AM and PM peak hours. The increasing trend of using multi-slots TPMSs (e.g. Miller and Roorda, 2003; Auld et al., 2016) has added to the importance of investigating and improving the interaction behaviour of the multiple traffic assignment models and the multi-slots travel scheduling (demand) models. Therefore, considering the interaction of demand and traffic assignment models in the context of network-based ATPs generators is an important concept that has not discussed in the literature, yet.

Technically, after scheduling the travel demands, the time-dependent ODs are calculated based on the travellers' scheduled trips in each time slot. Then, the ODs are imported into the traffic assignment models which results in the travel time of each link to be updated. While the models are conceptually intertwined, usually their outputs are not consistent in practice. In other words, the OD tables that are consequences of loading travel times into the scheduling models may produce updated travel times that are different from the initially loaded travel times to produce OD tables. It means that the lagged spatiotemporal prism in demand models is not compatible with the time-space prism of the traffic assignment model. To fix this issue, the necessity of an iterative procedure between the travel scheduling model and traffic assignment models is highlighted in the literature (Lin et al., 2008a).

Nevertheless, there is room to optimise/improve the distribution of travel demand across the time slots. To incorporate the influences of traffic assignment models in the ATPs generator, the travel times on the links in each time slot get iteratively updated which necessitates the rescheduling of the ATPs until convergence. This procedure is illustrated in Figure 6-5. To illustrate more, travel times $\boldsymbol{\tau}$, which are calculated in pre-processing step, play a key role in the iterative process. The pre-processing step is based on static link travel times and is performed at each iteration of the proposed algorithm, after solving the traffic assignment problems corresponding to each time slot, and prior to the solution of the ATPs generator. For each time slot, static equilibrium driven travel times for physical links are obtained and, for each pair of activity nodes, an activity-level link is introduced with a travel time equal to the shortest path travel time for the corresponding origin-destination pair in the physical network. Hence, the proposed pre-processing step does not violate the optimality conditions of the problem solved.

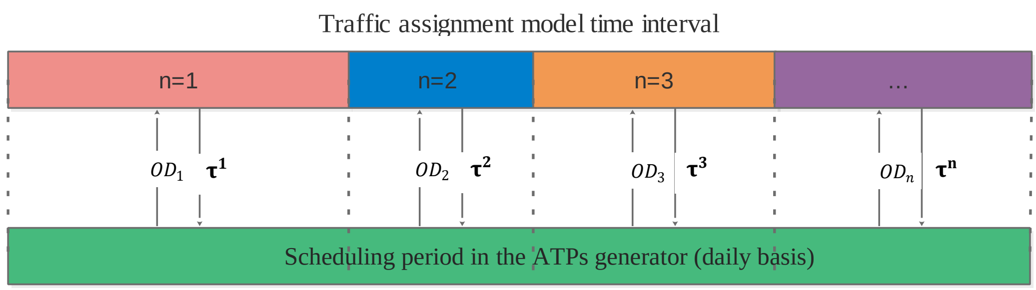



Figure 6-5 The interaction between the ATPs generator and traffic assignment model

The start time $\underline{\kappa}_n$ and closing time $\bar{\kappa}_n$ of time slots $n \in N$ are applied to partition the scheduling period into some time slots each of which corresponds to a traffic assignment model. Constraints (6-19) and (6-20) determine the time slot for the trip departing from node $i \in V$ by traveller $p \in P$. Also, the constraints ensure that each departure time belongs only to one time slot. The constraints affect $\tau_{ij}^n$ in Constraint (6-5). It is worth mentioning that $\tau_{ij}^n$ is endogenous in the whole structure of TPMS (ARP and TA models) and exogenous to the ARP model.

$$t_{il}^{p} - \bar{\kappa}_n - \left(\bar{\kappa}_{|N|} - \bar{\kappa}_1\right)\left(1 - \sum_{\substack{k\in PV, l'\in L\\ j:(i,j)\in E(k)}} x_{ijll'}^{p,k,n}\right) \leq 0 \qquad \forall\, p \in P, \forall\, i \in V, \forall l \in L, \forall\, n \in N \tag{6-19}$$

$$\underline{\kappa}_n - t_{il}^{p} - \underline{\kappa}_{|N|}\left(1 - \sum_{\substack{k\in PV, l'\in L\\ j:(i,j)\in E(k)}} x_{ijll'}^{p,k,n}\right) \leq 0 \qquad \forall\, p \in P, \forall\, i \in V, \forall l \in L, \forall\, n \in N \tag{6-20}$$

In the constraints, $\bar{\kappa}_{|N|} - \bar{\kappa}_1$ and $\underline{\kappa}_{|N|}$ are the least possible constant values where $\underline{\kappa}_{|N|}$ and $\bar{\kappa}_{|N|}$ are the start time and closing time for the last time slot of the day. Obviously, there is a trade-off between the number of time slots and the level of accuracy of the integrated model—models with higher number of time slots can capture the reality and congestion on the links more closely, but it demands more computational resources.

It should be mentioned that while the inclusion of feedback loops, in the literature, creates a stronger linkage between the demand-side and supply-side components, it still faces limitations due to the fact that the connection, usually, is only through updating travel time, not related to the calibration of model components. In other words, despite the universal usage of feedback loops, their application is limited to the simulation phase, for forecasting purposes, and their effects on the model performance in the calibration phase are usually neglected. Therefore, the effects of the feedback loops are not reflected in the calibrated parameters. The interested reader is referred to Najmi et al. (2018; 2019a) for more explanation about the integration of the model components in strategic transport models. In section 6.4.1, we include the feedback loops in the calibration process to capture their influences on splitting ratios as calibration parameters.

**System-level splitting ratios as calibration parameters**

As mentioned before, the proposed model is built on the HAPP model which is essentially a routing problem. According to Chow and Recker (2012), there are some characteristics in ARP which make using a utility maximisation approach for parameter estimation challenging. The characteristics are 1) the extremely large number of alternatives, 2) a combination of continuous and discrete variables, 3) non-mutually exclusive choices, and 4) the complexity of space-time constraints. Because of the complexity of the ARP and also the nature of its solution, their calibration is challenging. To tackle this issue, in Chow and Liu (2012), an inverse optimisation approach is proposed to estimate the coefficients of a set of given objective functions for each traveller. In other efforts, Regue et al. (2015) and Xu et al. (2018) provide calibration solutions by focusing on random utility estimation and goal programming approaches, respectively. Specifically, Xu et al. (2018) develop a random utility-based estimation framework for a variant of HAPP. Their estimation framework is treated as a pattern selection problem and the coefficients for activity selection, activity durations, and activity sequencing are calibrated. In these calibration solutions, the focus is on reproducing the ATPs of each household by adjusting the utilities (weights) of objective function terms; therefore, their calibration solutions are household-level while system-level properties are overlooked.

Considering TPMSs' system-level properties (such as link travel times among many others) is a critical aspect of the proposed formulation, which albeit indirectly affects travellers' individual level properties. Here, we introduce splitting ratios to control the system-level behavior of the model and of the transport network. The model distributes all generated trips into the network using splitting ratios based on 1) trip purposes on private vehicle network, $\beta_{yy'}^{PV,n}$, 2) time slots, $\delta^n$, and 3) public transport network, $\alpha_y^{PT,n}$. Not only do the splitting ratios control the system-level properties of the proposed TPMS, but they also consider the interaction among travellers. Equations (6-21)-(6-23) are the distributing constraints in the model. Note that $y, y' \in Y$ denotes the activities (trip purposes) that the travellers participate. We use activities instead of nodes to scale down the problem.

$$\sum_{\substack{p\in P,n\in N;l,l'\in L\\(i,j)\in E(PV),i\in y,j\in y'}} x_{ijll'}^{p,PV,n} - \sum_{\substack{p\in P,n\in N;l,l'\in L\\ j\in y,i:(i,j)\in E(PV)}} \beta_{yy'}^{PV,n} x_{ijll'}^{p,PV,n} - \epsilon \leq 0 \qquad \forall\, y, y' \in Y \tag{6-21}$$

$$\sum_{\substack{p\in P,n\in N;l,l'\in L\\ i\in y,j:(i,j)\in E(PT)}} x_{ijll'}^{p,PT,n} - \sum_{\substack{p\in P,n\in N;l,l'\in L\\ j\in y,i:(i,j)\in E(k)}} \alpha_y^{PT,n} x_{ijll'}^{p,k,n} - \epsilon \leq 0 \qquad \forall\, y \in Y \tag{6-22}$$

$$\sum_{\substack{p\in P,k\in K;l,l'\in L\\(i,j)\in E(k)}} x_{ijll'}^{p,k,n} - \sum_{\substack{p\in P,k\in K;l,l'\in L\\ n'\in N,(i,j)\in E(k)}} \delta^n x_{ijll'}^{p,k,n'} - \epsilon \leq 0 \qquad \forall\, n \in N \tag{6-23}$$

where $\epsilon$ is the numerical tolerance parameter added to the equations to avoid possible infeasibilities.

While the splitting ratios are parameters and exogenous to the model, they have a determinant role on the system output; therefore, their calibration can remarkably enhance the model capability in reproducing observed ATPs. These parameters should be calibrated in such a way that not only the model can reproduce system-level behaviours, but also be able to reproduce individual-level decisions (i.e. ATPs). In line with this, we introduce the objective function given in Equation (6-24).

**Objective function**

$$
\begin{aligned}
\mathbf{min} \quad & \sum_{\substack{k\in K,(i,j)\in E(k)\\ n\in N;l,l'\in L,p\in P}} \tau_{ij}^{n} x_{ijll'}^{p,k,n} + \sum_{\substack{k\in K,(i,j)\in E(k)\\ n\in N;l,l'\in L,p\in P}} \left(t_{jl'}^{p} - t_{il}^{p} - d_{jl'}^{p} - \tau_{ij}^{n}\right) x_{ijll'}^{p,k,n} \\
& + \sum_{\substack{k\in K,(i,j)\in E(PT)\\ n\in N;l,l'\in L,p\in P}} d_{il}^{p} x_{ijll'}^{p,PT,n} \\
& + \sum_{y,y'\in Y} \left| \sum_{\substack{p\in P,n\in N;l,l'\in L\\ (i,j)\in E(PV),i\in y,j\in y'}} x_{ijll'}^{p,PV,n} - \sum_{n\in N} \hat{X}_{yy'}^{PV,n} \right| \\
& + \sum_{y\in Y} \left| \sum_{\substack{p\in P,n\in N;l,l'\in L\\ i\in y,j:(i,j)\in E(PT)}} x_{ijll'}^{p,PT,n} - \sum_{n\in N} \hat{X}_{y}^{PT,n} \right| \\
& + \sum_{n\in N} \left| \sum_{\substack{p\in P,k\in K;l,l'\in L\\ (i,j)\in E(k)}} x_{ijll'}^{p,k,n} - \hat{X}^{n} \right|
\end{aligned}
\tag{6-24}
$$

Similar to other calibration approaches, we are looking for the best values for splitting ratios (as parameters) that compromise the ability of the model to reproduce the observed ATPs to an acceptable extent, with the generation of proper ATPs in terms of time and cost. In other words, in the proposed calibration procedure, there is a trade-off between generating optimum ATPs for travellers and reproducing the observed ATPs. While the first to third terms in objective function (24) seek optimum ATPs, the fourth to sixth terms reproduce observed ATPs.

The first term is the total travel time in the transport system. The second and third terms are the total waiting time in the system. A portion of time spent at each node is subject to waiting time. Although the ideal value for waiting time is 0, the time windows at departure times of the activity nodes, time windows for the activity durations, and the scheduled timetable of public transport vehicles may result in some undesirable waiting time. Specifically, the second term captures the spent time in the system that is not for dwelling and transport. The third term captures the waiting time in the public transport nodes and requires detailed explanation. The interpretation of the spent time (dwell time) $d_{il}^{p}$ is different for public transport and activity nodes. The spent time at activity nodes increases the utility but the spent time at public transport nodes reduces the utility. The reason is that the spent time at public transport nodes is due to waiting for arrival of public transport vehicles as public transport vehicles have their scheduled timetable. Therefore, arriving at the station sooner than the scheduled departure time increases the waiting time in the system. Thus, the third term captures the additional waiting time due to the waiting time for public transport vehicles. It should be emphasised that, compared to the original HAPP model, this model is not household-based; instead, we consider each traveller's attributes and considerations.

The fourth to sixth terms are used to minimise the deviation of the ATPs from observed ATPs and also to calculate the splitting ratios. Specifically, the fourth, fifth, and sixth terms, respectively, account for the total deviations of different generated purpose-specific trips, the total deviation of the generated origin-specific trips which use PT vehicles, and the total deviation of the generated trips in each time slot, from their corresponding observed trips. To calibrate the splitting ratios, the optimisation problem consisting of constraints (6-1)-(6-20) together with the objective function (6-24) should be solved, and the splitting ratios should be calculated subject to Constraints (6-25) and (6-26). It should be noted that having the generated ATPs, we can obtain various splitting ratios by calculating the trip distribution ratios over different purposes, modes, and time slots. The obtained splitting ratios are not calibrated yet as the effects of traffic assignment models are not yet considered in the ATPs generation model. Calibrating the splitting ratios is discussed in detail in Section 6.4.

$$\sum_{y' \in Y, n \in N} \beta_{yy'}^{n,PV} + \alpha_y^{n,PT} = 1 \qquad \forall\, y \in Y \tag{6-25}$$

$$\sum_{n \in N} \delta^n = 1 \tag{6-26}$$

At last, it should be mentioned that Equation (6-27) can be used to keep track of the time spent in parking lots.

$$\begin{aligned}\sum_{\substack{i: i \in V(S), (i,j) \in E(PV) \\ p \in P, n \in N; l, l' \in L}} x_{ijll'}^{p,PV,n}\, t_{il}^{p} - \sum_{\substack{i: i \in V(S), (i,j) \in E(PT) \\ p \in P, n \in N; l, l' \in L}} x_{ijll'}^{p,PT,n}\, t_{il}^{p} \\ + \sum_{\substack{j: j \in V(S), (i,j) \in E(PV) \\ p \in P, n \in N; l, l' \in L}} x_{ijll'}^{p,PV,n}\, d_{jl'}^{p}\end{aligned} \tag{6-27}$$

### 6.3.3 Post-processing

In the post-processing, after convergence of the model, the generated ATPs for all the travellers are mapped to the physical network to obtain the exact route of travellers. While the sequence of activities and the time slots of the departure times are available from the scheduling part of the proposed transport model, the physical routes can be obtained from the traffic assignment models.

## 6.4 Model convergence

In Section 6.3.2.3, we discussed the calibration model for the ATPs generator; nonetheless, its integration with the traffic assignment models is not discussed. In this section, we elaborate a calibration procedure to iteratively use the calibration model to obtain calibrated splitting ratios.

### 6.4.1 Calibration procedure

In practice, model calibration is usually a costly process mainly due to the costs associated with data gathering. Therefore, the standard practice is to calibrate models over a *proportion of the population*, as a representative of the overall population, and then apply the calibrated model to a *synthesised population* for simulation purposes (Ortúzar S. and Willumsen, 2011). Therefore, there are usually two datasets – observed tours (sample) and synthesised data for the entire population – that are used for calibration and simulation purposes. There are different techniques to form a sample representative of the population which fall outside of the scope of this study. Interested readers are referred to Meyer and Miller (1984), Auld et al. (2009), and Ortúzar S. and Willumsen (2011) for detailed descriptions.

While the ATPs generator in the calibration process should be run on a proportion of data, the traffic assignment models should be run on the generated tours of the whole population as the settings of traffic assignment models are for the whole population. Otherwise, we may have free flow traffic in the entire (or close to entire) network. To address the inconsistency between the ATPs generator and traffic assignment models, in the calibration process, there are two alternative solutions: 1) run the ATPs generator over a proportion of the population, then expand the generated tours to the full time-dependent OD matrices (for the whole population), and next load the generated ODs to traffic assignment models, and 2) run the ATPs generator, obtain the splitting ratios, run the ATPs generator on the synthesised data, generate ODs, and load the ODs to traffic assignment models (see Figure 6-6). The second approach which is a joint calibration structure is more appropriate as it allows us to capture the reciprocal interaction among all splitting ratios, the ATPs generator, synthesised population, and traffic assignment models and their impacts on the splitting ratios. As a result, the second approach is expected to perform better than the first alternative (Najmi et al., 2019b); hence, we use this alternative in this chapter.

As it is shown in Figure 6, the constraints (6-1)-(6-20) along with the objective function (6-24) are solved for a proportion of population with observed ATPs to calculate and adjust the splitting ratios. Next, the adjusted splitting ratios are used in the constraints (6-21)-(6-23) to generate ATPs for the synthesised population. At this stage, the constraints (6-1)-(6-23) along with the objective function (6-28), which incorporates the first three terms of the objective function (6-24), are used to generate the ATPs for the synthesised population. Then, the ODs for different time slots are generated and loaded to the traffic assignment model. Model convergence is constantly being investigated in the calibration process. In case of convergence, the latest calculated splitting ratios are the calibrated splitting ratios and the process ends; otherwise, the process should be reimplemented with the updated travel times obtained from traffic assignment models. Some convergence criteria are introduced in Section 6.4.2.

$$\begin{aligned} \mathbf{min} \quad & \sum_{\substack{k\in K,(i,j)\in E(k) \\ n\in N;l,l'\in L,p\in P}} \tau_{ij}^{n} x_{ijll'}^{p,k,n} + \sum_{\substack{k\in K,(i,j)\in E(k) \\ n\in N;l,l'\in L,p\in P}} \left(t_{jl'}^{p} - t_{il}^{p} - d_{jl'}^{p} - \tau_{ij}^{n}\right) x_{ijll'}^{p,k,n} \\ & + \sum_{\substack{k\in K,(i,j)\in E(PT) \\ n\in N;l,l'\in L,p\in P}} d_{il}^{p} x_{ijll'}^{p,PT,n} \end{aligned} \tag{6-28}$$

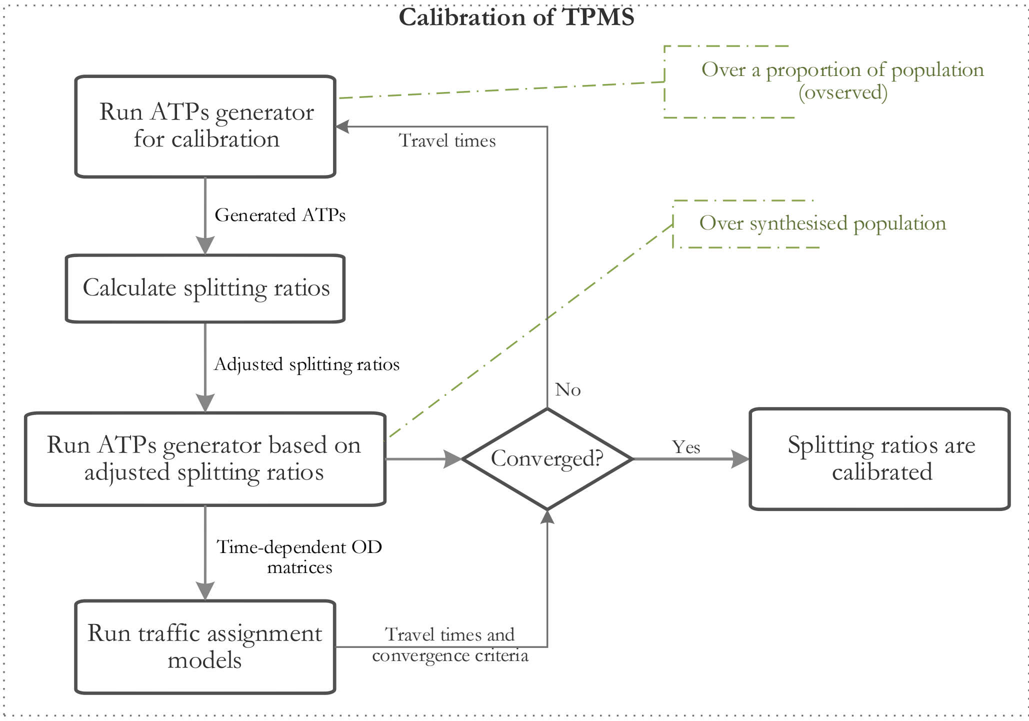



Figure 6-6 Calibration frameworks of TPMSs

The calibration process of the joint demand-supply model is summarised in Algorithm 1.

**Algorithm 1:** *Calibration of the joint model*

1 **Input:** activity lists, alternative choices lists (see Section 6.3.2.1), time windows, convergence criteria (see Section 6.4.2)

2 **Output:** calibrated splitting ratios (see Section 6.4.1)

3 Select a portion of travellers $\bar{P}$ randomly

4 Construct the network over the selected travellers while the splitting ratios are among variables

5 **While** not converged **do**:

6 Run the ATPs generator over a proportion of the population

7 Obtain the adjusted splitting ratios

8 Run the ATPs generator over a synthesised population based on adjusted splitting ratios

9 Generated ODs for each time slot ($OD_n$)

10 Run the traffic assignment models

11 Update travel times ($\boldsymbol{\tau}^{n}$)

12 **end while**

13 Obtain the calibrated splitting ratios values

A technical problem in the iterative structures is that the updated travel times cannot be directly used in calibration structures. Updating the ATPs schedules is not straightforward as all the travellers try to re-route and circumvent the congested links. As the travellers selfishly choose their routes purely based on the travel time, these concurrent updates may only shift the congestions to other links which then may even exacerbate the optimality gap in the models. The direct usage of the updated travel times in each iteration usually results in oscillations in performance criteria. The method of successive averages (MSA) (Sheffi, 1985) is used to average the travel times before running the ATP models to prevent an endless cycle of repeated alternation optimum routes in different iterations.

MSA converges to the equilibrium solution in static traffic assignment (STA) problems with well-behaved link-cost functions (Powell and Sheffi, 1982). However, the typically slow convergence rate of MSA in STA (Sheffi, 1985) can be a problem not only in the developed model in this chapter but also in large-scale TPMSs in practice, where the computation cost per iteration can be high due to time-space or even solely time expanded routing calculations.

### 6.4.2 Convergence criteria

As it was shown in Figure 6-6, the proposed model iteratively updates OD matrices and travel times. Although travel times and OD values form the main body of the objective function, investigating the convergence behaviour of the model can be fruitful not only with regard to the changes in travel times and OD values but also with regard to the changes in some other criteria such as trip generation rates and splitting ratios. The behaviours can determine the stopping criterion in practice.

Four measures of convergence can be used: 1) OD matrices convergence (ODC), 2) travel time convergence (TTC), 3) trip generation convergence (TGC), and 4) Splitting ratios convergence (SRC). If the average of difference in the subsequent iterations is less than a predefined stopping criterion, the algorithm stops whose output is the converged solution. The convergence criteria are outlined in equations (6-29a)-(6-29d):

$$ODC = \sum_{od \in OD} \frac{\left|OD_{od}^{r} - OD_{od}^{r-1}\right|}{OD_{od}^{r-1}} \times 100 \qquad \text{(6-29a)}$$

$$TTC = \sum_{p \in P} \frac{\left|TT_{p}^{r} - TT_{p}^{r-1}\right|}{TT_{p}^{r-1}} \times 100 \qquad \text{(6-29b)}$$

$$SRC = \sum_{y,y' \in Y} \left| \beta_{y,y'}^{r} - \beta_{y,y'}^{r-1} \right| \tag{6-29c}$$

$$TGC = \sum_{n \in N} \frac{|TG_n^r - TG_n^{r-1}|}{TG_n^{r-1}} \tag{6-29d}$$

where $OD_{od}^{r}$, $TT_p^r$, and $TG_n^r$ are the total number of trips between OD pair $od$, total travel cost for traveller $p$, and total number of trips at time slot $n$, at iteration $r$, respectively.

### 6.4.3 Model complexity

Finding a feasible solution for the ARP with time window problem in itself is an NP-complete problem (Savelsbergh, 1985). This is the reason that heuristics play a key role in solving the problems. Nevertheless, realistic size instances are solvable optimally through mathematical programming techniques when the problem is sufficiently constrained (Cordeau et al., 2007). As the proposed model in this study is a generalisation version of ARP with time window, and also the calibration constraints are introduced, the model is quite complex to solve. The complexity is indispensable because capturing the determinant rules in real-world activity scheduling of travellers requires an extensive number of variables as well as linear and integer constraints.

As the current study has concentrated on the development of a comprehensive formulation for any common transport system, we do not intend to introduce heuristic methods to solve the problem. Nonetheless, a simple version of the model with a reasonable size (to show the capability of the model) is solved in Section 6.5 through mathematical programming techniques.

## 6.5 Numerical example

In this section, we conduct numerical experiments to evaluate the performance of the proposed ATPs generator and its integration with traffic network assignment on the Sioux Falls network.

### 6.5.1 Data

The Sioux Falls network was originally proposed by LeBlanc (1988), based on a simplified road network of Sioux Falls. It originally contains 24 nodes and 76 links. The network's spatial configuration is shown in Figure 6-7. Although the link capacities and traffic flows are originally per hour, we modified the lane configuration of the network by changing the scheduling period (turning from one to 14 hours) and adjusting the link capacities. The scheduling period is from 7:00am to 9:00pm which, in some of the conducted experiments, is partitioned into four time slots of 7:00am to 10:00am, 10:00am to 2:00pm, 2:00pm to 5:00pm, and 5:00pm to 9:00pm. The original demand of Sioux Falls network approximates 336,000 veh/h, however, in these numerical experiments, we adjust the travel demand to about 130 veh/h based on the new roadway capacities. To have this number of trips, we generate activity-travel patterns for 600 people as synthesised datasets so that each person can have on average 3 trips in his/her activity pattern.

The parameters in Table 6-2 are used to generate the synthesised datasets. Ten random replications of travellers with randomly selected attributes are generated to be able to accurately compare and assess the performance of different variants of the model. To generate the random streams, we firstly generate the activity type and their sequences that the activity types must be met. We consider 4 activity types of work, shopping, service and education. All nodes on the Sioux Fall network are potential home and work locations. However, as it is depicted in Figure 6-7, a limited number of activity spots (2 shopping centres, 3 educational centres and 2 service centres) are chosen and located on the network.

After determining the activity types and their sequences, the activity locations are determined. We differentiate between different activities to be met. In these experiments, the home locations for each traveller is determined first, and then the location of fixed activities such as work and school are generated by giving the higher weights to the nodes closer to their home. For this purpose, a simple logit model is used with the alternative specific constants and travel-time coefficient parameters provided in Table 6-2. We assume that either the work trip or the educational one is allowed to be included in an activity-travel pattern, if any. After assigning the home and fixed activity locations, the flexible activity locations are generated for each traveller using the same logit model.

Table 6-2 Parameters used to generate synthetic population

| Parameters | Values |
|---|---|
| Alternative specific constant | 5 |
| Travel-time coefficient | -0.1 |
| Number of time slots | 4 |
| Number of home locations | 24 |
| Number of work locations | 24 |
| Number of shopping center locations | 2 |
| Number of service center locations | 2 |
| Number of educational locations | 3 |
| Commuting Probability | 0.7 |
| Going to a service center probability | 0.6 |
| Going to a shopping center probability | 0.8 |
| Going to an educational center probability | 0.5 |
| Time spent at home before leaving | Randomly from [0,350] |
| Work duration | Randomly from [300,540] |
| Service duration | Randomly from [15,120] |
| Shopping duration | Randomly from [15,120] |
| Education duration | Randomly from [240,360] |

The time window for the departure time and the duration of activities are randomly selected using a uniform distribution from the ranges provided in Table 6-2. Furthermore, since only four time periods are considered for a day in this study, and the time periods are wide, we intentionally use a relatively large time window for the departure time of the flexible activities such as shopping and service centres to allow them to easily move between time slots.

It should be mentioned that the public transport part of the model is not used in the configuration analysis due to the complexity of the formulation.

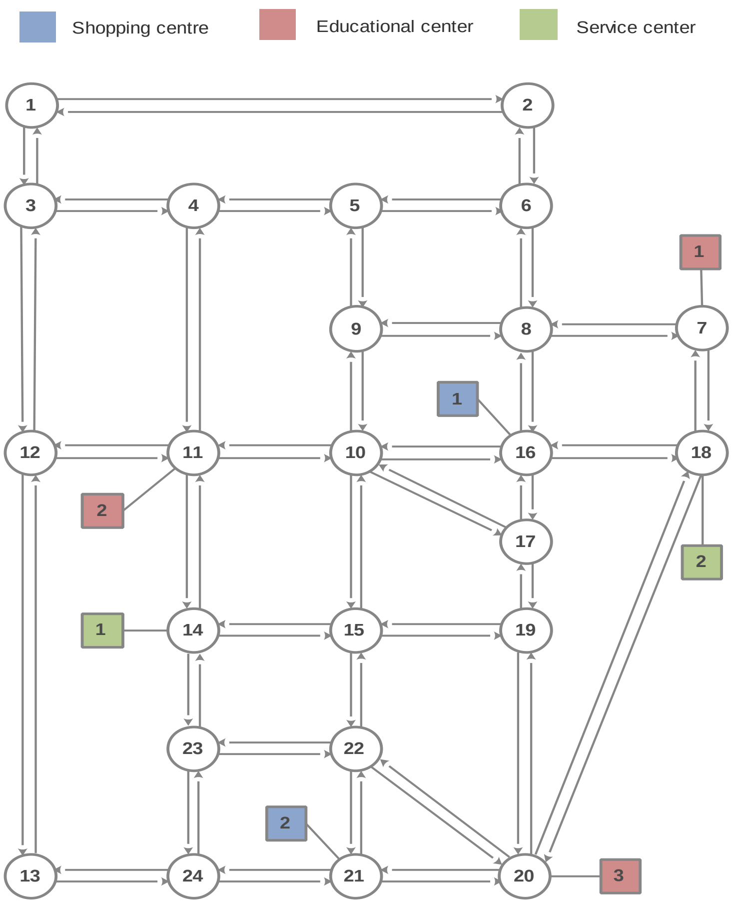



Figure 6-7 Network activity locations

### 6.5.2 Model configurations

The goal of the case study is to 1) analyse the convergence of the single-slot versus multiple-slots TPMSs, 2) analyse the performance of splitting ratios in reproducing the observed activity patterns, and 3) compare the performance of the single-slot versus multiple-slots TPMSs. To illustrate the application of the proposed model, there are six variants discussed in this chapter. These variants are abbreviated as follows: 1-TWOS (single time slot without splitting ratios), 1-TWS (single time slot with splitting ratios), 4-TWOS (four time slots without splitting ratios), 4-TWS (four time slot with splitting ratios), 8-TWOS (eight time slots without splitting ratios), and 8-TWS (eight time slot with splitting ratios). In 1-TWOS, there is a single time slot partition for the activity-travel pattern problem and consequently a single traffic assignment model. In addition, there is not any calibration model, thus the ARP model without the calibration constraints and network models are iteratively solved. The ATPs generator in 1-TWOS is equivalent to original HAPP model (Recker, 1995) that is linked with a traffic assignment model. In 1-TWS, the single time slot ARP and single traffic assignment model are iteratively solved in the presence of calibrated splitting ratios. In 4/8-TWOS, there are four/eight time-lots for ARP and four/eight traffic assignment models yet no splitting ratios. In 4/8-TWS, there are four/eight time-lots for ARP and four/eight traffic assignment models in the presence of the calibrated splitting ratios. It is worth to emphasise that the variants with the splitting ratios should be calibrated first to estimate the splitting ratios. In 1/4/8-TWOS variants, the ARP and traffic assignment models are iteratively solved to reach convergence. However, 1/4/8-TWS variants include two phases, 1) the ARP for calibration, ARP for simulation, and network models are iteratively solved to find the converged splitting ratios (discussed in Figure 6-6), and 2) the calibrated splitting ratios are used for simulation, which means that the ARP with calibrated splitting ratios and network models are run iteratively to reach convergence.

### 6.5.3 Simplified calibration model

The structure in Figure 6-6 is used to calibrate the model. Furthermore, only the splitting ratio $\beta$ is used for the calibration purposes. Therefore, the fifth and sixth terms of Equation (6-24) are ignored. Still, solving the ARP with the distributing constraint is complicated; thus, to solve the model with exact methods, we 1) use a proportion of the population (20 percent) to solve the ARP model, 2) ignore the time slot parameter in the splitting ratio and thus a purpose-specific splitting ratio is generated in the calibration model, and 3) consider the entire day as a single-slot and solve a single-slot ARP model which is in line with purpose-specific splitting ratio. Despite of the fact that the ARP model for calibration is single-slot, the ARP with adjusted splitting ratios is multiple slots in 4/8-TWS and 4/8-TWOS variants. Thus, the average of the travel times obtained from the network is used in the single-slot ARP model for calibration.

### 6.5.4 Convergence and evaluation criteria

To investigate the convergence behaviour of the variants, we use the convergence criteria (29a-c). Despite the fact that the convergence criteria can show the performance of the system, we use an activity-travel pattern reproduction (ATPR) measure, to evaluate the performance of the model in reproducing the observed activity-travel patterns.

Furthermore, ATPR can be used as another convergence criterion. Thus, Equation (6-30) is used to calculate the percentage of the observed activity-travel patterns that are generated by the proposed model.

$$ATPR = \left( 1 - \frac{\sum_{p \in P; y,y' \in Y} \left| \sum_{\substack{n \in N; l,l' \in L \\ i \in y, j:(i,j) \in E(PV)}} x_{ijll'}^{p,PV,n} - \hat{x}_{y,y'}^{p} \right|}{\sum_{p \in P; y,y' \in Y} \hat{x}_{y,y'}^{p}} \right) \times 100 \qquad (6\text{-}30)$$

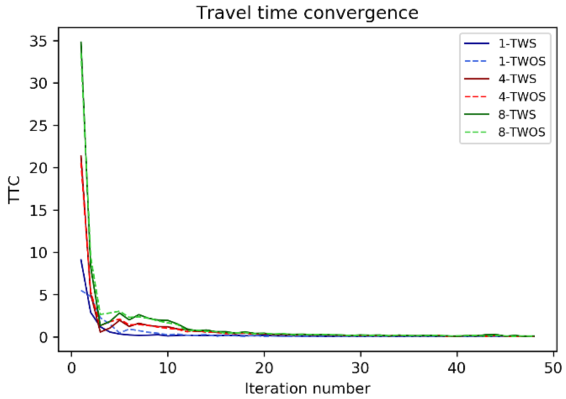
All algorithms of the proposed multi-modal trip chaining models are implemented in Python 2.7 on a machine with 16 GB of RAM with a processor of i7-4770. The optimisation problem is coded in Pyomo (Hart et al., 2011), a free and open-source algebraic modelling language developed in Python, and CPLEX solver is applied for solving the problem. The computational results are presented in the following subsection.

### 6.5.5 Computational results

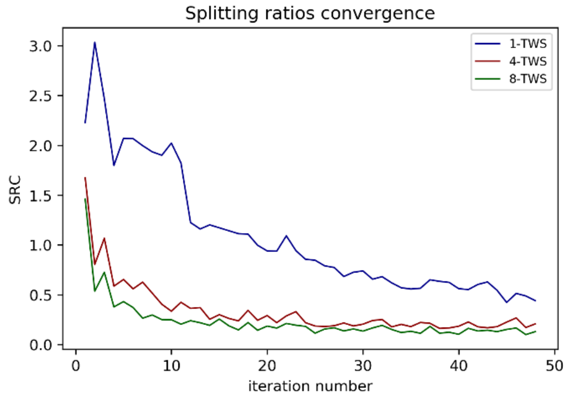
Figure 6-8 shows the convergence behaviour of different variants. Figure 6-8a reveals that the travel times for all the variants converge after a few iterations. It can be observed that the variants experience a steep nosedive in the very first iterations. For 1-TWS and 1-TWOS, the TTC values level out at about zero in the 5$^{th}$ and the 10$^{th}$ iterations; however, it is about the 20$^{th}$ iteration that 4/8-TWS and 4/8-TWOS meet zero. The TTC values for all the variants remain just above 0% after 20$^{th}$ iterations.

Figure 6-8b and c depict the performance of the variants in terms of SRC and ODC. The more the number of time slots, the higher the convergence rates in terms of SRC and ODC. Compared to the corresponding 1-TWS, its multiple time slot versions of the model (4/8-TWS) converges faster; both in terms of SRC and ODC. This is to some extent expected because partitioning the day allows for 1) more detailed travel time, and 2) higher number of splitting ratios both leading to more accurate predictions and as a result smaller gaps across iterations. The splitting ratios in 4/8-TWS converge after a few iterations while the SRC speed for 1-TWS is very slow. Specifically, the SRC for 4- and 8- TWS, respectively, remain below 0.5 and 0.3 after the 9$^{th}$ iteration to reach convergence.

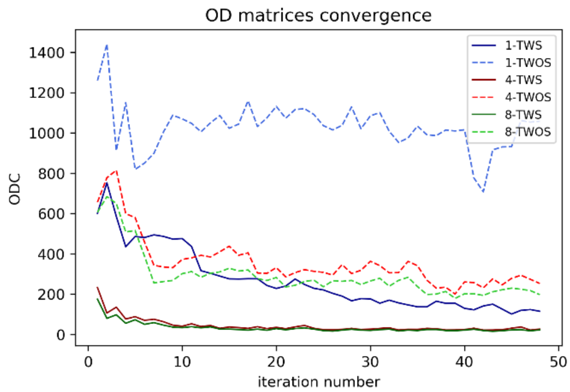
Comparing the behaviour of the variants reveals that the OD matrices that are generated in the variants without the splitting ratios are not converged. This means that the OD matrices in the subsequent iterations are not consistent although the total cost is converged.




a) Relative gap in travel times




b) Relative gap in splitting ratios




c) Relative gap in OD values

Figure 6-8 Evolution of the relative gap for the proposed TPMS variants

Figure 6-9 shows that the splitting ratios are absolutely effective in reproducing the observed patterns. The reproduction rates for 1/4/8-TWS variants are almost above 50 percent which shows significant improvement in the variants in comparison with 1/4/8-TWOS variants within which the splitting ratios are not included. Also, the figure reveals that 1/4/8-TWS variants converge in term of ATPR after a few iterations. Although there are a few spikes in the 1/4/8-TWS variants cases, they are not significant. An interesting result is that the 4/8-TWS variants converge fast after 8 iterations. Not only do the variants without splitting ratios generate disappointing ATPR rates, but also they hardly converge. This shows the determinant role of splitting ratios in the proposed model.

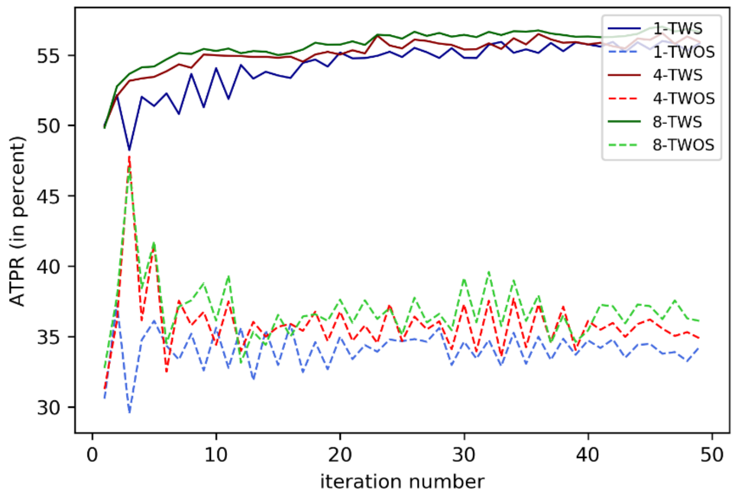
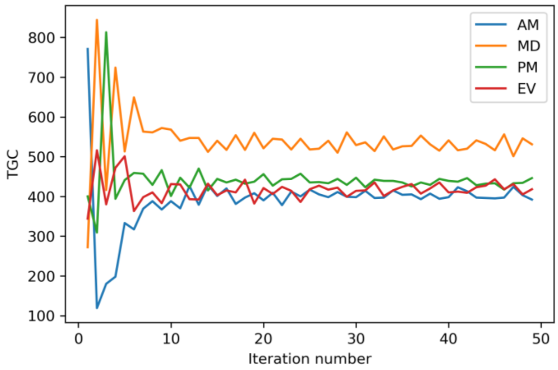


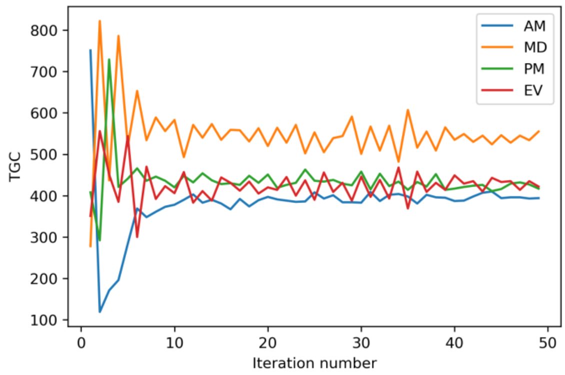

Figure 6-9 Reproducing the observed trip patterns (more is better)

Another interesting outcome is the trip generation profile of the multi-slots variants. Figure 6-10 presents the importance of the feedback loop in the variants. Before the 8th iteration, the number of trips over different time slots is extremely unstable. Afterward, the models have converged although there are a few spikes in the 4/8-TWOS cases. Furthermore, trip generation rates for the first iterations represent a condition that feedback loops are not presented in the model. It can be seen that the values for iteration 1 are significantly different from the corresponding rates after convergence (where the feedback loops are included). For example, the number of trips generated by 4-TWS for AM is 775 which is significantly different from 395 generated trips in 10th iteration. The figure also reveals the role of number of time slots on the TGC; the plots for the variants with eight time slots are smoother and less fluctuating.

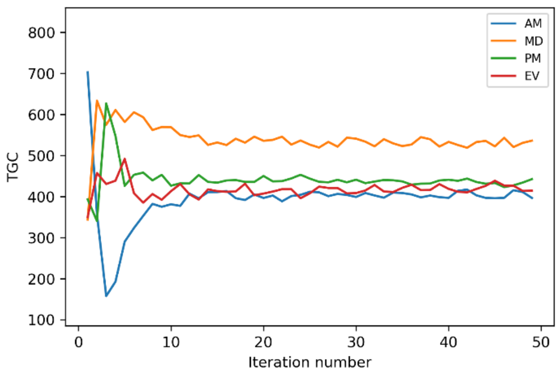
Figure 6-11 and Figure 6-12 depict the profiles of different trips of the travellers to get to the location of the activities and the profile of conducting different activities, respectively, over the 14 hours in minutes. In these figures, the plots for the 1st and last iterations of 1/4-TWS and 1/4-TWOS are provided; while the models have converged in the last iterations, they have not converged in the 1st iteration. In the plots for 4-TWS and 4-TWOS, the vertical lines separate the time slots. Furthermore, the plots for the 1-TWS and 1-TWOS variants are relatively gentler. The reason is that, in 4-TWS and 4-TWOS, each travel time varies prior to and after the limit point. It should be highlighted that explaining the shares of the trips and activities in each of the diagrams is not worthy as they are highly sensitive to the random streams (datasets); however, comparing the profiles of the variants across iterations highlights the behaviours of the splitting ratios and feedback loops.



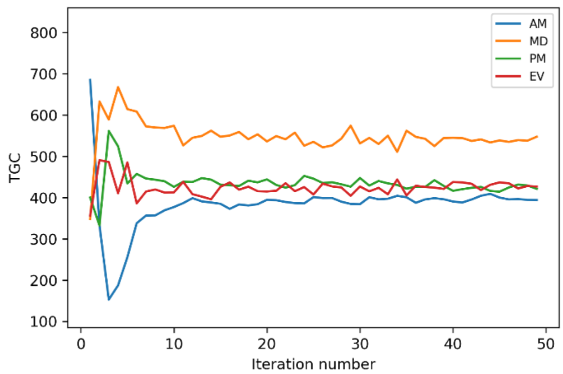

d) 4-TWS variant




e) 4-TWOS variant



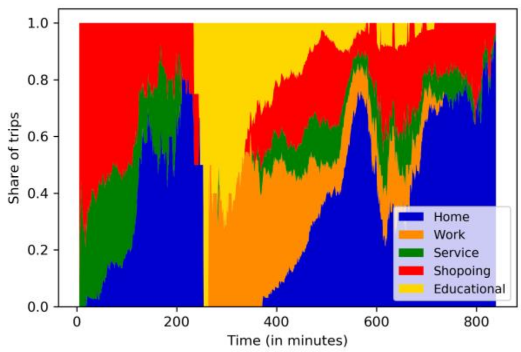

f) 8-TWS variant



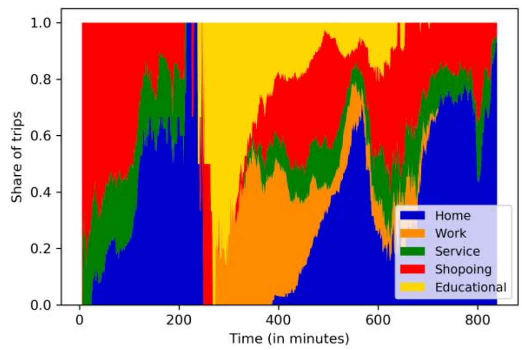

g) 8-TWOS variant

Figure 6-10 Trip generation profile

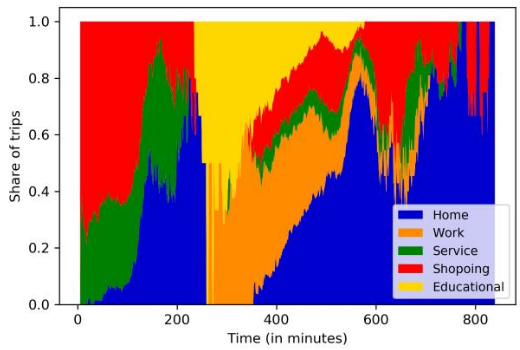
Figure 6-11 depicts that while there is a significant difference between the travelling profiles of 4-TWS and 4-TWOS at their first and last iterations, the differences are negligible for the 1-TWS and 1-TWOS variants. It discloses the importance and effectiveness of feedback loops in changing the share of trip profiles in multi-slots models. Comparing the variants which include splitting ratios versus those without splitting ratios reveals that the travelling profiles is to some extent insensitive to the existence of the splitting ratios in the multi-slots variants (see the plots for 4-TWS and 4-TWOS). Furthermore, the sensitivity is not significant for single-slot variants (see the plots for 1-TWS and 1-TWOS).



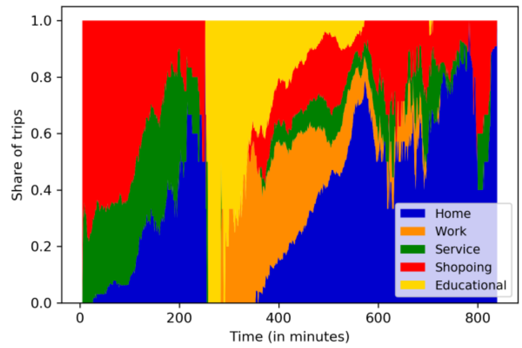

a) Share of trips for 1-TWS (1st iteration)



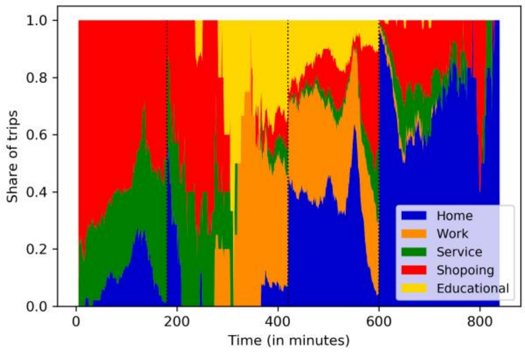

b) Share of trips for 1-TWS (last iteration)



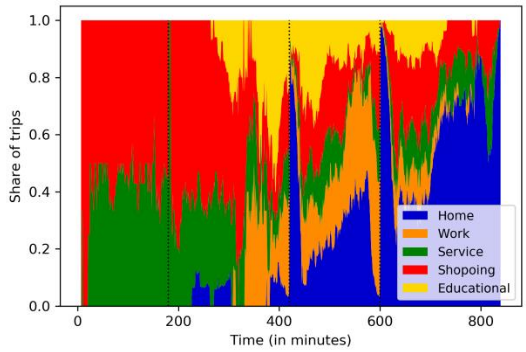

c) Share of trips for 1-TWOS (1st iteration)



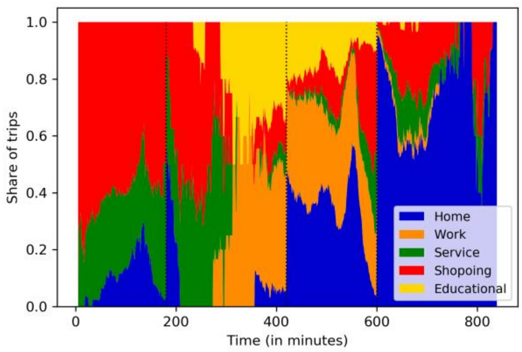

d) Share of trips for 1-TWOS (last iteration)



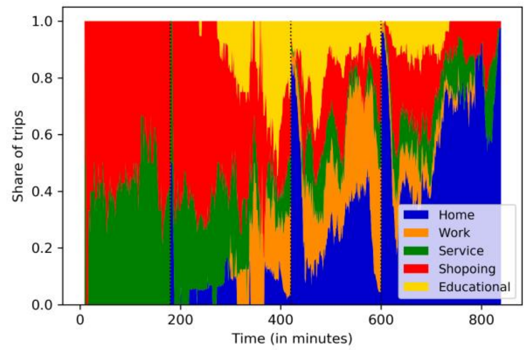

e) Share of trips for 4-TWS (1st iteration)




f) Share of trips for 4-TWS (last iteration)




g) Share of trips for 4-TWOS (1st iteration)




h) Share of trips for 4-TWOS (last iteration)

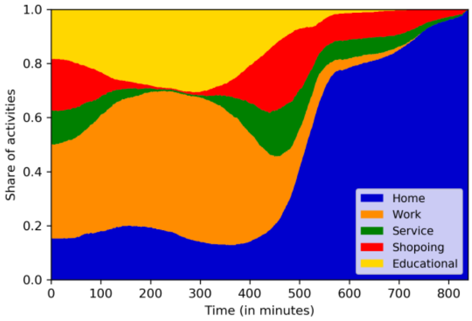
Figure 6-11 Trip generation profile for different variants

Figure 6-12 shows the distributions of conducting different activities (the share of time that people spend on activities) over the scheduling period in different variants. The results are to some extent the same as for the Figure 6-11. While the splitting ratios are more influential in changing the profiles of activities in single-slot variants, the feedback loops are more influential in changing the profile in multi-slots ones.

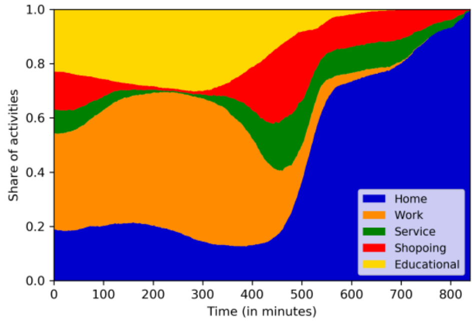
All in all, the experimental results highlights are: 1) the ARP outputs are extremely unstable at the first few iterations which reveal the importance of the existence of the feedback loops in the transport models, 2) using the splitting ratios can be an effective solution to calibrate ARP models, 3) the splitting ratios can speed up achieving the convergence considerably and improve models' performance in reproducing the observed patterns.

## 6.6 Discussion and Conclusion

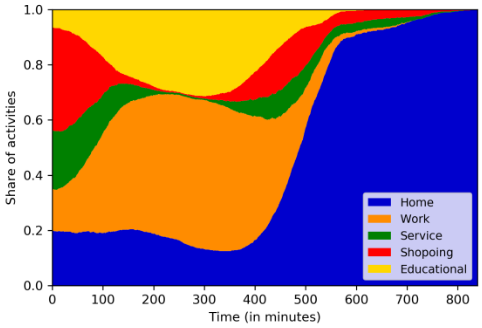
In this chapter, we developed a new TPMS which include a unified formulation to obtain the ATPs of travellers in a transport network across multiple dimensions of travel choice while accounting for congestion effects. ATPs generator of the TPMS is an expanded network-based model converted to a generalised ARP through pre-processing. In the activity-level representation of the problem, nodes are activities and facility spots (such as parking locations) that are joined by means of travel links. Any route that fulfils the spatiotemporal constraint is a feasible ATP, and the model seeks the optimal ATP (simultaneous determination of activity location, time of participation, duration, and route choice decisions) for each traveller considering the constraints imposed for each traveller. It should be noted that while all the analysis is done at the activity-level, the map of the solutions on the physical network can be obtained by post-processing. Furthermore, in the proposed model, the splitting ratios are used not only to calibrate the model but also to speed up the convergence speed of the model.



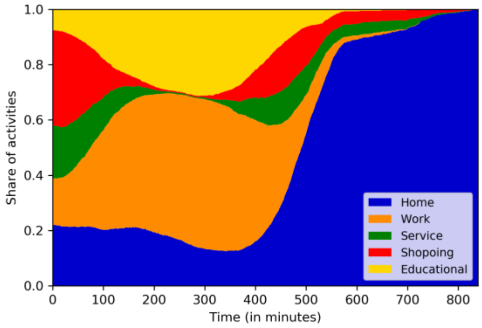

a) Share of activities for 1-TWS (1st iteration)



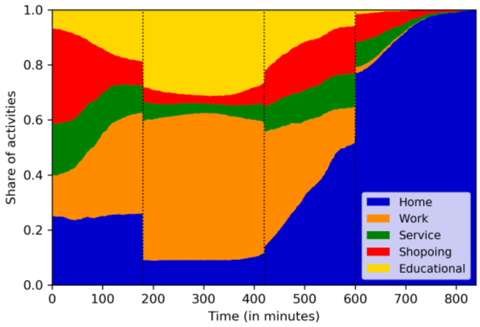

b) Share of trips for 1-TWOS (last iteration)



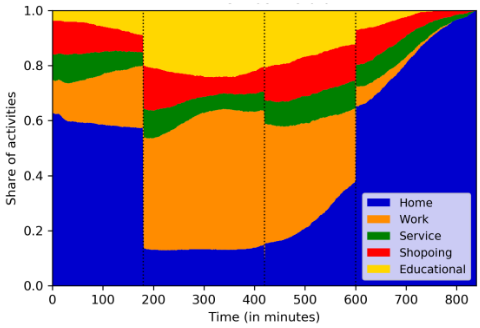

c) Share of activities for 1-TWOS (1st iteration)



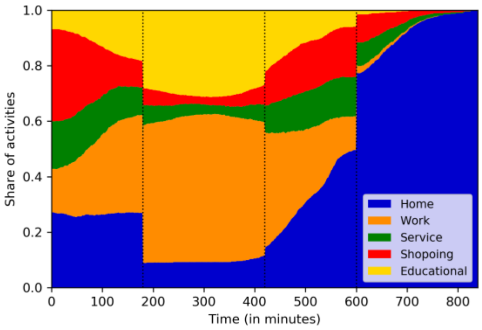

d) Share of trips for 1-TWOS (last iteration)



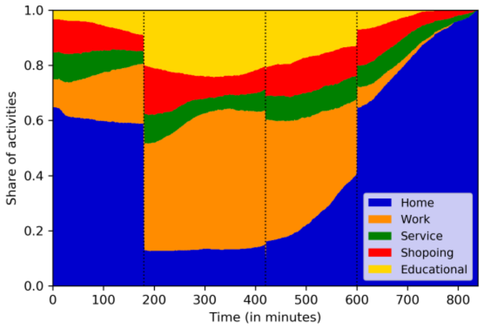

e) Share of activities for 4-TWS (1st iteration)




f) Share of trips for 4-TWS (last iteration)




g) Share of activities for 4-TWOS (1st iteration)




h) Share of trips for 4-TWOS (last iteration)

Figure 6-12 Activity profile for different variants

The numerical results highlight the practicality of using the feedback loops and splitting ratios in the numerical experiments which can be potential implications for transport models in practice. While feedback loops are indispensable to reach a convergence in ARPs, splitting ratios can remarkably speed up convergence. Specifically, comparing the variants with and without splitting ratios put accent on the following issues: First, the OD matrices that are generated in the variants without the splitting ratios are less similar to observed data. This means that the OD matrices are not consistent in subsequent iterations despite the fact that the total cost is converged. Second, the higher number of splitting ratios, the more SRC and ODC speed up. Third, the splitting ratios converge after a few iterations in multi-slot variants while the SRC speed for single-slot is very low.

# Chapter 7

# An Emerging Model Component: A Ride-sharing Formulation

***This chapter is in line with Aim 4 and formulates an emerging model component suitable to be embedded in conventional TPMSs. As Ride-sharing is recognised as an emerging mode in Chapter 2, a novel dynamic formulation for this mode is proposed in this chapter.***

*This chapter proposes new objective functions for the matching problem arising in ride-sharing systems based on trips' spatial attributes. Novel dynamic matching policies are then proposed to solve the problem dynamically in a rolling horizon framework. Finally, a new clustering heuristic is presented to tackle instances with a large number of participants efficiently. It is found that the proposed models maximise the matching rate while maintaining distance-savings at an acceptable level, which is an appealing achievement for ride-sharing systems. Further, the solution method is capable of solving large-scale instances in real-time. The chapter not only proposes a novel ride-sharing model, but also determines the best objective function and matching policy if the purpose is to embed the ride-sharing model in dynamic travel planning model systems (TPMSs) such as activity-based models.*

## 7.1 Introduction

Travel cost, traffic congestion, limited capacity for car park and environmental concerns have continually encouraged people to shift their travel modes toward emerging alternatives. Ride-sharing is a promising and competitive approach to reduce private car ownership. In its original form, ride-sharing consists of picking-up riders along a trip incidental to the principal purpose of the driver. In this case, the driver intends to reach a destination and not to transport people just for profit.

It is widely acknowledged that ride-sharing may be able to meet the mobility needs of a significant share of the travellers (Stiglic et al. 2015). Smartphones have facilitated the development of ride-sharing systems by linking riders and drivers in a dynamic and on-demand environment. Hence, in modern ride-sharing systems, drivers and riders are matched automatically and both parties can be notified within short notice (Agatz et al. 2011, Gargiulo et al. 2015, Stiglic et al. 2016). Depending on the level of dynamism of the ride-sharing system, a trip notification can be sent anytime from a few hours to a few minutes before departure time.

Coordination mechanisms between drivers and riders, especially the matching problem therein, have been the focus of the research on ride-sharing models (Kamar and Horvitz 2009). Improving system-wide and trip attributes such as the matching rate, total travel times, or total trip distances have been considerably studied in the literature. Further, for wide uptake and real-time applications, ride-sharing systems should be computationally scalable.

Due to their significant computational requirements, the majority of dynamic ride-sharing models are only applicable to small and medium scale problems, hence compromising their implementation over large metropolitan areas. For example, over 13.5 million trips are currently made in Melbourne on a daily basis. Assuming that only 0.5% of the travellers decide to opt for a ride-sharing solution, the existing solution methods are not capable of efficiently finding near-optimal solutions.

In this chapter, a real-time ride-sharing system is developed that iteratively solves a matching problem in a rolling horizon approach. The matching problem solved therein is based on the formulation proposed by Agatz et al. (2011). This chapter builds on this research by proposing novel objective functions for the ride-sharing matching problem and comparing their performance against two alternative objectives. Further, multiple dynamic matching policies are proposed to implement the proposed rolling horizon approach. Analysis of the interaction between objective functions and matching policies can guide the modellers in selecting the fittest ride-sharing system in the dynamic TPMSs. Finally, an efficient clustering approach is proposed to decompose the announcements issued by the participants into smaller subsets and show that this heuristic approach is competitive compared to an exact solution method.

The rest of the chapter is structured as follows. The literature on ride-sharing optimisation models is reviewed in Section 7.2. Section 7.3 formally presents the ride-sharing problem and its mathematical formulation. Section 7.4 presents a rolling horizon approach to solve the problem dynamically and introduces three classes of dynamic matching policies. In Section 0, a heuristic clustering algorithm is introduced to solve the ride-sharing problem on large-scale instances. Numerical results obtained from solving realistic instances derived from Melbourne's metropolitan area are presented in Section 7.6. Finally, the findings and possible extensions are summarised in Section 7.7.

## 7.2 Literature review

In this section, the existing research on ride-sharing models is reviewed. Then the performance measures used for evaluating ride-sharing systems are discussed.

### 7.2.1 Ride-sharing models

Ride-sharing models have recently received an increasing attention in the literature. The proposed models differ in their approach to solve the optimisation problem as well as in the level of input data required. Amey (2011) proposes a data-driven methodology for estimating the viability of ride-sharing at an institutional scale, the MIT campus in Cambridge, Massachusetts, USA. Given commuter-specific trip characteristics (housing location, vehicle availability, arrival/departure time and route deviation time), the author compares the potential of using ride-sharing as a travel mode based on observed trip characteristics and ridesharing patterns among commuters. In this study, the optimisation problem seeks to maximise the number of matched driver-rider pairs and must decide on both the role assignment (driver or rider) to each participant and the assignment of riders to drivers. This study shows a potential system-wide vehicle miles travelled savings from 9% to up to 27%.

Agatz et al. (2011) utilise a rolling horizon solution approach to periodically optimise unmatched announcements. In each iteration of the rolling horizon, a matching problem is solved with an objective function aiming to maximise the total travel distance savings. In this model, the system is allowed to delay trip notifications until departure time. This leads to notifications often being postponed as late as possible. The authors use the Bass diffusion model (Mahajan et al. 1995) to model the adoption and the sustainability of the proposed dynamic ride-sharing system. The diffusion model contains three parameters: the total number of potential adopters, a coefficient of innovation that represents the exogenous likelihood that a new participant joins the system, and a coefficient of imitation that relates to the increase in this likelihood based on the number of participants that are already in the system. They report that when innovation and imitation rates are sufficiently high, the proposed ride-sharing system converges to a steady announcement stream in two to three weeks. As in Amey (2011), the system assigns participants' role, i.e. driver or driver.

Xing et al. (2009) introduce a dynamic ride-sharing system where drivers and riders are matched en-route. Trip preferences such as gender and smoking as well as a maximum acceptable service response time for riders are included in their model. They investigate the relationship between the number of drivers and passengers' travel time. Using a simulation-based experiment on an urban network of Bremen's metropolitan area, the authors find that increasing the number of available drivers results in higher matching rates.

Stiglic et al. (2015) design an algorithm that matches drivers and riders in a ride-sharing system with meeting points. Meeting points increase the flexibility of the ride-sharing system by expanding the set of feasible matches. They consider two objective functions in a lexicographic optimisation approach: their primary objective is to maximise the total number of matches while their secondary objective aims to maximise the total travel distance savings. In line with addressing the impact of participants' flexibility, Stiglic et al. (2016) use the same model to investigate the impact of matching flexibility, detour flexibility, and scheduling flexibility on matching rates.

Ghoseiri et al. (2011) formulate a ride-sharing problem in which several constraints for vehicle occupancy, waiting time to pick up, the number of connections, detour distance for vehicles and relocation distance for passengers are considered. In addition, trip preferences based on age, gender, smoking, and pet restrictions are incorporated. As in most approaches, the authors maximise the number of matches.

In a recently published paper by Masoud et al. (2017), a peer-to-peer ride exchange mechanism is proposed to increase the matching rate and customer retention in a ride-sharing system. In the mechanism, riders have the opportunity to purchase a previously-matched rider's itinerary while the exchange of rides is accompanied with an exchange of money through the ride-sharing system. For a more comprehensive review on the state of the art of current ride-sharing systems and the existing challenges to their adoption, the reader is referred to Furuhata et al. (2013).

This chapter builds on the existing literature and proposes new objective functions for the matching sub-problem arising in the dynamic ride-sharing problem. In addition, it introduces three classes of dynamic matching policies for the rolling horizon framework that provide a range of trip notification deadlines.

### 7.2.2 Large-scale solution approaches

One of the main challenges of dynamic ride-sharing is to deal with a large number of participants and some heuristics have been proposed to develop scalable solutions. Shen et al. (2015) use a Filter-and-Refine framework to scale down the ride-sharing problem. In their framework, the road network is first partitioned using a gird and driver and rider requests are then filtered based on a spatio-temporal index. Pelzer et al. (2015) partition the road network into distinct regions representing certain sub-structures of the road network to reduce the solution space. In their algorithm, a match may be finalised only if the rider's destination lies on the driver's corridor. Nourinejad and Roorda (2016) use a decomposition algorithm to partition participants' announcements based on their spatial positions. The algorithm matches a driver to a rider if the origin or the destination of the rider is in the vicinity of one of the zones in which the driver's route fall.

In these proposed algorithms, the existence of a rider in the vicinity of the driver's route is the criterion used for clustering the solution space. This requires drivers' routes be periodically scanned in real-time which could pose considerable computational challenges. In this chapter, a new clustering heuristic based on both the origin and the destination of participants is presented, to solve the dynamic ride-sharing problem for large scale problems. Using this approach, computation time can be reduced by a factor of 3 while only marginally impacting solution quality.

### 7.2.3 System-wide ride-sharing performance measures

Multiple agents including drivers, riders, and ride-sharing providers participate in a ride-sharing system, each with their own objective functions. However, the objectives of all individual participants are not necessarily in line with system-wide objectives such as maximising social welfare. Since the focus of this chapter is on system-wide objectives, the performance measures to be taken into account when generating ride-sharing matches are reviewed. The *matching rate*, the *total vehicle-distance savings*, the *total travel time savings* and the *total finalisation time* are the performance measures that are used to assess the quality of the solutions.

The total vehicle-distance savings represents the total distance driven by all participants travelling to their destinations, either in a shared ride or driving alone (Agatz et al. 2012).Similarly, the total travel time savings represents the total travel time spent by all the participants travelling to their destinations. Minimising the total vehicle-distance and total travel time surrogate minimising travel costs, that is a determinant factor for all the participants. Agatz et al. (2012) and Winter and Nittel (2006) used total vehicle-distance savings and total travel time savings, respectively, as performance measures.

The matching rate evaluates the number of finalised matches in the system. Unlike vehicle-distance savings which targets drivers and riders' benefits, improving the matching rate is desirable for all the stakeholders in the ride-sharing system, i.e. drivers, riders, and the ride-sharing provider. This criterion is all the more critical if the ride-sharing provider charges a commission per successful matches, either a fixed fee or a fare proportional to the trip cost. In addition, a higher matching rate may promote the use of the ride-sharing system, thus potentially leading to higher participants' utilities. This criterion is used by Winter and Nittel (2006), Ghoseiri et al. (2011), Amey (2011) and Xing et al. (2009) to evaluate their ride-sharing models.

These performance measures have frequently been used in the literature, individually or together, to evaluate model performance. In turn, measuring the finalisation (trip notification) time of an accepted match has not receiving much attention. The trip finalisation time can be used to assess customer experience since early notifications allow for better planning for both drivers and riders. In contrast, although delaying trip notification offers more flexibility from a system perspective, it does not guarantee that a better match will ultimately be found.

Since both the vehicle-distance savings and total travel time savings criteria are often highly correlated, this study focuses on one of these travel disutility criteria. In this chapter, the following performance measures are considered to evaluate the performance of the proposed ride-sharing models:

1. Matching rate (MR): the total number of matched driver and rider announcements divided by the total number of trip announcements;
2. Average total vehicle-kilometres savings (AKS): total kilometres saved as a result of matching algorithms versus the scenario in which all individual trips are performed; and
3. Average finalisation time (AFT): the average time between the announcement time and the time when the announcement is matched in minutes. A mathematical definition for the finalisation time is provided in Section 7.6.2.

It should be highlighted that the above performance criteria may have different weights across different decision makers. For example, a small percentage improvement in the matching rate may have the same value for a decision maker as a higher relative improvement in the total distance savings.

## 7.3 Problem statement and formulation

In this section, firstly the mathematical formulation of the proposed ride-sharing system is presented and novel objective functions for the matching problem arising therein are introduced. In addition, a solution algorithm is presented that combines a pre-processing procedure and a matching algorithm to solve the static ride-sharing problem.

### 7.3.1 Problem statement

Consider a set of drivers $D$ and a set of riders $R$. Let $a \in D \cup R$ be a trip announcement from a participant (driver or rider), we denote $\omega_a$ and $\delta_a$ the origin and the destination of this announcement, respectively. For each announcement $a$, it is assumed to know the announcement time $\tau(a)$, the earliest time at which the participant can depart from his/her origin $e(a)$, and its latest arrival time at his/her destination $l(a)$. In addition, the pairwise distances between all origin and destination locations $S(\omega_a, \delta_a)$ and the respective trip time $T(\omega_a, \delta_a)$ of each announcement $a$ are assumed to be known. The departure time window of announcement $a$ is then $[e(a), q(a)]$ where $q(a) = l(a) - T(\omega_a, \delta_a)$ is the latest departure time of the participant. The length of the departure time window, $f(a) = q(a) - e(a)$, is hereby referred to as the *flexibility* of this participant.

Each announcement $a \in D \cup R$ is either a driver announcement ($D$) or a rider announcement ($R$). Henceforth $d$ and $r$ are denoted a driver announcement and a rider announcement, respectively. As in Agatz et al. (2011), it is assumed that each shared ride consists of a single pick-up and a single drop-off. This assumption does not imply that multiple riders cannot be accommodated in a vehicle if they have the same origin and the same destination simultaneously. In this case, it is assumed that a single announcement will be considered. Hence, if a match between driver $d \in D$ and rider $r \in R$ is found, driver $d$ drives the distance between his/her origin and the origin of rider $r$, $S(\omega_d, \omega_r)$ to pick up the rider and then drives the distance $S(\omega_r, \delta_r)$ to the rider's destination $r_j$ before completing his/her trip by driving the distance $S(\delta_r, \delta_d)$ between the destination of the rider and his/her destination.

### 7.3.2 Pre-processing

In this section, a pre-processing procedure is presented that aims to reduce the solution space by identifying infeasible matches and removing the corresponding driver-rider pair from consideration. A match between driver $d$ and rider *r*, henceforth referred to as the pair $(d, r)$, is said to be *feasible* if the time windows of driver $d$ and rider $r$ overlap such that there exists at least a pair of departure time and arriving time for the driver, and a pair of pick-up time and drop off time for the rider, that satisfy the time windows of both participants. To check for pair-feasibility, the overlap between the driver and the rider time windows can be calculated by comparing the latest time that the driver $d$ must depart $k_d = \min[\, l(r) - T(\omega_r, \delta_r) - T(\omega_d, \omega_r)\,,\ l(d) - T(\delta_r, \delta_d) - T(\omega_r, \delta_r) - T(\omega_d, \omega_r)\,]$ and the earliest departure times of both the driver and the rider. The match $(d, r)$ is feasible only if $\Delta T_d = k_d - Max[t, e(d)] \geq 0$ and if $\Delta T_r = k_d + T(\omega_d, \omega_r) - Max[t, e(r)] \geq 0$, where $t$ is the time at which the matching problem is solved.

Let denote $P = \{(d, r): d\epsilon D,\ r\epsilon R\}$ the set of all pairs of drivers and riders. Before solving the ride-sharing matching problem, $P$ is pre-processed to identify the subset of feasible pairs according to the aforementioned feasibility check. Formally, let $\bar{P}$ be the set of feasible driver-rider pairs: $\bar{P} = \{(d, r) \in P: d\epsilon D\ ,\ r\epsilon R\ ,\ \Delta T_d \geq 0,\ \Delta T_r \geq 0, \}$. Limiting the set *P* to $\bar{P}$ reduces the size of the matching problem by $|P| - |\bar{P}|$.

### 7.3.3 Matching problem formulation

Let $x_{dr}$ be a binary decision variable equal to 1 if the pair $(d, r)$ is matched, and 0 otherwise, and let $w_{dr} \geq 0$ be a weight representing the contribution of matching driver $d$ with rider $r$ in the objective function. The objective of the ride-sharing matching problem is to maximise the weighted sum $\sum_{(d,r)\in\bar{P}} w_{dr}x_{dr}$ and the complete formulation of the problem is summarised in equations (7-1) to (7-4).

$$\max \sum_{(d,r)\in\bar{P}} w_{dr}x_{dr} \tag{7-1}$$

*Subject to:*

$$\sum_{r\epsilon R:(d,r)\in\bar{P}} x_{dr} \leq 1 \qquad \forall d \in D \tag{7-2}$$

$$\sum_{d\epsilon D:\,(d,r)\in\bar{P}} x_{dr} \leq 1 \qquad \forall\, r \in R \tag{7-3}$$

$$x_{dr} \in \{0,1\} \qquad \forall (d, r) \in \bar{P} \tag{7-4}$$

According to Guillaume and Latapy (2006), the resulting mathematical problem is equivalent to a bipartite graph matching problem. Bipartite graphs are a particular class of graphs whose nodes can be divided into two disjoint sets, in which only the link between two nodes in different sets is permitted (Ou et al. 2007, Blattner et al. 2007). In the proposed ride-sharing model, driver-rider interactions can be represented as a bipartite graph *G*, such that each announcement is represented by a node and the nodes are classified into two sets of drivers ($D$) and riders ($R$).

Depending on whether the objective function of the matching problem uses uniform or non-uniform weights, a maximum cardinality matching algorithm or a maximum weight matching algorithm may be used for its resolution. For unweighted matching problems, the most popular approach is Hopcroft-Karp's algorithm (Hopcroft and Karp 1973) whereas weighted matching problems are typically solved using the Hungarian algorithm (Harold, 1955), Ford-Fulkerson's algorithm (Ford and Fulkerson 1956), Blossom algorithm (Edmonds 1965a), or Edmonds-Karp's algorithm (Edmonds and Karp 1972). A comprehensive review of matching algorithms can be found in Galil (1986).

In the matching problem, the weights $w_{dr}$ of each edge play a critical role in forming the best solution. Hence, these weights must be calculated in line with the ultimate objective of the ride-sharing system. The impact of using different weights in the matching problem objective function on the performance of the model is proposed to be evaluated. Specifically, it is considered four weighting strategies discussed below.

**Maximising the total net distance savings (DS):** A match results in distance savings only if the length of the matched trip – including the pick-up trip, the shared trip and the drop-off trip – $S_u(d,r) = S(\omega_d,\omega_r) + S(\omega_r,\delta_r) + S(\delta_r,\delta_d)$ is shorter than the sum of the lengths of the individual respective trips for both the driver and the rider $S_v(d,r) = S(\omega_d,\delta_d) + S(\omega_r,\delta_r)$. Therefore, the net distance savings is $\Delta S(d,r) = S_v(d,r) - S_u(d,r)$. The motivation behind using net distance savings in the objective function is to reduce travel cost, which in turn increases participants' utilities. Formally, this is achieved by replacing $w_{dr}$ in Equation (7-1) with $\Delta S(d,r)$ for each pair $(d,r) \in \bar{P}$ and gives the objective function:

$$\max \sum_{(d,r)\in\bar{P}} \Delta S(d,r) x_{dr} \tag{7-5}$$

**Maximising the total number of matches (NM):** The number of matched announcements is critical for the long-term sustainability of a ride-sharing service to ensure customer satisfaction and profitability (Stiglic et al. 2016). Hence, maximising the number of matches can be interpreted as a measure of reliability of the ride-sharing system (Nourinejad and Roorda 2016). Formally, this objective is modelled with uniform weights $w_{dr} = 1$ in the objective function:

$$\max \sum_{(d,r)\in\bar{P}} x_{dr} \tag{7-6}$$

**Maximising the total distance proximity index (DP):** A new index is proposed that can be used as the weight in the ride-sharing matching problem based on the proximity of the driver and the rider initial trips, hereby referred to as the DP index. The DP index is defined in Equation (7-7).

$$DP(d,r) = \min\left(\frac{S(\omega_d,\delta_d)}{S(\omega_r,\delta_r)}, \frac{S(\omega_r,\delta_r)}{S(\omega_d,\delta_d)}\right) \tag{7-7}$$

DP is conceptually different from NM and DS so that this objective function is not directly related to the performance measures of the system, i.e. MR and AKS. DP indirectly steers the optimisation in the right direction within the rolling horizon framework.

The intuition behing the DP index is that driver and rider trips of similar distance will be good match if their origin and destinations are in close vicinity. In particular, this applies to commuting trips. In turn, it is likely that trips with similar distances have spatially correlated origins and destinations. While it is worth noting that commute distance is blind to the direction of the trip, extensive computational experiments suggest that the DP index is useful in revealing information about potential trips with similar properties, especially if trips are temporally correlated. The effectiveness of this hypothesis is examined later in the chapter (see Section 7.6.2). Using the DP index in the objective function, we get:

$$\max \sum_{(d,r)\in\bar{P}} DP(d,r)x_{dr} \tag{7-8}$$

The DP index does not take into account the spatial correlation between origins and destinations or trips. To illustrate this limitation, consider the problem depicted in Figure 7-1 which shows two pairs with identical DP indices. In the first pair, the rider's trip is twice longer than the driver's while in the second pair, the driver's trip length is twice longer than rider's. In both cases the DP index is 0.5, however, the length of the matched trip for the second pair is 3 compared to 8 for the first pair. This highlights the need for considering the length of the matched trip, i.e. from the driver's origin to the rider's origin, from the rider's origin to the rider's destination, and from the rider's destination to the driver's destination, within the objective function. Therefore, an adjustment factor to the DP index is proposed to accommodate this.

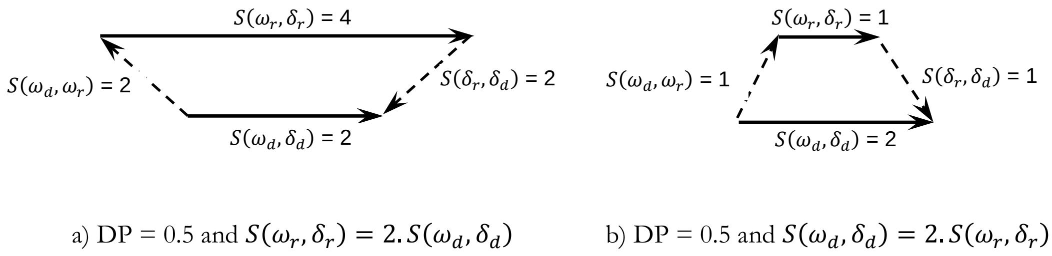



Figure 7-1 Different matched trip distances for identical DP indices

**Maximising the total adjusted distance proximity index (ADP):** To include the impact of the length of the matched trip into the total trip length, an adjustment factor (AF) for pair $(d, r)$ is defined as follows:

$$AF(d, r) = \frac{S(\omega_d, \delta_d)}{S(\omega_d, \omega_r) + S(\omega_r, \delta_r) + S(\delta_r, \delta_d)} \quad (7\text{-}9)$$

$AF(d, r)$ measures the length of driver's individual compared to the length of the matched trip. Matches with smaller matched trip distances, in comparison with the driver initial trip, should receive higher priority in the objective function. Hence, the ADP index is introduced as defined in Equation (7-10).

$$ADP(d, r) = AF(d, r) \times DP(d, r) \quad (7\text{-}10)$$

Using the ADP index in the objective function, we get:

$$\max \sum_{(d,r)\in\bar{P}} ADP(d, r) x_{dr} \quad (7\text{-}11)$$

In section 6.2, it will be shown that both DP and ADP indices lead to non-dominated solutions.

To illustrate the influence of $w_{dr}$ in the matching problem, consider the ride-sharing problem depicted in Figure 7-2. In this example, there are two drivers $(d1, d2)$ and three riders $(r1, r2, r3)$ in the ride-sharing system at time period $t$. Assume that the pairs $(d2, r1)$ and $(d2, r2)$ cannot be matched due to incompatible time windows. The possible distance savings are: $\Delta S(d1, r1) = 1,\ \Delta S(d1, r2) = 1,\ \Delta S(d1, r3) =$

5, and $\Delta S(d2, r3) = 1$. If $DS$ is used as the objective function (i.e. $w_{dr} = \Delta S(d, r)$), solving the matching problem results in $x_{d1,r3} = 1$ while if $NM$ is used (i.e. $w_{dr} = 1$) the optimisation problem results in either $x_{d1,r1} = 1$ and $x_{d2,r3} = 1$; or $x_{d1,r2} = 1$ and $x_{d2,r3} = 1$. In turn, if $DP$ is used the following values are obtained: $DP(d1, r1) = 1$, $DP\ (d1, r2) = \frac{11}{17}$, $DP\ (d1, r3) = \frac{7}{11}$ and $DP\ (d2, r3) = \frac{7}{9}$. Therefore, if $DP$ is used as the objective function, we obtain $x_{d1,r1} = 1$ and $x_{d2,r3} = 1$. Finally, using ADP as the objective function we get: $ADP(d1, r1) = \frac{11}{21}$, $ADP\ (d1, r2) = \frac{11}{17} \times \frac{11}{27}$, $ADP\ (d1, r3) = \frac{7}{11} \times \frac{11}{13}$ and $ADP\ (d2, r3) = \frac{7}{9} \times \frac{9}{15}$ which results in $x_{d1,r3} = 1$ and $x_{d2,r3} = 1$.

Assume now that a new driver $d3$ enters the system at $t + 1$. Based on the outcome of the matching problem at time period $t$, $d3$ can be either matched to $r1$ or $r2$; or remain unmatched if both riders have already been matched.

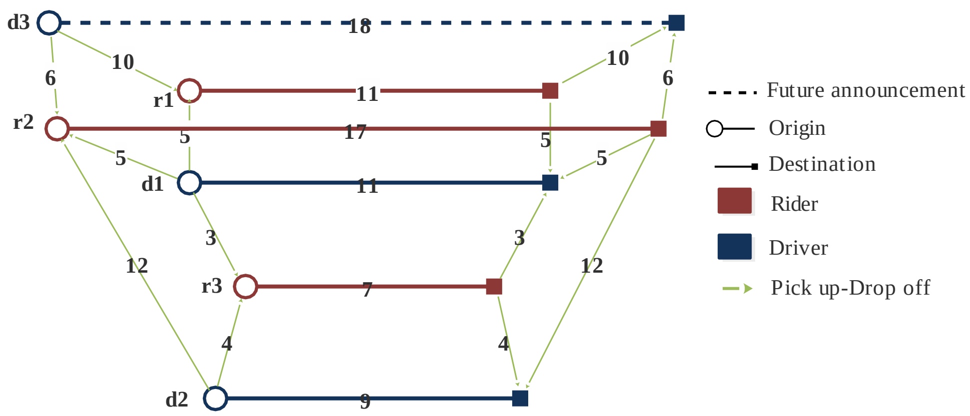



Figure 7-2 A ride-sharing problem

### 7.3.4 DS $\varepsilon$-condition

If DS is used in the objective function a matched pair $(d, r)$ will verify the condition such that: $\Delta S(d, r) \geq 0$. In turn, this may not be the case if DP, ADP or NM is used in the objective function. Instead the corresponding solutions may lead big negative distance savings, which may considerably compromise the overall quality of the solution. To balance the performance of the ride-sharing system across the performance measures (MR, AKS), this study proposes to use the condition $\Delta S(d, r) \geq \varepsilon$ in the pre-processing procedure to exclude pairs with distance savings lower than $\varepsilon$. For this purpose, this study proposes to extend the formulation (7-1) to (7-4) by adding side-constraints of the form:

$$\Delta S(d, r) \geq \varepsilon \quad \text{(i)}$$

This condition aims to help in combining multiple criteria in the optimisation.

### 7.3.5 Static solution algorithm

The steps that are illustrated in the previous sub-sections are summarised in Algorithm 7-1, henceforth referred to as STATIC. This algorithm will be used in each iteration of the dynamic ride-sharing algorithms to periodically solve the matching problem as new announcements enter the system.

Algorithm 7-1: STATIC

**Input:** Set of driver announcements $D$, set of rider announcements $R$, Objective function (DS, NM, DP or ADP)

**Output:** A weighted bipartite graph $G$, a matching vector $\boldsymbol{x}$ for all pairs of driver-rider in $\bar{P}$

$P \leftarrow \{(d, r): d \in D, r \in R\}$

$\bar{P} \leftarrow \emptyset$

**for** $(d, r)$ in $P$:

    **if** $\Delta T_d \geq 0,\ \Delta T_r \geq 0$, and $\Delta S(d, r) \geq \varepsilon$ **then**:

        $\bar{P} \leftarrow \bar{P} \cup \{(d, r)\}$

    **end if**

**end for**

$\boldsymbol{w} \leftarrow$ Determine weight vector based on the objective function and $\bar{P}$

$G \leftarrow (D \cup R, \bar{P}, \boldsymbol{w})$

$\boldsymbol{x} \leftarrow$ Execute the maximum-weight bipartite matching algorithm on $G$

## 7.4 Rolling horizon framework

Driver and rider announcements may enter the ride-sharing system continuously at any time, thus making the problem dynamic and calling for event-driven modelling frameworks. In this section, a *rolling horizon* approach is presented to solve the on-demand ride-sharing problem in real-time. The rolling horizon approach is motivated by the following. First, the system is assumed to be highly dynamic so that driver and rider requests enter and leave the system continuously. Second, due to the unpredictable nature of the problem, future driver and rider requests are assumed to be unknown.

There exist several approaches to determine the frequency of the iterations in a rolling horizon framework. The main two approaches include periodic optimisation with fixed time step and event-driven optimisation where an event can include a new announcement or a batch of new announcements. However, event-driven approaches are usually used when systems are expected to react quickly to changes in their environment while periodical optimisation may imply longer reaction delay (Pillac et al. 2012). Moreover, defining proper "events" requires sophisticated techniques compared to simply reacting to time steps that is the cost of optimising very complicated systems. The appropriate approach is highly dependent on the policy and the time step that is used to finalise matches. In the current research, the former approach is adopted and it is assumed that the rolling horizon algorithm is executed for a given set $T$ of time steps, i.e.: $T = \{0, p, 2p, 3p, \dots\}$.

In the proposed ride-sharing system, an infinite look-ahead time horizon approach is adopted to slide the horizon with a predefined time step $p$, and then the STATIC algorithm is executed to update the pairs periodically (for each time step). Then, in each iteration of the rolling horizon, the matching problem presented in Section 7.3.3 is solved with one of the proposed objective functions (DS, NM, DP or ADP) for the set of active announcements. At any time $t \in T$, an announcement is labelled *active* if its latest departure time is greater than the execution time of the STATIC algorithm, i.e. $q(a) \geq t$. Further, an announcement is labelled *inactive* if it is matched to another announcement or *expired* if $q(a) < t$. The proposed rolling horizon approach may allow planners to handle demand uncertainty since decisions made based on the current available data may be re-considered at a later stage as long as the associated announcements have not expired.

In each iteration of the rolling horizon framework, a matched pair $(\mathrm{d}, \mathrm{r})$ can either be finalised, i.e. the match is accepted by the ride-sharing system, or its finalisation can be delayed. Postponing the finalisation time can be advantageous if a better match for either the driver, the rider or both of them can be found in the future. Henceforth, this process is referred to as the *dynamic matching policy*. Further, let $\bar{x}_{dr}$ denote the finalised value of variable $x_{dr}$, i.e. $\bar{x}_{dr} = 1$ means that the match $(d, r)$ is accepted by the ride-sharing system and $\bar{x}_{dr} = 0$ means that at least $d$ or $r$ is involved in another finalised match, thus these two announcements will not be matched together. If a match is finalised, the respective driver and rider exit the system and will not be considered at the next iteration. This rolling horizon iterates until all announcement exit the system either by being matched or by having expired.

The rolling horizon approach cannot ensure the goodness of the solution (Li and Ierapetritou 2010) since, at each period of time, some of the matches are finalised and cannot be reconsidered. Thus, it should be supported with a high-quality optimisation procedure. In a real-time ride-sharing system, choosing a suitable objective function and matching policy, can significantly impact the quality of the solutions.

Next, three classes of dynamic matching policies are presented that can be used within the proposed ride-sharing system to decide when driver-rider matches and the corresponding trip should be finalised.

### 7.4.1 As late as possible (ALAP) dynamic matching policy

From a system perspective, the most versatile policy consists in finalising trips *as late as possible*: under this policy, matched trips are not finalised until the next time period exceeds the latest departure time of either driver or rider, $q(d) < t + p$ or $q(r) < t + p$. Therefore, a match is finalised at time period $t \in T$ if the *finalisation condition* $x_{dr} = 1$ and $\min\,[q(d), q(r)] < t + p$ is satisfied.

### 7.4.2 As soon as possible (ASAP) dynamic matching policy

An alternative dynamic matching policy consists in finalising matches *as soon as possible*: under this policy, any matched trip among drivers and riders is finalised on its first occurrence within the rolling horizon algorithm. The finalisation condition for the ASAP policy is $x_{dr} = 1$. This policy provides less flexibility from a system perspective but potentially offers a better service to users in that they are likely to be notified significantly earlier than under the ALAP policy.

### 7.4.3 As soon as α (ASAα) dynamic matching policy

The third policy discussed in this chapter finalises matches as soon as a condition α is met. The idea behind this approach is to borrow advantages from both the ASAP and ALAP policies. In the ASA$\alpha$ policy, a match is finalised if the next time period exceeds the latest departure time of either the driver or the rider; or if the weight of the matched announcements in the objective function exceeds the critical value of $\alpha$. The finalisation condition for $ASA\alpha$ is $x_{dr} = 1$ and either $\min[q(d), q(r)] < t + p$ or $w_{dr} \geq \alpha$. This policy collapses to the ASAP policy if $\alpha = 0$.

The pseudo code of the dynamic matching policies algorithm is presented in Algorithm 7-2 and henceforth referred to as the ROLLING HORIZON algorithm.

To illustrate the impact of dynamic matching policies, Figure 7-3 depicts an example of a ride-sharing system with two drivers and two riders. In this example, the time window of $r1$ overlaps with that of both $d1$ and $d2$ while the time window of $r2$ only overlaps with that of $d2$. Assume that the feasible matches set is $\bar{P} = \{(d1, r1), (d2, r1), (d2, r2)\}$. For each announcement, a match can be found only in the time window between the time when announcement $a$ is received $\tau(a)$, and the time step prior to its latest departure time $q(a)$. If the Policy ASAP is used, the match $(d1, r1)$ will be finalised at $t = p$. The setting of the system can be changed so that the decision on finalisation of the found match to be made whenever in between $\tau(a)$ and $q(a)$. In the example, the system may postpone the assignment of $r1$ until its latest departure time $q(r1)$ in the hope to find a better match at a later time period. For instance, the system can find the pair $(d2, r1)$ to be a better match for $r1$ at $t = 2p$.

This example and the example provided in Section 7.3.3 highlight that the ride-sharing problem is highly dynamic and that the selected objective function and matching policy can considerably impact its solution.

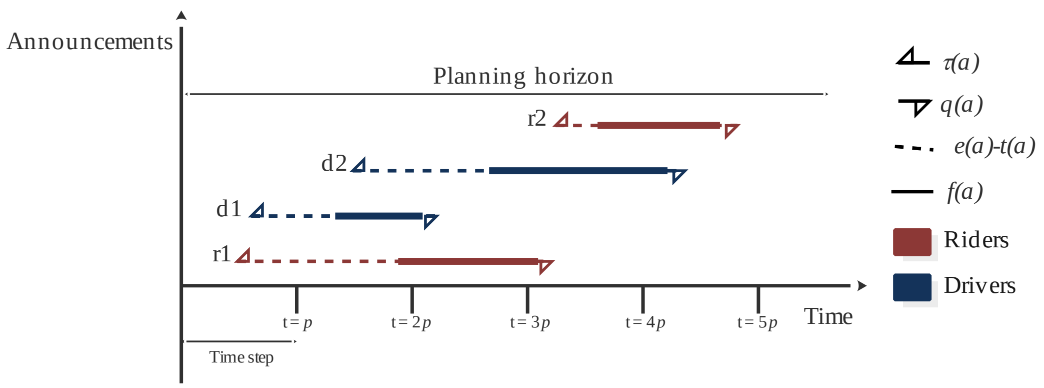



Figure 7-3 Dynamic policies scheme

Algorithm 7-2: ROLLING HORIZON

**Input:** Announcement$s$ sets $D$ and $R$, objective function (DS, NM, DP, ADP), dynamic matching policy (policy)
**Output:** A finalised vector $\bar{\boldsymbol{x}} = [\bar{x}_{dr}]$
**for** $t \in \{0, p, 2p, 3p, \dots\}$:
    $D_t \leftarrow \{a \in D: q(a) \geq t, \tau(a) \leq t\}$
    $R_t \leftarrow \{a \in R: q(a) \geq t, \tau(a) \leq t\}$
    $G \leftarrow$ STATIC ($D_t$, $R_t$, objective function)
    $\boldsymbol{x} \leftarrow$ Execute the maximum-weight bipartite matching algorithm on $G$
    **for** $(d, r) \in \bar{P}_t : x_{dr} = 1$:
        **if** policy = ALAP **then:**
            **if** $\min[q(d), q(r)] < t + p$:
                $\bar{x}_{dr} \leftarrow 1$
                $D_t \leftarrow D_t \setminus \{d\}$
                $R_t \leftarrow R_t \setminus \{r\}$
            **end if**
        **else if** policy = ASAP **then:**
            $\bar{x}_{dr} \leftarrow 1$
            $D_t \leftarrow D_t \setminus \{d\}$
            $R_t \leftarrow R_t \setminus \{r\}$
        **else if** policy = ASA$\alpha$ **then:**
            **if** $(\min[q(d), q(r)] < t + p)$ or $w_{dr} \geq \alpha$
                $\bar{x}_{dr} \leftarrow 1$
                $D_t \leftarrow D_t \setminus \{d\}$
                $R_t \leftarrow R_t \setminus \{r\}$
            **end if**
        **end if**
    **end for**
    **for** $a_{i,j} \epsilon (D_t \cup R_t)$:
        **if** $q(a) < t + p$ **then**
            remove the announcement from either $D_t$ or $R_t$
        **end if**
    **end for**
**end for**

## 7.5 Clustering heuristic

Although the pre-processing steps and the maximum weighted bipartite matching algorithms have polynomial-time worst case time complexities, solving instances with a large number of participants in real-time can be challenging. Given the dynamic component of the problem, the algorithms must be solved periodically over short periods of time, thus emphasising the need for large-scale solution methods. In this section, a novel clustering algorithm based on *k*-means clustering (Lloyd 1982) is proposed to address this challenge.

The proposed clustering algorithm attempts to solve the original ride-sharing problem by assigning the active announcements to a number of smaller sub-problems that are faster to solve. Firstly, the clustering algorithm in a static context is presented, where all the announcements are assumed to be available and then explain how this algorithm can be embedded within the proposed ROLLING HORIZON algorithm.

Let $|N|$ be the desired number of clusters and let $N$ be the set of such clusters. It is assumed that the ride-sharing announcements $a \in D \cup R$ can be divided into potentially intersecting subsets $D_n$ and $R_n$ for $n \in N$ where $D_n$ and $R_n$ are the sets of driver and rider announcements assigned to cluster $n$. At first, the latitude and the longitude of the origin $\omega_a$ and destination $\delta_a$ of driver announcements $a \in D$ are used to create $|N|$ clusters using the *k*-means algorithm. Then, the origin and destination of riders are assigned to the closest cluster based on their spatial coordinates. Here closeness is defined as the Euclidean distance from the rider's origin or destination to the centroid of the cluster (Lloyd 1982).

At this point the origin and destination of an announcement (driver or rider) may not belong to the same cluster. In this case, the corresponding announcement is assigned to both clusters; otherwise, both the origin and destination belong to the same cluster and the announcement is assigned to this cluster only (see Figure 7-4). The pseudo-code of the clustering algorithm is presented in Algorithm 7-3.

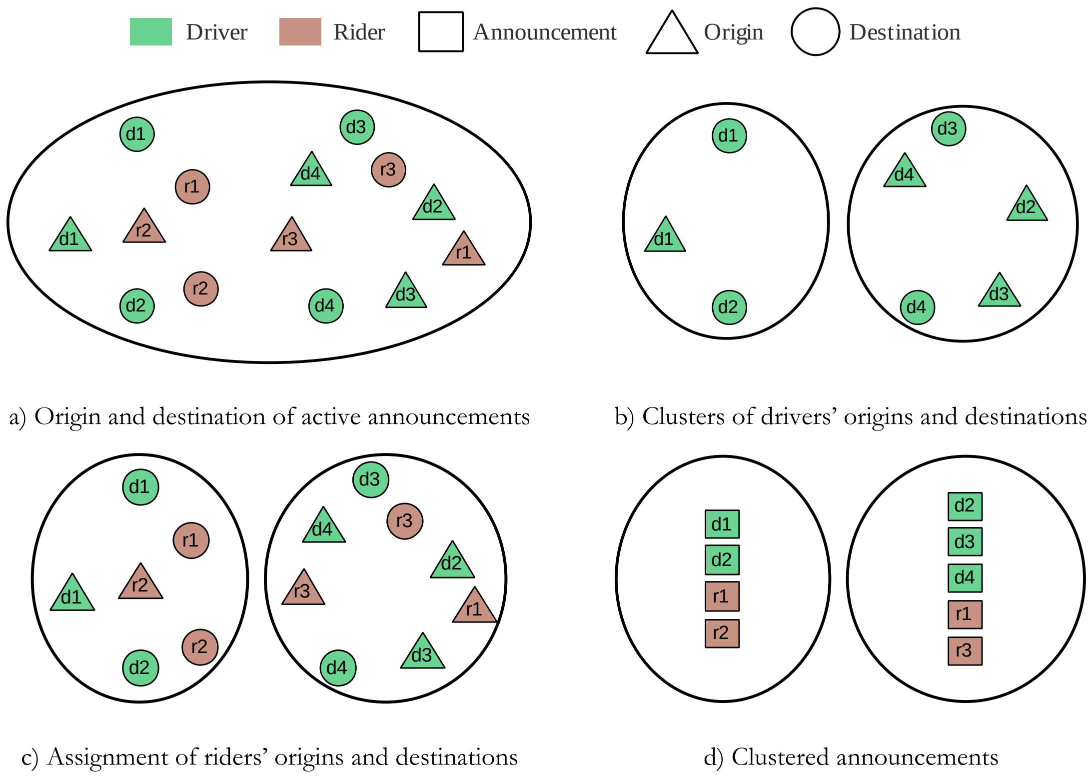



Figure 7-4 Illustration of the intersecting clustering algorithm with $|N| = 2$

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Algorithm 7-3: CLUSTERING

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**Input:** number of clusters $|N|$, $D$, $R$

**Output:** $\{D_n, R_n : n \in N\}$

$D_n \leftarrow \emptyset$

$R_n \leftarrow \emptyset$

$X \leftarrow \{\omega_a, \delta_a : a \in D, q(a) \geq t, \tau(a) \leq t\}$

$\{D_n : n \in N\} \leftarrow$ *k*-means($|N|, X$)

**for** $a$ in $R$:

    $n \leftarrow$find the closest cluster to $\omega_a$

    $R_n \leftarrow R_n \cup \{a\}$

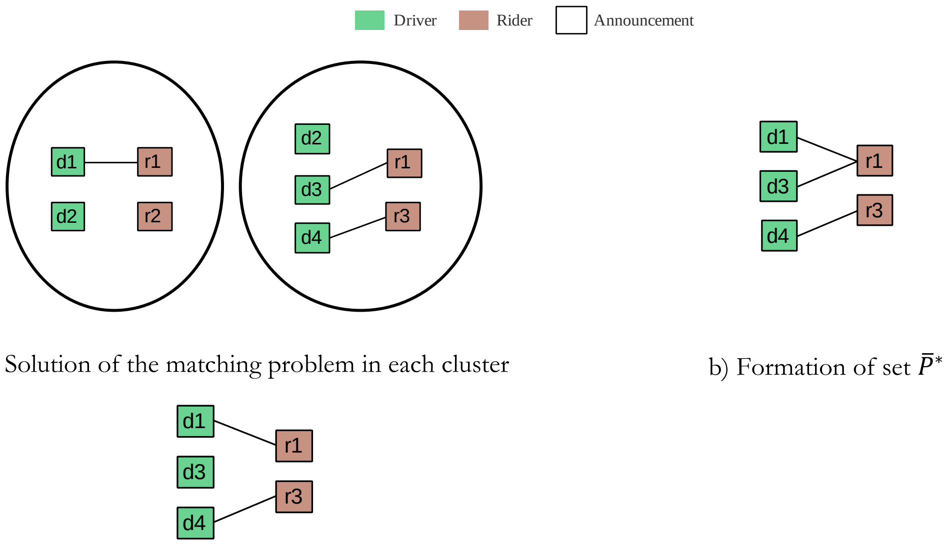
    $n \leftarrow$find the closest cluster to $\delta_a$

    $R_n \leftarrow R_n \cup \{a\}$

**end for**

---

For each cluster $n \in N$, the matching problem is then solved and the resulting matched pairs are stored in a set $\bar{P}_n^*$. Should an announcement be matched twice (i.e. this announcement is matched in two clusters), the resulting solution is not feasible and another matching problem should be solved among the set of matched pairs $\bar{P}^* = \bigcup_{n \in N} \bar{P}_n^*$. This optional matching step ensures that the final solution is feasible, i.e. an announcement can be matched at most once (see Figure 7-5). The pseudo-code of the cluster-based matching step is summarised in Algorithm 7-4.




a) Solution of the matching problem in each cluster

b) Formation of set $\bar{P}^*$

c) Solution of the optional matching problem over the set $\bar{P}^*$

Figure 7-5 Cluster-based matching with $|N| = 2$

To embed the clustering heuristic within an on-demand ride-sharing framework, this study proposes to periodically re-cluster the announcements and uses the proposed cluster-based approach to solve the matching problems therein. In particular, to save computation time, the clustering heuristic may be executed less frequently than the matching problems are solved. Extensive testing suggests that this strategy provides a good compromise between computational runtime and solution quality. Specifically, a set $T'$ of time steps, i.e.: $T' = \{p', 2p', 3p', \dots\}$ where $p' \geq p$ is introduced. In each iteration $t$ of the ROLLING HORIZON algorithm, the algorithm checks if $t \geq kp'$ where $k$ is an integer incremented after each execution of the clustering heuristic and re-cluster the announcement if this condition is verified. Hence, clusters are only recalculated with a period $p'$ following the CLUSTERING procedure, as depicted in Figure 7-4. In turn, the matching problems are solved based on the cluster-based approach as depicted in Figure 7-5, i.e. new announcements entering the system at each time period $t \in \{p, 2p, 3p, \dots\}$ are assigned to the current clusters, a matching problem is solved for each cluster and an optional matching problem is solved if one or more announcements are assigned and matched in more than one cluster.

Algorithm 7-4: Cluster-based Matching

**Input:** $\{D_n, R_n : n \in N\}$
**Output:** a matching vector $\boldsymbol{x}$
$D^* \leftarrow \emptyset$
$R^* \leftarrow \emptyset$
**for** $n \in N$:
  $\bar{P}_n^* \leftarrow$ STATIC ($D_n$, $R_n$, objective function)
**end for**
**if** an announcement has been matched twice **then**:
  $\bar{P}^* = \bigcup_{n \in N} \bar{P}_n^*$
  $G \leftarrow$ form the graph based on the matched pairs in $\bar{P}^*$
  $\boldsymbol{x} \leftarrow$ Execute the maximum-weight bipartite matching algorithm on $G$
**else**:
  $\boldsymbol{x} \leftarrow$ Construct matching vector using all sets $\bar{P}_n^*$ for $n \in N$

To evaluate the impact of the number of clusters onto solution quality and computational performance, a sensitivity analysis of this input is conducted in Section 7.6.3.

## 7.6 Numerical experiments

This section evaluates the performance of the proposed objective functions and dynamic matching policies introduced in Section 7.3 and Section 7.4 as well as the proposed clustering algorithm in Section 0.

### 7.6.1 Data and simulation

To test and validate the proposed ride-sharing system, data from the Melbourne metropolitan area, Australia is used. Melbourne is the second most populated city of Australia and capital of the state of Victoria with the population of 4.88 million spread across an area of about 10,000 km$^2$. Zenith strategic transport/land use model provided by Veitch Lister Consulting is used to build the simulation scenarios (VLC 2013). Zenith is a large-scale, multi-modal travel model which is implemented in OmniTRANS software package, and currently operates in eight Australian cities and works by simulating the daily travel behaviour of all the residents (and visitors). Zenith uses road and public transport networks, tolls, parking charges, public transport fares and vehicle operating costs, demographic, land use data of 4,003 geographic zones in Victoria. The model outputs used in the simulation exercise of this chapter are travel volumes, travel time, and origin-destination demand volume and origin-destination distance matrices.

As a result, three demand scenarios of 0.25%, 0.5% and 0.75% participation rates are considered between 6:00am and 9:00pm. In these scenarios, driver and rider announcements are randomly generated based on time of day and the inter-zonal density of trips. Drivers are randomly chosen from trips that are made by single occupant cars; while riders are randomly chosen from transit based and multiple occupancy trips. According to the Integrated Survey of Travel and Activities (VISTA) in 2007 (Department of Transport 2009), the total number of trips in Melbourne is about 13.5 million, with 55% by private cars and around 30% by public transport or as a passenger. According to Parker (2004), 70% of the vehicles in Melbourne are single occupancy vehicles. As a result, it is assumed that the percentage of trips by single occupancy cars is 38.5%. Ten random streams of trips per participation rate are generated to be able to accurately compare and assess the performance of different combinations of objective functions and dynamic matching policies.

Although departure time and travel time of each trip is available, the above dataset does not provide information on the participants' travel time window. As in Agatz et al. (2011), trip flexibility is considered fixed rather than allowing it to be a function of travel time. This prevents underestimating or overestimating the flexibility of short and long trips, respectively. Further, it is not differentiated between different trip purposes. Let $b$ and $c$ be departure time and travel time of a trip generated. Its earliest departure time $e$ and its latest arrival time $l$ are determined as $e = b - 10$ and $l = b + c + 10$ (in minutes), respectively. Finally, announcement times are randomly generated using a uniform distribution with parameters ($b$ - 60, $b$).

In all experiments, a period of $p = 2$ min (time step) is used for the rolling horizon algorithm and a total of 450 time periods are considered ($|T| = 450$). Further, a period of $p' = 20$ minutes is used in the proposed clustering algorithm. It is assumed full compliance of the participants, i.e. if a ride is finalised, then the corresponding driver and rider are immediately notified and accept the trip.

To illustrate the scale of the instances considered, the stream with the participation rate of 0.5% corresponds to 25,987 drivers and 20,250 riders. In one of the streams picked randomly among the generated random streams with 0.75% participation rate, on average 154 announcements (69,355/450) and in the worst case, 313 new announcements enter the system in each time step. Nonetheless, the number of active announcements (accumulated entered announcements at previous time periods that are still active) may be much larger than this value. For example, in the noted randomly picked sample, for the ALAP policy, on average 971 announcements and, in the worst case, 1,910 announcements are active in the system.

All algorithms of the proposed ride-sharing system are implemented in Python 3.5 on a machine with 16 Gb of RAM with a processor of i7-4770. In this study, Hopcroft-Karp's algorithm (Hopcroft and Karp 1973) and Edmonds' algorithm (Edmonds 1965b, 1965a) are used to solve the unweighted (for the NM) and weighted (for the DP, ADP and DS) matching problems which are implemented in Networkx, a Python package for scientific computing applications which includes a suite of network algorithms implemented based on seminal research papers (Hagberg et al. 2008). In the Networkx implementation, Hopcroft-Karp's and Edmonds' algorithms have a worst-case time complexity of $O(|E|\sqrt{|V|})$ and $O(|V|^3)$, respectively; where $E$ and $V$ are the set of edges and the set of nodes in the network.

### 7.6.2 Computational results

In this section, the simulation results of the scenarios explained before are presented. For each experiment, the performance of objective functions and the dynamic matching policies presented in sections 7.3.3 and 7.4 are evaluated. Then, the quality of their solutions is compared with regard to the performance measures discussed in Section 7.2.3. For the AFT, the finalisation time for each finalised match is calculated as the sum of the waiting times of the driver, $t-\tau(d)$, and that of the rider, $t-\tau(r)$.

#### 7.6.2.1 Static problem benchmark

In a static ride-sharing problem wherein all announcements are known prior to the start of the day, performance is assessed. The results for participation rate of 0.25% are provided in Table 7-1: for this static case, the analysis focuses on the MR and AKS. It is found that the performance of objectives DP and ADP are very close to the optimal MR (58.68%) obtained using the NM objective. This suggests that the DP and ADP indices work toward maximising the number of matches.

Table 7-1 Objective functions' performance measures in the static model

| Objective function | MR (%) | AKS (%) |
|---|---|---|
| DS | 15.47 | 4.21 |
| DP | 58.66 | -7.66 |
| ADP | 58.67 | -6.76 |
| NM | 58.68 | -7.23 |

In turn, the results using DS are quite different from that of the other objectives: this objective yields a much lower MR but improves on the AKS achieved by the other objectives and provides a positive (4.21%) AKS.

Figure 7-6 depicts the performance of the ride-sharing system with respect to MR and AKS for the static benchmark with different pairwise distance saving thresholds, i.e.: $\varepsilon = \{-10, -9, \dots, 0, \dots, 10\}$. The figure depicts similar performance for DP, ADP and NM with regard to MR across different $\varepsilon$ values; whereas, there is a noticeable difference among the objective functions with regard to the AKS. This shows that proposed indices tend to significantly improve the AKS while maximising the MR. Further, the AKS performance of DP and ADP objective functions approach the values obtained from optimising the DS objective function. The figure shows that the proposed objective functions DP and ADP can find non-dominated solutions in terms of the AKS and MR performance measures.

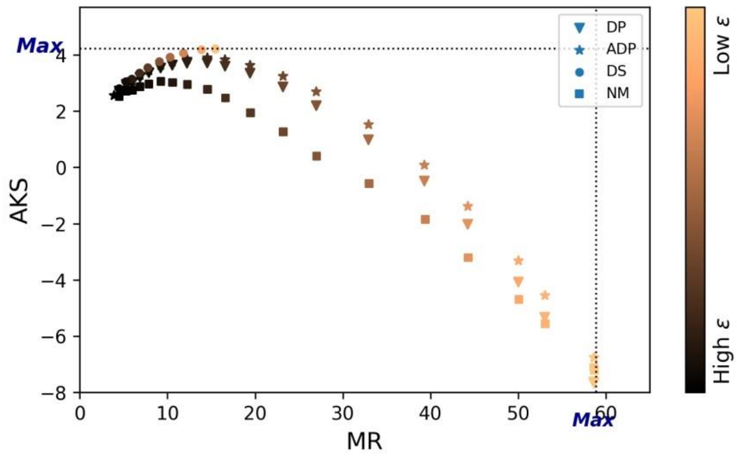



Figure 7-6 Performance of different objective functions on the static ride-sharing problem (participation rate = 0.25%).

#### 7.6.2.2 Dynamic problem benchmark

To conduct the dynamic problem analysis, the values of 0 and -5 are chosen for $\varepsilon$ in the condition $\Delta S(d,r) \geq \varepsilon$ for filtering matches in the DS $\varepsilon$-condition setting. The first value guarantees cost reduction for each matched drivers and riders (assuming that the travel costs are proportional to the travelled distances). The second value for $\varepsilon$ is chosen based on the static benchmark conducted in Section 7.6.2.1. Specifically, for this setting the performance measure AKS remains near zero, thus providing a more flexible matching condition while ensuring that the overall system performance beneficial from a travel cost perspective.

To evaluate different solutions, especially solutions generated by the proposed DP and ADP objective functions, NM-Static (in this chapter, for instance, NM-Static refers to a NM objective function that is implemented in a static problem) and DS-Static are used to obtain extreme values for NM and AKS, respectively. Table 7-2 and Figure 7-7 summarise the results of multiple combinations of objective functions and dynamic matching policies. Specifically, different combinations of NM, DP, ADP and DS objective functions and dynamic matching policies of ASAP, ASA$\alpha$ and ALAP are considered. Further, the static versions of the model for each of the objective functions, as the benchmarks, are reported in the table. Since negative weights are always ignored in the maximum weight matching problem, using DS as the objective function produces similar results with both $\varepsilon = -5$ and $\varepsilon = 0$, hence only one set of results is presented for this objective function.

Table 7-2 Performance measures for the dynamic problem benchmark

| Objective function | Dynamic matching policy | participation rate | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | 0.25% | | | 0.5% | | | 0.75% | | |
| | | MR (%) | AKS (%) | AFT | MR (%) | AKS (%) | AFT | MR (%) | AKS (%) | AFT |
| *NM* ($\varepsilon = 0$) | ASAP | 13.44 | 2.26 | 7.55 | 16.07 | 2.66 | 6.68 | 17.05 | 2.86 | 6.21 |
| | ALAP | 14.26 | 2.27 | 26.17 | 17.01 | 2.75 | 25.21 | 17.97 | 2.91 | 25.83 |
| | Static | 16.61 | 2.47 | - | 19.12 | 2.91 | - | 19.96 | 3.02 | - |
| *NM* ($\varepsilon = -5$) | ASAP | 31.71 | -1.35 | 6.41 | 35.50 | -1.37 | 5.65 | 36.76 | -1.31 | 5.16 |
| | ALAP | 34.79 | -1.50 | 25.95 | 38.73 | -1.55 | 25.16 | 39.99 | -1.38 | 25.58 |
| | Static | 39.40 | -1.85 | - | 42.74 | -1.75 | - | 43.68 | -1.90 | - |
| *DP* ($\varepsilon = 0$) | ASAP | 13.45 | 2.52 | 7.61 | 16.08 | 3.27 | 6.76 | 17.14 | 3.63 | 6.19 |
| | ASA$\alpha$ = 0.1 | 13.49 | 2.58 | 7.68 | 16.09 | 3.27 | 6.88 | 17.15 | 3.65 | 6.43 |
| | ASA$\alpha$ = 0.2 | 13.54 | 2.69 | 8.56 | 16.14 | 3.44 | 7.49 | 17.16 | 3.82 | 7.00 |
| | ASA$\alpha$ = 0.3 | 13.67 | 2.81 | 10.38 | 16.19 | 3.57 | 8.79 | 17.20 | 3.98 | 8.13 |
| | ASA$\alpha$ = 0.4 | 13.81 | 2.88 | 13.41 | 16.34 | 3.67 | 11.30 | 17.36 | 4.08 | 10.40 |
| | ASA$\alpha$ = 0.5 | 13.91 | 2.90 | 15.52 | 16.47 | 3.71 | 13.17 | 17.47 | 4.13 | 12.18 |
| | ASA$\alpha$ = 0.6 | 14.02 | 2.93 | 17.56 | 16.61 | 3.75 | 15.19 | 17.64 | 4.16 | 14.10 |
| | ASA$\alpha$ = 0.7 | 14.06 | 2.92 | 19.08 | 16.74 | 3.76 | 16.81 | 17.73 | 4.17 | 15.90 |
| | ASA$\alpha$ = 0.8 | 14.10 | 2.93 | 20.38 | 16.81 | 3.76 | 18.22 | 17.81 | 4.18 | 17.28 |
| | ASA$\alpha$ = 0.9 | 14.14 | 2.93 | 21.33 | 16.88 | 3.77 | 19.44 | 17.85 | 4.17 | 18.55 |
| | ALAP | 14.27 | 2.96 | 26.08 | 17.00 | 3.80 | 25.67 | 17.99 | 4.21 | 25.68 |
| | Static | 16.57 | 3.60 | - | 19.08 | 4.49 | - | 19.92 | 4.89 | - |
| *DP* ($\varepsilon = -5$) | ASAP | 32.54 | -1.04 | 6.63 | 36.24 | -0.60 | 5.90 | 37.54 | -0.35 | 5.33 |
| | ASA$\alpha$ = 0.1 | 32.59 | -0.90 | 6.61 | 36.42 | -0.64 | 5.88 | 37.77 | -0.33 | 5.46 |
| | ASA$\alpha$ = 0.2 | 32.77 | -0.79 | 7.13 | 36.53 | -0.43 | 6.24 | 37.83 | -0.15 | 5.77 |
| | ASA$\alpha$ = 0.3 | 33.06 | -0.61 | 8.33 | 36.72 | -0.20 | 7.12 | 37.98 | 0.10 | 6.53 |
| | ASA$\alpha$ = 0.4 | 33.40 | -0.53 | 10.07 | 37.09 | -0.09 | 8.44 | 38.28 | 0.25 | 7.76 |
| | ASA$\alpha$ = 0.5 | 33.83 | -0.50 | 12.20 | 37.48 | -0.03 | 10.19 | 38.63 | 0.30 | 9.34 |
| | ASA$\alpha$ = 0.6 | 34.19 | -0.56 | 13.98 | 37.89 | -0.06 | 11.85 | 38.98 | 0.27 | 10.79 |
| | ASA$\alpha$ = 0.7 | 34.44 | -0.60 | 15.63 | 38.18 | -0.11 | 13.40 | 39.31 | 0.21 | 12.36 |
| | ASA$\alpha$ = 0.8 | 34.59 | -0.61 | 16.87 | 38.37 | -0.16 | 14.69 | 39.53 | 0.18 | 13.67 |
| | ASA$\alpha$ = 0.9 | 34.67 | -0.62 | 17.73 | 38.49 | -0.16 | 15.63 | 39.64 | 0.16 | 14.57 |
| | ALAP | 34.89 | -0.66 | 26.04 | 38.78 | -0.21 | 25.93 | 40.00 | 0.11 | 25.77 |
| | Static | 39.30 | -0.48 | - | 42.65 | 0.11 | - | 43.60 | 0.43 | - |
| *ADP* ($\varepsilon = 0$) | ASAP | 13.49 | 2.67 | 7.57 | 16.13 | 3.29 | 6.77 | 17.12 | 3.69 | 6.30 |
| | ASA$\alpha$ = 0.1 | 13.39 | 2.72 | 7.95 | 16.00 | 3.35 | 6.86 | 17.11 | 3.73 | 6.44 |
| | ASA$\alpha$ = 0.20 | 13.39 | 2.79 | 9.20 | 16.02 | 3.57 | 7.76 | 17.12 | 3.94 | 7.16 |

Table 7-2 Performance measures for the dynamic problem benchmark

| Objective function | Dynamic matching policy | participation rate | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | 0.25% | | | 0.5% | | | 0.75% | | |
| | | MR (%) | AKS (%) | AFT | MR (%) | AKS (%) | AFT | MR (%) | AKS (%) | AFT |
| | ASA$\alpha$ = 0.25 | 13.47 | 2.83 | 10.62 | 16.06 | 3.67 | 8.91 | 17.15 | 4.06 | 8.09 |
| | ASA$\alpha$ = 0.30 | 13.54 | 2.91 | 12.17 | 16.23 | 3.78 | 10.20 | 17.25 | 4.17 | 9.44 |
| | ASA$\alpha$ = 0.35 | 13.68 | 2.95 | 14.91 | 16.38 | 3.85 | 12.52 | 17.39 | 4.23 | 11.67 |
| | ASA$\alpha$ = 0.40 | 13.75 | 2.97 | 16.84 | 16.48 | 3.88 | 14.31 | 17.51 | 4.29 | 13.44 |
| | ASA$\alpha$ = 0.45 | 13.85 | 2.99 | 18.58 | 16.61 | 3.92 | 16.15 | 17.65 | 4.32 | 15.39 |
| | ASA$\alpha$ = 0.50 | 13.94 | 3.02 | 20.02 | 16.72 | 3.93 | 17.96 | 17.77 | 4.36 | 17.13 |
| | ASA$\alpha$ = 0.525 | 14.01 | 3.06 | 21.15 | 16.83 | 3.95 | 19.55 | 17.82 | 4.37 | 18.69 |
| | ALAP | 14.27 | 3.11 | 26.25 | 17.02 | 4.00 | 25.88 | 17.99 | 4.47 | 25.91 |
| | Static | 16.56 | 3.83 | - | 19.04 | 4.87 | - | 19.61 | 5.16 | - |
| *ADP* ($\varepsilon = -5$) | ASAP | 32.30 | -0.75 | 6.59 | 36.15 | -0.44 | 5.89 | 37.41 | -0.11 | 5.48 |
| | ASA$\alpha$ = 0.1 | 32.60 | -0.81 | 6.74 | 36.00 | -0.22 | 6.23 | 37.41 | -0.07 | 5.57 |
| | ASA$\alpha$ = 0.20 | 32.92 | -0.63 | 7.79 | 36.10 | 0.05 | 6.81 | 37.54 | 0.28 | 6.23 |
| | ASA$\alpha$ = 0.25 | 33.22 | -0.49 | 9.28 | 36.37 | 0.23 | 8.01 | 37.74 | 0.51 | 7.18 |
| | ASA$\alpha$ = 0.30 | 33.85 | -0.38 | 12.34 | 37.00 | 0.32 | 10.49 | 38.20 | 0.64 | 9.39 |
| | ASA$\alpha$ = 0.35 | 34.31 | -0.39 | 18.18 | 37.59 | 0.31 | 15.93 | 38.79 | 0.62 | 15.01 |
| | ASA$\alpha$ = 0.40 | 34.59 | -0.37 | 20.78 | 37.98 | 0.30 | 18.71 | 39.28 | 0.60 | 17.94 |
| | ASA$\alpha$ = 0.45 | 34.79 | -0.41 | 22.80 | 38.27 | 0.28 | 20.89 | 39.57 | 0.58 | 20.40 |
| | ASA$\alpha$ = 0.50 | 34.92 | -0.39 | 23.82 | 38.40 | 0.29 | 22.42 | 39.73 | 0.62 | 22.02 |
| | ASA$\alpha$ = 0.525 | 34.73 | -0.26 | 24.15 | 38.62 | 0.25 | 23.16 | 39.78 | 0.62 | 22.70 |
| | ALAP | 34.86 | -0.22 | 26.26 | 38.81 | 0.32 | 25.97 | 39.96 | 0.72 | 25.96 |
| | Static | 39.29 | 0.08 | - | 42.53 | 0.63 | - | 42.76 | 0.99 | - |
| *DS* | ASAP | 13.28 | 2.68 | 7.86 | 15.72 | 3.46 | 6.85 | 17.01 | 3.84 | 6.33 |
| | ASA$\alpha$ = 1 km | 13.20 | 2.81 | 9.68 | 15.71 | 3.60 | 8.63 | 16.64 | 3.99 | 8.15 |
| | ASA$\alpha$ = 2 km | 13.14 | 2.93 | 12.44 | 15.65 | 3.72 | 11.24 | 16.57 | 4.12 | 10.67 |
| | ASA$\alpha$ = 3 km | 13.15 | 3.01 | 14.34 | 15.66 | 3.83 | 13.25 | 16.54 | 4.23 | 12.68 |
| | ASA$\alpha$ = 4 km | 13.15 | 3.08 | 15.88 | 15.68 | 3.90 | 14.73 | 16.58 | 4.32 | 14.27 |
| | ASA$\alpha$ = 5 km | 13.23 | 3.14 | 17.51 | 15.75 | 3.98 | 16.34 | 16.63 | 4.40 | 15.90 |
| | ASA$\alpha$ = 6 km | 13.28 | 3.18 | 18.76 | 15.78 | 4.04 | 17.56 | 16.68 | 4.48 | 17.19 |
| | ASA$\alpha$ = 7 km | 13.31 | 3.22 | 19.87 | 15.82 | 4.10 | 18.55 | 16.74 | 4.55 | 18.19 |
| | ASA$\alpha$ = 8 km | 13.35 | 3.26 | 20.80 | 15.87 | 4.15 | 19.46 | 16.79 | 4.61 | 19.07 |
| | ASA$\alpha$ = 9 km | 13.37 | 3.28 | 21.56 | 15.91 | 4.19 | 20.33 | 16.81 | 4.65 | 19.91 |
| | ALAP | 13.50 | 3.43 | 26.19 | 16.06 | 4.44 | 25.62 | 17.02 | 4.95 | 25.73 |
| | Static | 15.47 | 4.21 | - | 17.78 | 5.26 | - | 18.63 | 5.76 | - |

Comparing ASAP and ALAP policies with the static approach highlights the following issues: First, the gap between the static values and the ASAP policy measures demonstrates the potential improvement when prior information becomes available through participants before finalising matches. When no prior information is received, a better solution might be obtained if finalisation of matches is postponed using a rolling horizon based policy. Further, although the ALAP policy may improve the quality of solutions in terms of MR and AKS, it significantly increases the AFT value. Hence, from a customer service perspective, there exists a trade-off between the ASAP and the ALAP policies. Second, these results demonstrate that the ALAP-based approaches can generate competitive results to static situations where all information is available. For instance, DP-ALAP provides on average 90% of the MR value achieved by the DP-Static; however, this policy does not perform well in terms of the AFT measure. From the AFT measure point of view, ASAP policies outperform ALAP policies by a factor of four. Further, in terms of both ASAP and ALAP policies, the NM and DS objective functions dominate each other based on MR and AKS values, respectively.

DP and ADP objective functions yield non-dominated solutions. Specifically, DP dominates ADP with regard to MR, while it is dominated by ADP with regard to AKS. These differences can be explained in part due to lack of the length of the matched trip consideration in the DP. In fact, DP results in outstanding MR values.

When the ADP index is used in the objective function, the ADP-ASA$\alpha$ (for a wide range of $\alpha$ values) policy significantly outperforms DS-ASA$\alpha$ policies in terms of the MR and AKS (see Figure 7-7). Further, using DP and ADP as objective functions, it is observed that increasing the flexibility of the dynamic matching policy, i.e. from ASAP, to ASA$\alpha$ and then to ALAP, improves MR and AKS. In contrast, the DS-ASA$\alpha$ policy does not steadily improve the MR compared to DP-ASA$\alpha$ and ADP-ASA$\alpha$ policies (see Figure 7-7). Another notable observation is that DP-ASA$\alpha$ and ADP-ASA$\alpha$ policies rapidly converge to the AKS value obtained from DP-ALAP and ADP-ALAP combinations, respectively. This means DP-ASA$\alpha$ and ADP-ASA$\alpha$ policies can significantly improve AKS while maintaining AFT at an acceptable level.

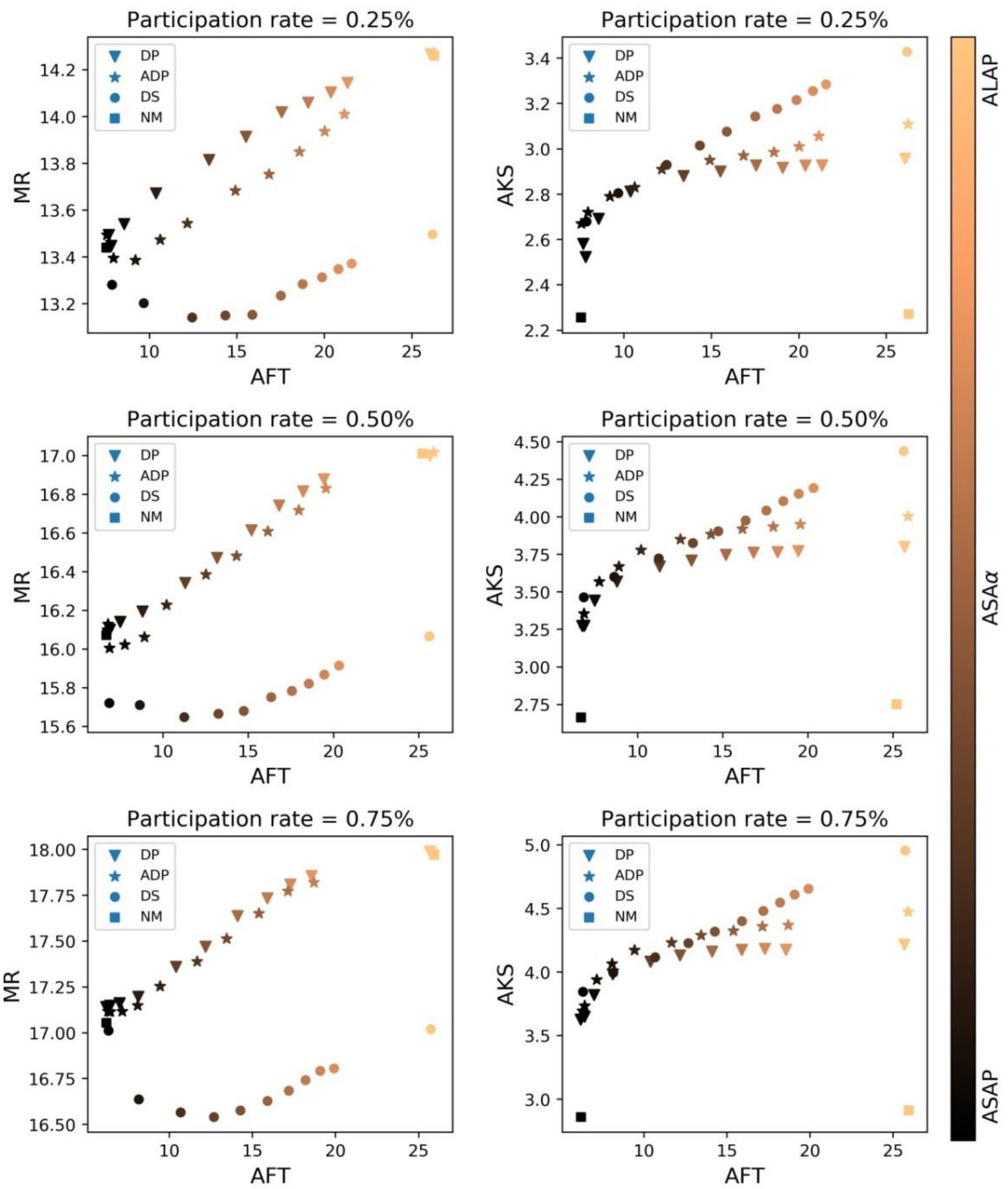



Figure 7-7 Comparison of objective functions over different dynamic matching policies ($\varepsilon = 0$).

Also, Figure 7-7 reveals the critical roles that the ADP and DP may play in dynamic systems like TPMSs where the system should finalise proper matches at different time steps. As implementing ALAP policy is complicated in dynamic TPMSs, and the existence of high compatibility between the objective functions, and ASAP and ASA$\alpha$, it can be concluded that the best combinations to be used in TPMSs are DP and ADP in conjunction with ASAP or ASA$\alpha$ policies.

A closer inspection of the figure above shows that for both ASAP and ALAP dynamic matching policies, the DP and ADP objective functions outperform the NM objective function in terms of both MR and AKS measures. This suggests that even if maximising MR is the main objective of the dynamic ride-sharing system, the DP and ADP indices would be desirable weighting strategies for the objective function of the matching problems in a dynamic, rolling-horizon based framework. The DP and ADP indices outperform the NM objective function since in comparison with a pure matching strategy, they prioritise announcements based on the announcements' original distances.

As mentioned by Stiglic et al. (2016), the spatial density of participants is important in ride-sharing systems. The same outcome is observed in Figure 7-7; higher participation rate (and as a result, density) produces higher number of matches as well as higher distance savings.

Figure 7-8 shows the impact of different objective functions across multiple participation rates. As can be perceived from the figure (and also Figure 7-7), with higher participation rates, ASA$\alpha$ policies result in better AFT. This means service providers can choose higher values of $\alpha$ to obtain higher improvement with no change in AFT of the system. Another remarkable issue is that DP-ASA$\alpha$ outperforms DP-ASAP and DP-ALAP in terms of AKS for many values for $\alpha$.

Comparing AFT values for ADP-ASA$\alpha$ for $\varepsilon = -5$ (Figure 7-8) and $\varepsilon = 0$ (Figure 7-7) reveals that the ADP objective function is sensitive to the value of $\varepsilon$. The former case, $\varepsilon = -5$, requires higher AFT for ADP-ASA$\alpha$ to converge to ADP-ALAP compared to DP-ASA$\alpha$.

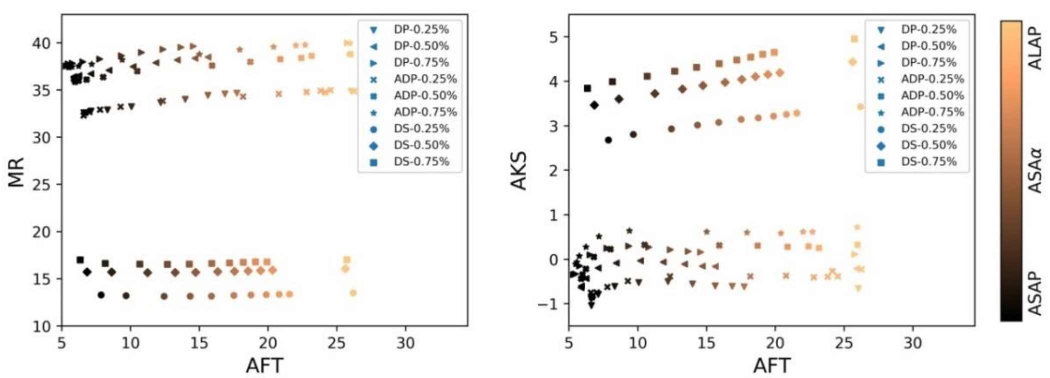
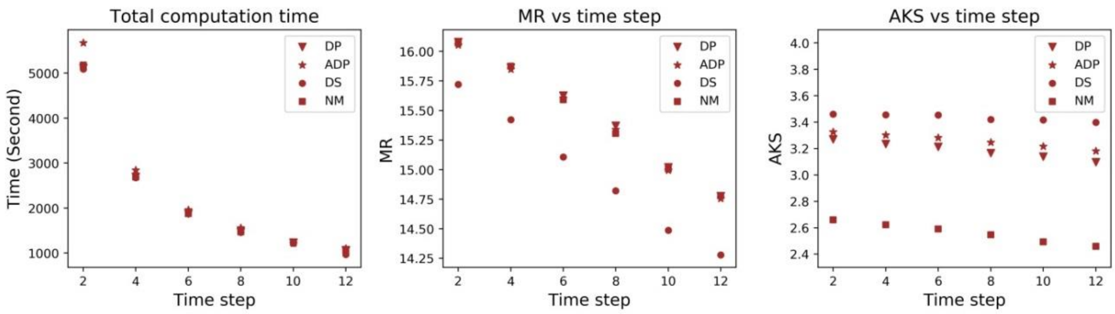


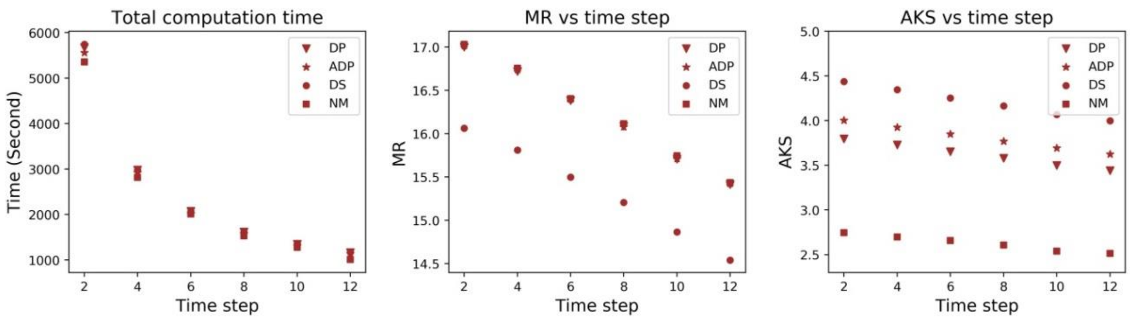

Figure 7-8 Comparison of objective functions over different dynamic matching policies and participation rates ($\varepsilon = -5$).

The analysis above reveals that the DP-ASAP and DP- ASA$\alpha$ are promising strategies that a ride-sharing system can apply in practice. Furthermore, these strategies would come in handy in dynamic TPMSs where finalised matches in each time-step should be returned to TPMSs dynamically.

The computational performance of the ROLLING HORIZON algorithm is analysed in Figure 7-9 for a range of time steps ($p$). Combinations of ASAP and ALAP matching policies, and different objective functions are considered for the setting of participation rate = 0.50% and $\varepsilon = 0$. The computation time refers to the total time required for running the algorithms in all iterations. The results show that increasing the time step decreases the total computation time at the cost of decreasing the MR and the AKS criteria.



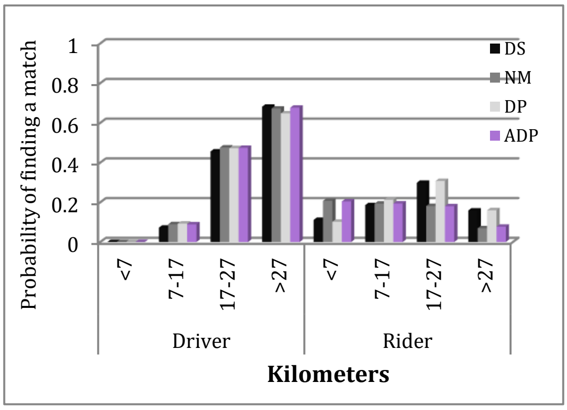

a) Matching policy is ASAP



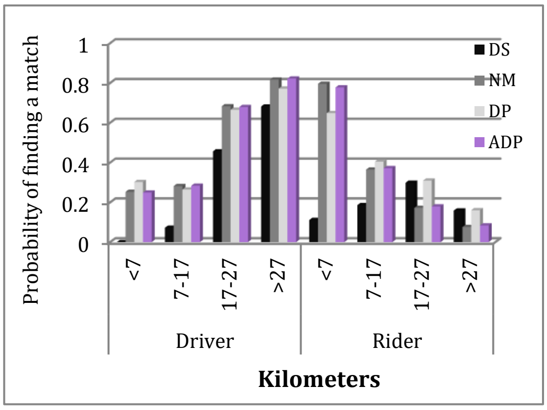

b) Matching policy is ALAP

Figure 7-9 The effects of time step on the performance of the system ($\varepsilon = 0$ and participation rate = 0.50%).

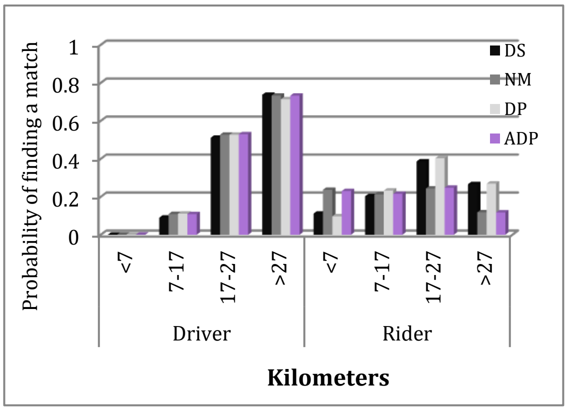
Next, the probability of finding a match based on participant's trip length is investigated. Figure 7-10 breaks down trip announcements based on the participants' individual trip distance to investigate their success rate in finding a match. As shown in the figure, except for $\varepsilon = -5$ for DP, for all other cases, the probability of finding a match for drivers steadily increases with an increase in the trip length.



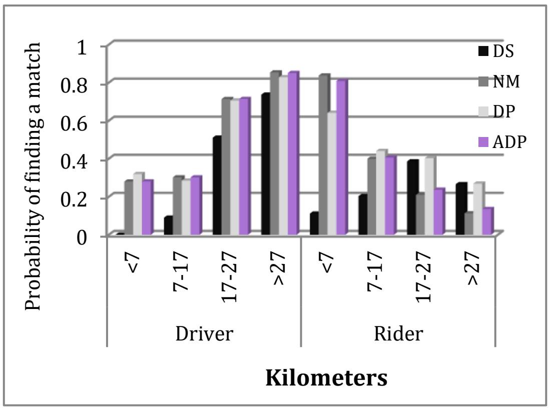

a) 0.25% participation rate ($\varepsilon = 0$)



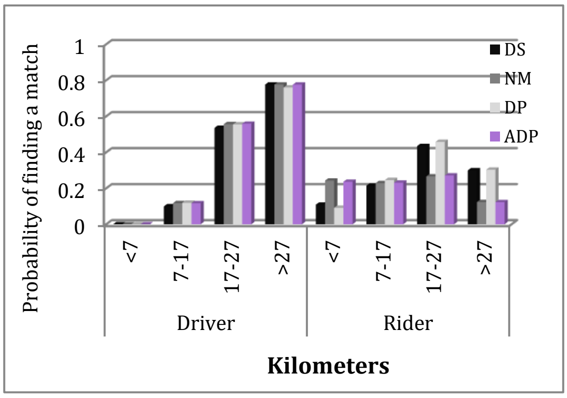

b) 0.25% participation rate ($\varepsilon = -5$)



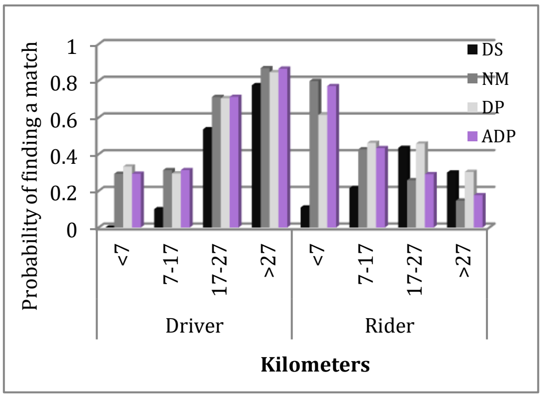

c) 0.50% participation rate ($\varepsilon = 0$)




d) 0.50% participation rate ($\varepsilon = -5$)




e) 0.75% participation rate ($\varepsilon = 0$)




f) 0.75% participation rate ($\varepsilon = -5$)

Figure 7-10 Probability of finding a match vs. participants' individual trip distance.

Longer trips increase the probability of finding a compatible rider both en-route and detour which can then result in having more potential distance savings. For rider trips, it is found that the probability of finding a match is highly dependent on the type of objective function and the value of $\varepsilon$. For example, using DP as the objective function, for rider trips shorter than 7 km a higher chance exists for $\varepsilon = -5$ while they have the lowest probability with $\varepsilon = 0$. Further, the likelihood of finding a match for a rider trip shorter than 7 km is low if DS is used in the objective function. Although short rider trips may easily be matched to compatible drivers, they are unlikely to result in significant distance savings. Finally, it is found that a higher trip density usually increases the probability of finding a match.

### 7.6.3 Performance of the clustering heuristic

In this section, the performance of the proposed clustering heuristic for the presented ride-sharing system is analysed. To compare the results obtained from the CLUSTERING algorithm with the proposed exact approach, this study focuses on participation rate of 0.5% and the ALAP policy, which is the setting that performed the worst in terms of computation time. In addition, let $\varepsilon = -5, p = 2$; and the ROLLING HORIZON algorithm is executed over 450 time periods. To explore the sensitivity of the heuristic with regards to the number of clusters, the experiments are conducted with $|N|$ =2, 3, 4 and 5 clusters.

The results are shown in Table 7-3. The computation time values for both the STATIC and ROLLING HORIZON algorithms are provided in the 3rd an 4th columns for each number of clustered considered. It is notable that the matching algorithm is included under ROLLING HORIZON in the table. The average runtime per iteration is given in the 5th column. In addition, the performance of the algorithm with regards to MR, AKS and AFT is provided in the 6th, 8th and 9th columns, respectively. Further, the cumulative loss of MR for each number of clustered considered in the 7th column.

According to the results, the ROLLING HORIZON algorithm together with the NM objective function is significantly faster where the clustering algorithm does not affect the computation time of the algorithm. However, the clustering algorithm is considerably effective for reducing computation time for the STATIC algorithm. For DP, ADP and DS cases, using the clustering heuristic significantly reduces the total computational time by 44.3% to 68.8%, 50.8% to 75% and 45.3% to70.7% respectively. The impact on the MR translates into reductions within the range of 1.4% to 2.9% in the case of two clusters, 2.1% to 3.9% in the case of three clusters, 2% to 4% in the case of four clusters, and 3% to 4.9% in the case of five clusters. With regard to the AKS, while the clustering algorithm does not notably affect the quality of the solution for DP and NM, this criterion is more influenced if ADP or DS are used. The AKS quality reduction for DS is within the range of 1.6% to 7%. This shows that the overall impact of the clustering heuristic is marginal compared to the quality of solutions.

Table 7-3 Performance of clustering algorithm (policy = ALAP, $\varepsilon = -5, p = 2$, and participation rate = 0.50%).

| Objective function | No. of clusters | STATIC computation time (seconds) | ROLLING HORIZON computation time (seconds) | Average runtime per iteration | MR | Cumulative loss of MR performance (%) | AKS | AFT |
|---|---|---|---|---|---|---|---|---|
| DP | 1 | 5440.27 | 1806.67 | 16.10 | 38.78 | 100 | -0.20 | 25.77 |
| | 2 | 2934.56 | 1101.08 | 8.97 | 38.09 | 98.22 | -0.16 | 26.02 |
| | 3 | 2550.55 | 1023.26 | 7.94 | 37.95 | 97.86 | -0.21 | 26.12 |
| | 4 | 1756.81 | 1100.28 | 6.35 | 37.98 | 97.94 | -0.31 | 26.14 |
| | 5 | 1398.75 | 865.81 | 5.03 | 37.62 | 97.01 | -0.30 | 26.26 |
| ADP | 1 | 5575.23 | 2534.95 | 18.02 | 38.84 | 100.00 | 0.37 | 25.88 |
| | 2 | 2763.29 | 1227.74 | 8.87 | 37.96 | 97.74 | 0.05 | 26.07 |
| | 3 | 2074.88 | 1021.47 | 6.88 | 37.78 | 97.28 | 0.03 | 26.17 |
| | 4 | 1798.89 | 1061.21 | 6.36 | 37.92 | 97.62 | -0.21 | 26.12 |
| | 5 | 1244.63 | 782.29 | 4.50 | 37.36 | 96.19 | -0.28 | 26.21 |
| DS | 1 | 5337.77 | 1314.25 | 14.78 | 16.06 | 100 | 4.44 | 25.73 |
| | 2 | 2881.73 | 754.04 | 8.08 | 15.84 | 98.63 | 4.37 | 25.98 |
| | 3 | 2486.79 | 709.29 | 7.10 | 15.68 | 97.63 | 4.28 | 26.08 |
| | 4 | 1749.79 | 733.96 | 5.52 | 15.42 | 96.01 | 4.20 | 26.29 |
| | 5 | 1376.37 | 575.57 | 4.34 | 15.28 | 95.14 | 4.13 | 26.34 |
| NM | 1 | 5321.20 | 18.99 | 11.87 | 38.73 | 100 | -1.44 | 25.83 |
| | 2 | 2850.37 | 18.62 | 6.38 | 37.59 | 97.06 | -1.40 | 25.84 |
| | 3 | 2302.29 | 20.52 | 5.16 | 37.22 | 96.10 | -1.43 | 25.92 |
| | 4 | 1772.98 | 21.43 | 3.99 | 37.46 | 96.72 | -1.45 | 25.96 |
| | 5 | 1458.28 | 18.97 | 3.28 | 36.93 | 95.35 | -1.39 | 26.05 |

## 7.7 Conclusion

This chapter proposed a new on-demand ride-sharing system, including novel objective functions for the matching problem therein, new dynamic matching policies and a clustering heuristic to tackle large-scale instances. It was found that the choice of the objective function and the dynamic matching policy can substantially improve the performance of the ride-sharing system. The results highlighted that the proposed objective functions DP and ADP are able to outperform the traditional NM objective function. However, combination of DP, ADP and DS objective functions with ASAP and ALAP matching policies generate a set of non-dominated solutions so that none of the approaches is absolutely better than the other. It was also reported that the ASA$\alpha$ policies are not compatible with the DS objective function (compared with DP and ADP objective functions). Further, it was found that the results obtained using Policy DS-ASA $\alpha$ outperform both Policies DP-ASA$\alpha$ and ADP-ASA$\alpha$ with regards to MR. However, it was observed that DP and ADP objective functions are well compatible with ASA$\alpha$ policies so that DP-ASA$\alpha$ and ADP-ASA$\alpha$ combinations outperform DS-ASA$\alpha$ in some AFT values. Moreover, the combinations can result in MR and AKS values at acceptable levels while their AFT measure has a significant difference to those of DP-ALAP, ADP-ALAP and DS-ALAP. In term of their inclusion in TPMSs, the proposed DP and ADP in conjunction with ASAP or ASA$\alpha$ policies are the best alternatives to be included in TPMSs.

# Chapter 8

# Conclusion and Future Research

## 8.1 Summary

This thesis began with four aims:

1. Review the states of the practice of the TPMSs development and their potential implications.
2. Develop systematic approaches to enhance TPMSs calibration process considering both demand-side and traffic assignment models in a unified structure.
3. Formulate an integrated TPMS to have different model components in a unified structure.
4. Formulate an emerging model component for conventional TPMSs.

The first aim involved reviewing mainly the standard practice of developing TPMSs, calibrating the models, and then recognising the theoretical and practical issues of transport models. The motivation for this aim was to identify research gaps in the literature as well as to recognise the main issues in the structure of the TPMSs so that these gaps could be tackled in the next stages of the research efforts under this PhD thesis. The review was to be used to argue replacement of the conventional TPMSs structures with more advanced TPMSs formulations, or at least to apply some auxiliary models to enhance the process of conventional TPMSs development. This aim was fulfilled in chapters 2, 3, and the introduction and literature review sections of the main chapters (chapters 4 to 7). This thesis did not include all the literature review in a specific chapter; instead, it was distributed among the main chapters so that the elaborated research gaps in the literature and the provided solutions for them were put together.

Chapter 2 began by explaining the general terminologies and concepts that are frequently used in the next chapters. Also, the existing processes of developing and integrating demand-side and network models were discussed. After that, in Chapter 3, a numerical experiment was conducted to show a critical issue that may appear in one of the prevalent calibration techniques, that is OD calibration methods (as a traditional calibration solution). The results showed that the standard OD calibration procedure causes unrealistic changes in the OD matrix. The literature reviews in chapters 4 and 5 focused on the weaknesses of conventional TPMSs within which the interactions between demand-side and traffic assignment models are not properly addressed. Furthermore, the literature in Chapter 5 focused on the lack of synchronisation between all the model components in conventional TPMSs (and not only between demand-side and traffic assignment models) and the necessity of providing an alternative solution.

The second aim involved finding alternative calibration solutions for the standard practice in the calibration process of conventional TPMSs (e.g. four-step and activity-based models) in which their model components are partly developed individually, and then connected in a sequential and ad-hoc manner. Despite the fact that the models have theoretically some critical problems, they are widely developed in practice; a main reason is their relatively fast running speed. The widespread use of the models was the main motivation of Aim 2, such that while the models cannot be replaced easily, the quality of the models can be enhanced by developing some advanced calibration approaches. This aim was fulfilled in Chapters 4 and 5 in which two different models were presented based on the recognised issues in the literature.

Chapter 4 firstly discussed the unstructured calibration process in developing large-scale TPMSs and elaborated the significant role of modellers' expertise in the calibration process. Then, the chapter discussed the common problems in the calibration process of conventional TPMSs. This chapter also developed a novel calibration solution that systematically calibrates TPMSs. The model accounts for the multi-objectivity nature of the calibration process, the calibration and validation of the TPMSs in a unified structure, and the interactions of TPMS constituent models and parameters. The chapter used variants of model systems built on GTAModel, Ontario Canada, to illustrate the application of the proposed calibration model. The results shed light on the outstanding performance of the calibration model over the unstructured calibration approach. The chapter concluded with a discussion of the over-calibration problem, the issue that threatens some of the variants that are weakly built.

Chapter 5 began with a description of the complexity of using unstructured methods in calibration of large-scale TPMSs and the role of error terms in their simulation results. This was followed by a discussion of the importance of robustness and its importance in TPMSs. Then, it explained the independent calibration of demand-side and traffic assignment models and their impact on the robustness of the system. Similar to chapter 4, the proposed calibration model in this chapter was a systematic model to calibrate TPMSs, but its focus was on the minimisation of the impacts of the error terms on the TPMS results. The chapter applied the proposed calibration model to calibrate the initial version of GTAModel. The usefulness of the calibration model was evaluated and discussed at the end of the chapter.

The proposed approaches in chapters 4 and 5 have tried to integrate already-estimated model components in the calibration process. Therefore, the calibration process is restricted by the estimated values of the parameters. Furthermore, the estimated model components are usually estimated individually where the interactions among the estimated parameters are ignored. This may affect the quality of the final calibrated model system even if a suitable structured calibration process has been applied. Therefore, the integration of the model components in the calibration process (and not in the estimation process) is still not ideal. The solution may be to develop a fully-integrated model by joint estimation and calibration of the parameters of the model components in the TPMS. In other words, the calibration and estimation processes are performed in an iterative process until the discrepancy between the simulated and observed statistics is eliminated.

The need for the simultaneous estimation and calibration of the TPMSs as well as the lack of synchronisation among the outputs of the conventional TPMSs model components were the main motivations for Aim 3. Accordingly, Chapter 6 involved formulating and calibrating an integrated TPMS in which a single comprehensive ATPs generator is formulated and integrated with multiple traffic assignment models. The chapter began with a discussion about the typical sources of asynchronisation in the conventional models with sequential structures. After that, the calibration complexity of the integrated models was discussed which is followed by a debating on the efforts in developing ATPs generators and their linkage with traffic assignment models. The chapter then described how a unified structure can be developed to solve the asynchronisation issue in the conventional models. Accordingly, an expanded network-based (supernetwork-based) model was formulated in which the demand-side choice facets including the choices of activity, activity sequence, mode, departure time, and parking location are all unified into one time-dependent activity travel pattern choice. In the formulation, a comprehensive model was developed regardless of whether the model is solvable within a reasonable time or not. Following this, the chapter described how to connect the ATPs generator and traffic assignment models in the structure of the TPMS. Then, an effective calibration solution using splitting ratios was proposed which could significantly affect the performance of the developed TPMS. Next, a numerical example with simulated scenarios was provided to demonstrate the advantages of the proposed structure. The chapter concluded with a discussion on the convergence and behaviour power of the developed TPMS.

The fourth aim involved developing a novel formulation for an emerging model component suitable to be embedded in the structure of conventional TPMSs. This aim was fulfilled in Chapters 7 in which a novel dynamic ride-sharing model was proposed. The chapter began with a discussion of state of the art in the area of ride-sharing. This was followed by a description of common performance measures of the systems in the literature. Next, the chapter formulated a novel rolling horizon-based ride sharing model by focusing on the types of objective functions and matching policies. This chapter also proposed a clustering algorithm to enhance the performance of the model components when large a number of agents are in the system. The chapter concluded with a discussion on the numerical results obtained from running different variants of the model on an simple network.

## 8.2 Future directions

Regarding the traditional calibration techniques, the most immediate research direction would be to conduct numerically-based research to show, examine, and compare the potential effects of the calibration techniques on the forecasting capabilities of the models. Also, it would be considered whether the calibration techniques cause unrealistic changes in the model outputs or not. Furthermore, the critical role of modellers in developing transport models was highlighted. Calibration techniques are commonly used by the modeller to calibrate TPMSs, in some cases, it may be detrimental. Thus, the usage of the calibration techniques should be organised to limit the devastating effects of the techniques. Therefore, developing conceptual models and theoretical standards are essential to control the usage of the techniques.

Although Chapter 5 introduced a new model formulation for joint estimation and calibration of different travel aspects, it has few limitations such that it opens up some research directions. First, the developed model is NP-Hard and is solvable by exact algorithms only for problems of small sizes. Proposing heuristics for solving the model is highly appreciated. Second, in Chapter 6,it is tried to develop a comprehensive transport model; thus the model is tested on some highly simplified scenarios; nonetheless, analysing more complicated scenarios using the model is left for future research. Despite the fact that the proposed model allows considering the interactions between public transport and private vehicles modes, investigating the interaction would be a challenging stream of research. Also, analysing and investigating the behaviour of individuals in different scenarios has been left to future research. The impact of change in network structure on the people's travel behaviour is a general category of scenarios. Third, the proposed model's structure is different from the standard transport models that are being applied in practice. Comparing the performance of these transport models and recognising the performance measures with significant differences can put accent on the shortcomings of standard models. Fourth, the model can be extended to include the timetable synchronisation in public transport as a useful strategy utilised to mitigate the transfer waiting time and as a result improve service connectivity. Because of the multimodality and the tour-based structure of the model, optimising the timetable of public transport may be more realistic.

## 8.3 Policy implications

Even though more recently developed TPMSs, such as activity-based models, are promising and conceptually have many capabilities superior to traditional models, their success is closely tied to the quality of their calibration process. As discussed earlier in chapters 4 and 5, the iterative unstructured adjustment of parameters via the classic calibration techniques is no longer sufficient for the calibration and validation of emerging transport models due to their massive number of interactive parameters. Furthermore, the unstructured calibration process is hampered by a number of challenges that may arise in simulation. Smart adjustment of parameters can substantially improve the performance of TPMS calibration processes. However, there is no single solution for parameter calibration. There are three main reasons why numerous possible solutions may exist: 1) the solution space of the calibration process is non-convex, 2) the calibration process is a multi-objective problem, and 3) the parameters are interconnected. Therefore, relying on modellers' expertise does not guarantee a proper solution for parameter adjustment. Hence, developing systematic calibration approaches that guide modellers in the calibration process are of utmost significance, and was the purpose of chapters 4 and 5. The proposed approaches may be of interest to transport modellers who are interested in developing large-scale models systematically and coherently, especially when modelling expertise is limited.

Furthermore, most existing approaches fall short of fully representing activity-travel patterns such as different aspects of activity pattern generations which are more or less missed. Meanwhile, the models are usually downgraded from activity patterns to trips or to a sequential structure. Furthermore, without taking into account temporal and spatial dimensions of activity locations and without considering their dependencies, the structure of conventional transport models, the sequence of activities and also activity locations may be drastically affected. Thus, the model may output inaccurate or even wrong predictions in activity patterns and locations. In chapter 6, a novel model was proposed to address all the travel choice components in a unified structure. It took the benefit of incorporation of spatial-temporal characteristics in activity selection. The proposed model may be utilised to investigate different scenarios with a higher accuracy. The scenarios include: 1) traffic policies such as road improvement, public transport improvement, adding or removing facility spots such as shopping centres, parking lots and parks, 2) behavioural policies such as the impact of flexible working time on the behaviour of people and the congestion of the roads and the impact of changes in tolling corridors on the activity travel patterns.

Many components are embedded in transport planning model systems, one of the most emerging one is ride-sharing component. Although ride-sharing is a promising and competitive approach to replace private car ownership, its incorporation in transport planning model systems tied to the performance of the developed model component for ride-sharing and to its compatibility with conventional transport planning model structures. A smart selection of dynamic matching policies and objective functions, which are defined to reflect the preferences of the parties involved, can substantially improve the performance of the ride-sharing system, as discussed in the Chapter 7. The results revealed that if the proposed "distance proximity" and "adjusted distance proximity" indices combined with "as soon as possible" matching policy, the resulting model component not only can offer a competitive alternative for commercial ride-sharing companies but also can be embedded in the body of microsimulation and activity-based models.

## 8.4 Final remarks

The motivation for this thesis was to enhance the model development process of transport planning model systems and their predicting power mainly by both structuring the calibration process of the models and developing integrated models. A significant advantage of using structured calibration model is that it provides a systematic and consistent approach for analysis. The calibration processes in practice are unstructured which are fully dependant on modellers' expertise and their judgement. On the condition that there are frameworks and structured approaches, they can facilitate calibrating complicated models and steer modellers' decisions. In other words, they provide a platform to prevent unnecessary adjustments in the already estimated model components in the transport planning model system structures, some of which may otherwise override theoretical standards and rules. Furthermore, developing integrated models can be an elegant solution to circumvent asynchronisations between the model components in the body of conventional transport planning model systems.

It is hoped that the exposition of the complicated interactions between transport model components and the developed solutions in this thesis make it easier for future researchers and practitioners to estimate and calibrate their models. This can also improve the effectiveness of transport models for the well-being of urban societies.

# Bibliography and appendixes

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# Appendix A – Calibration with Taguchi and ANOVA

In the current study, the Taguchi and ANOVA analyses are used in order to select the best combination of the factors. In the proposed model, factors are either candidate models or model parameters. Further, the Taguchi method helps to recognise the models and parameters that form the robust structure. ANOVA is applied to determine the effectiveness of models and parameters having significant impact on the robustness and outputs.

For doing one round of Taguchi, some factors $f \in F$ have to be chosen. Then, several alternatives (we call an alternative as level $l \in L$ ) should be selected for further investigations. After that, a number of experiments have to be conducted on the selected factors and their respective levels. In the Taguchi design, the experiments should be conducted according to a pre-specified experimental design. Each experiment is defined as a trial $i \in I$, where $I$ is the set of all trials defined by a proper orthogonal array in the Taguchi method. In order to reduce the random error effects, each trial should be repeated with certain replications, $N$. Notation $r_{in}$is the response for $n^{th}$ repetition of trial $i$ where $n \epsilon \{1,2, \ldots, N\}$. Then, the average response $\bar{r_i}$ and the signal-to-noise ratio $(S/N)_i$ for each trial $i$ are calculated per Equations (A-1) to (A-4).

$$\bar{r_i} = \frac{1}{N} \sum_n r_{in} \qquad \text{(A-1)}$$

Depending on the type of the response, different formulations for calculating $(S/N)_i$ is proposed in the Taguchi method:

- Smaller the better (for making the system response as small as possible):

$$(S/N)_i = -10 log\ (\frac{1}{N} \sum_{n \in N} {r_{in}}^2) \qquad \text{(A-2)}$$

- Nominal the best (for reducing variability around a target):

$$(S/N)_i = 10 log\ (\frac{\bar{r_i}^2}{S_i^2}) \qquad \text{(0A-3)}$$

- Larger the better (for making the system response as large as possible):

$$(S/N)_i = -10log\ (\frac{1}{N}\sum_{n\in N}\frac{1}{{r_{in}}^2}) \tag{A-4}$$

where $S_i$ is the standard deviation of the responses in trial $i$. After that, to determine the impact of each level $l \in L^f$ of factor $f$, Equation (A-5) and Equation (A-6) are used.

$$\bar{r}_l^f = \frac{1}{\left(\frac{|I|}{|L^f|}\right)}\sum_{i\in I}(\bar{r}_i \times x_{il}^f) \tag{A-5}$$

$$(\mathrm{S/N})_l^f = \frac{1}{\left(\frac{|I|}{|L^f|}\right)}\sum_{i\in I}((S/N)_i \times x_{il}^f) \tag{A-6}$$

where $x_{il}^f$ is binary and equal to 1 if level $l$ of factor $f$ is active in trial $i$ (based on the selected orthogonal array in Taguchi). $\bar{r}_l^f$ and $(S/N)_l^f$ are the average of responses and the average of signal-to-noise with regard to level $l \in \mathrm{L}^f$ of factor $f$. The number of times that a specific level under factor $f$ appears is $\frac{|I|}{|L^f|}$, since in the orthogonal arrays, the levels of a factor equally appear in the experiments.

The (S/N) ratios and the average responses are used to design the parameters. (S/N) ratios are used for determining the factors that minimise the variances. Average responses are utilised for determining the factors that their adjustments are the best solution to reduce the discrepancy between model system outputs and observed statistics. The difference between the simulated and observed screen line values is an example of quality characteristic where its objective point is zero. To determine if a factor has significant impact on $(\mathrm{S/N})$ and $\bar{\mathrm{r}}$, the ANOVA test can be used. For each factor, ANOVA determines whether there is any statistically significant difference between the performance of its different levels.

The current study borrow the parameter design steps from Park and Antony (2008) to continue the process. Accordingly, in each iteration, after conducting all experiments, the following steps should be considered:

(i) $P^s$ and $P^r$ are the sets of control factors having significant impacts on (S/N) and $\bar{r}$ respectively. For each factor in $P^s$, choose the level which maximises the (S/N) ($f^* \leftarrow argmax\{(S/N)_l^f, l \in L^f\}$). For example, the lower level of a factor $f \in \bar{P}^s$ is selected if its lower level maximises the S/N ratio,

(ii) For factors $f$ that do not have significant impact on (S/N) ratios ($f \notin P^s$) while has significant impact on mean of responses ($f \in P^r$), the level $l$ whose $\bar{r}_l^f$ is closer to objective point will be selected. For instance, if the calibration purpose is minimising the difference between simulated and estimated traffic counts, the level $l$ with the smallest $\bar{r}_l^f$ will be selected. The factors are recognised as adjustment factor,

(iii) Factors with no significant impact on S/N ratio nor on $\bar{r}$ ($f: f \notin (P^s \cup P^r)$), are kept unchanged.

The pseudo code for one iteration of choosing the best combination is presented in Algorithm. Actually, Algorithm is the combination selection procedure for the proposed model in this chapter.

Algorithm A-1: The Taguchi and ANOVA procedures in one iteration

**Input:** Factors ($f \in F$), Number of replications $N$

**Output:** Calibrated factors $f^*$

$P \leftarrow$ Select the control factors from $F$

$L^f \leftarrow$ Choose the candidate levels for each factor $f \in P$

$I \leftarrow$ form the appropriate orthogonal array (experimental design),

**for** $i \in I$:

    **for** $n \in \{1,2,\dots,N\}$:

        $r_{in} \leftarrow$ run the model according to level settings for trial $i \in I$

    **end for**

    $(S/N)_i \leftarrow$ Calculating Signal-to-Noise

    $\bar{r}_i \leftarrow \frac{1}{N}\sum_n r_{in}$

**end for**

**for** $f \in P$:

    **for** $l \in L^f$:

        $\bar{r}_l^f = \frac{1}{\left(\frac{|I|}{|L^f|}\right)} \sum_{i \in I} \left(\bar{r}_i \times x_{il}^f\right)$

        $(S/N)_l^f = \frac{1}{\left(\frac{|I|}{|L^f|}\right)} \sum_{i \in I} \left((S/N)_i \times x_{il}^f\right)$

    **end for**

**end for**

$P^s \leftarrow$ significant factors over (S/N) ratios
$P^r \leftarrow$ significant factors over responses ($r_{in}$)

**for** $f \in \bar{P}^s$:

    $f^* \leftarrow argmax\{(S/N)_l^f, l \in L^f\}$

**end for**

**for** $\{f: f \in P \; and \; p \notin P^s\}$:

    **if** $p \in P^r$ **then:**

        $f^* \leftarrow argmin\{\bar{r}_l^f, l \in L^f\}$

    **end if**

**end for**

# Appendix B – Selected parameters for case studies in chapters 4 and 5 and experimental results

Table B1. Selected parameters, their deviation limits, and the solution in the *first iteration* of the algorithm

| Factors | Parameters | | Calibrated Values (UCT) | Initially Estimated | Deviation bounds | | Solution (SCTR-C&C and SCTR-C) | | Solution (SCT) | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Lower | Upper | deviation | calibrated | deviation | calibrated |
| A | Constant of Drive Access Transit model for students | General jobs | -5.43E+00 | -5.43E+00 | -1 | 2 | 1.3385 | -4.09E+00 | -3.11E-01 | -5.74E+00 |
| | | Sales jobs | -6.41E+00 | -6.41E+00 | -1 | 2 | 1.3385 | -5.07E+00 | -3.11E-01 | -6.72E+00 |
| | | Manufacturing jobs | -7.19E+00 | -7.19E+00 | -1 | 2 | 1.3385 | -5.85E+00 | -3.11E-01 | -7.50E+00 |
| | | Students | -6.73E+00 | -7.23E+00 | -1 | 2 | 1.3385 | -5.89E+00 | -3.11E-01 | -7.54E+00 |
| | | Non-worker students | -7.82E+00 | -7.82E+00 | -1 | 2 | 1.3385 | -6.48E+00 | -3.11E-01 | -8.13E+00 |
| B | Constant of Drive Access Transit model for professional jobs | | -5.27E+00 | -5.27E+00 | -1 | 2 | 1.409 | -3.86E+00 | 1.9865 | 4.32E-01 |
| C | Constants of Walk Access Transit models for | Professional jobs | 9.93E-01 | -1.01E+00 | -0.5 | 2.5 | 2.026 | 1.02E+00 | 5.36E-01 | -4.72E-01 |
| | | General jobs | -4.29E-01 | -2.43E+00 | -0.5 | 2.5 | 2.026 | -4.03E-01 | 5.36E-01 | -1.89E+00 |
| | | Sales jobs | 2.27E+00 | 2.70E-01 | -0.5 | 2.5 | 2.026 | 2.30E+00 | 5.36E-01 | 8.06E-01 |
| | | Manufacturing jobs | 2.54E-01 | -1.75E+00 | -0.5 | 2.5 | 2.026 | 2.80E-01 | 5.36E-01 | -1.21E+00 |
| | | Non-worker students | -1.00E+00 | -3.00E+00 | -0.5 | 2.5 | 2.026 | -9.74E-01 | 5.36E-01 | -2.46E+00 |
| D | Constants of Walk Access Transit model for students | | 1.52E+00 | -1.78E-01 | -0.5 | 2.5 | 1.813 | 1.64E+00 | 2.0365 | 5.16E-01 |
| E | Constants of Carpool models for | Professional jobs | -3.60E+00 | -2.90E+00 | -1.5 | 0.5 | -1.469 | -4.37E+00 | 8.02E-02 | -2.82E+00 |
| | | General jobs | -1.00E+00 | -1.05E-05 | -1.5 | 0.5 | -1.469 | -1.47E+00 | 8.02E-02 | 8.02E-02 |
| | | Sales jobs | -4.00E+00 | -3.00E+00 | -1.5 | 0.5 | -1.469 | -4.47E+00 | 8.02E-02 | -2.92E+00 |
| | | Manufacturing jobs | -4.00E+00 | -3.00E+00 | -1.5 | 0.5 | -1.469 | -4.47E+00 | 8.02E-02 | -2.92E+00 |
| | | Students | -3.99E+00 | -2.99E+00 | -1.5 | 0.5 | -1.469 | -4.46E+00 | 8.02E-02 | -2.91E+00 |
| | | Non-worker students | -2.25E+00 | -1.25E+00 | -1.5 | 0.5 | -1.469 | -2.72E+00 | 8.02E-02 | -1.17E+00 |
| F | Constants of Walk models for | Professional jobs | 1.76E+00 | 2.26E+00 | -1.5 | 0.5 | -1.342 | 9.20E-01 | 2.24E-01 | 2.49E+00 |

Table B1. Selected parameters, their deviation limits, and the solution in the *first iteration* of the algorithm

| Factors | Parameters | | Calibrated Values (UCT) | Initially Estimated | Deviation bounds | | Solution (SCTR-C&C and SCTR-C) | | Solution (SCT) | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Lower | Upper | deviation | calibrated | deviation | calibrated |
| | | General jobs | 1.34E+00 | 1.84E+00 | -1.5 | 0.5 | -1.342 | 5.01E-01 | 2.24E-01 | 2.07E+00 |
| | | Sales jobs | -5.00E-01 | 7.17E-11 | -1.5 | 0.5 | -1.342 | -1.34E+00 | 2.24E-01 | 2.24E-01 |
| | | Manufacturing jobs | -4.99E-01 | 7.82E-04 | -1.5 | 0.5 | -1.342 | -1.34E+00 | 2.24E-01 | 2.25E-01 |
| | | Non-worker students | -5.00E-01 | 2.52E-06 | -1.5 | 0.5 | -1.342 | -1.34E+00 | 2.24E-01 | 2.24E-01 |
| G | Constants of Walk model for students | | 1.90E+00 | 2.40E+00 | -1.5 | 0.5 | -0.797 | 1.61E+00 | -1.0410 | -3.64E-01 |
| H | Constants of Bicycle models for | Professional jobs | -2.70E+00 | -4.00E+00 | -0.5 | 2 | 1.05 | -2.95E+00 | 2.43E-01 | -3.76E+00 |
| | | General jobs | -1.95E+00 | -3.25E+00 | -0.5 | 2 | 1.05 | -2.20E+00 | 2.43E-01 | -3.01E+00 |
| | | Sales jobs | -2.56E+00 | -3.86E+00 | -0.5 | 2 | 1.05 | -2.81E+00 | 2.43E-01 | -3.62E+00 |
| | | Manufacturing jobs | -2.51E+00 | -3.81E+00 | -0.5 | 2 | 1.05 | -2.76E+00 | 2.43E-01 | -3.57E+00 |
| | | Non-worker students | -2.70E+00 | -4.00E+00 | -0.5 | 2 | 1.05 | -2.95E+00 | 2.43E-01 | -3.76E+00 |
| J | Constants of Bicycle model for students | | -2.19E+00 | -3.49E+00 | -0.5 | 2 | 1.05 | -2.44E+00 | 2.0000 | 3.45E-05 |
| K | Constants of Passenger models for | Professional jobs | 2.42E+00 | 3.82E+00 | -2 | 0.5 | -1.135 | 2.68E+00 | 2.77E-01 | 4.10E+00 |
| | | General jobs | -5.40E+00 | -4.00E+00 | -2 | 0.5 | -1.135 | -5.13E+00 | 2.77E-01 | -3.72E+00 |
| | | Sales jobs | 2.60E+00 | 4.00E+00 | -2 | 0.5 | -1.135 | 2.87E+00 | 2.77E-01 | 4.28E+00 |
| | | Manufacturing jobs | 2.60E+00 | 4.00E+00 | -2 | 0.5 | -1.135 | 2.87E+00 | 2.77E-01 | 4.28E+00 |
| | | Non-worker students | 2.60E+00 | 4.00E+00 | -2 | 0.5 | -1.135 | 2.87E+00 | 2.77E-01 | 4.28E+00 |
| L | Constants of Passenger model for students | | -1.16E+00 | 2.36E-01 | -2 | 0.5 | -0.98 | -7.44E-01 | -0.1725 | 3.50E-01 |
| M | Constant of Destination Choice Model for Market purpose in the same districts for PM | | 9.97E-01 | 9.97E-01 | -1 | 1 | 0.829 | 1.83E+00 | 0.5070 | -3.39E-01 |
| N | Constant of Destination Choice Model for Market purpose in the same districts for AM | | 1.00E+00 | 1.00E+00 | -1 | 1 | -0.589 | 4.11E-01 | 0.5050 | 2.73E-01 |

Table B1. Selected parameters, their deviation limits, and the solution in the *first iteration* of the algorithm

| Factors | Parameters | | Calibrated Values (UCT) | Initially Estimated | Deviation bounds | | Solution (SCTR-C&C and SCTR-C) | | Solution (SCT) | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Lower | Upper | deviation | calibrated | deviation | calibrated |
| O | Constant of Destination Choice Model for Market purpose in the same districts for Evening | | 1.00E+00 | 1.00E+00 | -1 | 1 | -0.63 | 3.70E-01 | -0.6170 | 3.41E-02 |
| P | Constant of Destination Choice Model for Market purpose in the same districts for Midday | | 1.00E+00 | 1.00E+00 | -1 | 1 | -0.997 | 2.86E-03 | -0.9700 | -2.77E-01 |
| Q | Constant of Toronto districts for Market purpose (Location Choice) | AM | 3.98E+00 | 3.98E+00 | -1 | 1 | -0.748 | 3.23E+00 | 3.09E-01 | 4.29E+00 |
| | | Midday | 5.16E-04 | 5.16E-04 | -1 | 1 | -0.748 | -7.47E-01 | 3.09E-01 | 3.09E-01 |
| | | PM | 8.17E-04 | 8.17E-04 | -1 | 1 | -0.748 | -7.47E-01 | 3.09E-01 | 3.10E-01 |
| | | Evening | 3.65E+00 | 3.65E+00 | -1 | 1 | -0.748 | 2.90E+00 | 3.09E-01 | 3.96E+00 |
| R | Constant of planning district of CBD of Toronto for Market purpose (Location Choice) | AM | 7.99E+00 | 7.99E+00 | -0.5 | 0.5 | 0.1655 | 8.16E+00 | 1.19E-01 | 8.11E+00 |
| | | Midday | 7.58E-12 | 7.58E-12 | -0.5 | 0.5 | 0.1655 | 1.66E-01 | 1.19E-01 | 1.19E-01 |
| | | PM | 3.70E-05 | 3.70E-05 | -0.5 | 0.5 | 0.1655 | 1.66E-01 | 1.19E-01 | 1.19E-01 |
| | | Evening | 8.00E+00 | 8.00E+00 | -0.5 | 0.5 | 0.1655 | 8.17E+00 | 1.19E-01 | 8.12E+00 |
| S | Constant of Toronto districts in Other purposes (Location Choice) | AM | 5.64E-08 | 5.64E-08 | -0.5 | 0.5 | 0.4685 | 4.69E-01 | -1.47E-02 | -1.47E-02 |
| | | Midday | 2.60E-05 | 2.60E-05 | -0.5 | 0.5 | 0.4685 | 4.69E-01 | -1.47E-02 | -1.47E-02 |
| | | PM | 5.02E-03 | 5.02E-03 | -0.5 | 0.5 | 0.4685 | 4.74E-01 | -1.47E-02 | -9.68E-03 |
| | | Evening | 5.95E-03 | 5.95E-03 | -0.5 | 0.5 | 0.4685 | 4.74E-01 | -1.47E-02 | -8.76E-03 |
| T | Constant of planning district of CBD of Toronto for Other purposes (Location Choice) | AM | 4.00E-05 | 4.00E-05 | -0.5 | 0.5 | 0.5 | 5.00E-01 | 6.94E-02 | 6.94E-02 |
| | | Midday | 1.26E-05 | 1.26E-05 | -0.5 | 0.5 | 0.5 | 5.00E-01 | 6.94E-02 | 6.94E-02 |
| | | PM | 4.82E-01 | 4.82E-01 | -0.5 | 0.5 | 0.5 | 9.82E-01 | 6.94E-02 | 5.52E-01 |
| | | Evening | 9.25E-03 | 9.25E-03 | -0.5 | 0.5 | 0.5 | 5.09E-01 | 6.94E-02 | 7.87E-02 |

Table B1. Selected parameters, their deviation limits, and the solution in the *first iteration* of the algorithm

| Factors | Parameters | | Calibrated Values (UCT) | Initially Estimated | Deviation bounds | | Solution (SCTR-C&C and SCTR-C) | | Solution (SCT) | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Lower | Upper | deviation | calibrated | deviation | calibrated |
| U | Constant of Closest Station in Access Station Model | AM | 1.20E+00 | 1.20E+00 | -0.5 | 0.5 | 0.0205 | 1.22E+00 | -1.07E-03 | 1.20E+00 |
| | | Midday | 3.98E+00 | 3.98E+00 | -0.5 | 0.5 | 0.0205 | 4.00E+00 | -1.07E-03 | 3.97E+00 |
| | | PM | 2.36E-03 | 2.36E-03 | -0.5 | 0.5 | 0.0205 | 2.29E-02 | -1.07E-03 | 1.28E-03 |
| | | Evening | 2.99E+00 | 2.99E+00 | -0.5 | 0.5 | 0.0205 | 3.02E+00 | -1.07E-03 | 2.99E+00 |
| V | Constant of Walk | Market purpose | -4.39E+00 | -2.49E+00 | -2.5 | 0.5 | -1.39 | -3.88E+00 | -5.13E-01 | -3.00E+00 |
| | | Other purpose | -4.40E+00 | -2.50E+00 | -2.5 | 0.5 | -1.39 | -3.89E+00 | -5.13E-01 | -3.01E+00 |
| | | School purpose | 1.10E+00 | 2.50E+00 | -2.5 | 0.5 | -1.39 | 1.11E+00 | -5.13E-01 | 1.99E+00 |
| W | Constants of Walk Access Transit model | Market purpose | -1.50E+00 | 0.00E+00 | -2 | 1 | -1.997 | -2.00E+00 | 2.48E-01 | 2.48E-01 |
| | | Other purpose | -1.10E+00 | 0.00E+00 | -2 | 1 | -1.997 | -2.00E+00 | 2.48E-01 | 2.48E-01 |
| X | Constants of Carpool model | Market purpose | -5.00E-01 | -2.50E+00 | -0.5 | 2.5 | 0.4975 | -2.00E+00 | 3.25E-01 | -2.18E+00 |
| | | Other purpose | -5.00E-01 | -2.50E+00 | -0.5 | 2.5 | 0.4975 | -2.00E+00 | 3.25E-01 | -2.18E+00 |
| Y | Constants of Bicycle model | Market purpose | -5.00E-01 | 2.50E+00 | -4 | 0.5 | 0.25 | 2.75E+00 | 5.11E-04 | 2.50E+00 |
| | | Other purpose | -2.41E+00 | 5.90E-01 | -4 | 0.5 | 0.25 | 8.40E-01 | 5.11E-04 | 5.91E-01 |
| | | School purpose | 3.50E+00 | 2.50E+00 | -4 | 0.5 | 0.25 | 2.75E+00 | 5.11E-04 | 2.50E+00 |
| Z | Constants of Passenger model | School model | -1.14E+00 | -1.64E+00 | -0.5 | 1.5 | 0.177 | -1.47E+00 | 3.49E-01 | -1.29E+00 |
| AA | Flag of Passenger to share a point | | 4.51E+00 | 6.50E-03 | -0.5 | 5 | 5 | 5.01E+00 | 7.90E-01 | 7.96E-01 |
| AB | Constant of having a licence by passenger | | -1.99E+00 | -2.49E+00 | -0.5 | 1.5 | 1.254 | -1.23E+00 | 3.68E-01 | -2.12E+00 |
| AC | Constants of Passenger model | Market purpose | 5.00E+00 | 0.00E+00 | 3 | 7 | 4.648 | 4.65E+00 | 5.28E+00 | 5.28E+00 |
| | | Other purpose | 5.00E+00 | 0.00E+00 | 3 | 7 | 4.648 | 4.65E+00 | 5.28E+00 | 5.28E+00 |

Table B2 Selected parameters, their deviation limits, and the solution in the *second iteration* of the algorithm

| Factors | Parameters | | Calibrated Values (UCT) | Initially Estimated | Deviation bounds (SCTR-C&C) | | Solution (SCTR-C&C) | | Deviation bounds (SCT) | | Solution (SCT) | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Lower | Upper | deviation | calibrated | Lower | Upper | deviation | calibrated |
| A | Coefficient of travel time for Professional jobs in | Auto Drive model | -5.92E-02 | -5.92E-02 | -0.05 | 0.05 | -3.14E-01 | -1.57E-02 | -5.92E-03 | 5.92E-03 | 1.98E-03 | 1.98E-03 |
| | | Passenger model | -5.92E-02 | -5.92E-02 | -0.05 | 0.05 | -3.14E-01 | -1.57E-02 | -5.92E-03 | 5.92E-03 | 1.98E-03 | 1.98E-03 |
| B | Coefficient of travel time for Professional jobs in | DAT model | -5.40E-02 | -5.40E-02 | -0.05 | 0.05 | -1.00E+00 | -5.00E-02 | -5.40E-03 | 5.40E-03 | 3.03E-03 | 3.03E-03 |
| | | WAT model | -5.40E-02 | -5.40E-02 | -0.05 | 0.05 | -1.00E+00 | -5.00E-02 | -5.40E-03 | 5.40E-03 | 3.03E-03 | 3.03E-03 |
| C | Coefficient of travel cost factor for Professional jobs in | Auto Drive model | 2.31E+00 | 2.31E+00 | -1 | 1 | -4.79E-01 | -4.79E-01 | -2.31E-01 | 2.31E-01 | -2.14E-03 | -2.14E-03 |
| | | Passenger model | 2.31E+00 | 2.31E+00 | -1 | 1 | -4.79E-01 | -4.79E-01 | -2.31E-01 | 2.31E-01 | -2.14E-03 | -2.14E-03 |
| | | Carpool model | 2.31E+00 | 2.31E+00 | -1 | 1 | -4.79E-01 | -4.79E-01 | -2.31E-01 | 2.31E-01 | -2.14E-03 | -2.14E-03 |
| | | WAT model | 2.31E+00 | 2.31E+00 | -1 | 1 | -4.79E-01 | -4.79E-01 | -2.31E-01 | 2.31E-01 | -2.14E-03 | -2.14E-03 |
| | | DAT model | 2.31E+00 | 2.31E+00 | -1 | 1 | -4.79E-01 | -4.79E-01 | -2.31E-01 | 2.31E-01 | -2.14E-03 | -2.14E-03 |
| D | Coefficient of travel time for | Auto Drive model-General jobs | -5.89E-02 | -5.89E-02 | -0.05 | 0.05 | 7.79E-01 | 3.89E-02 | -5.89E-03 | 5.89E-03 | 4.44E-03 | 4.44E-03 |
| | | Passenger model-General jobs | -5.89E-02 | -5.89E-02 | -0.05 | 0.05 | 7.79E-01 | 3.89E-02 | -5.89E-03 | 5.89E-03 | 4.44E-03 | 4.44E-03 |
| | | WAT model-Manufacturing jobs | -6.00E-02 | -6.00E-02 | -0.05 | 0.05 | 7.79E-01 | 3.89E-02 | -6.00E-03 | 6.00E-03 | 4.52E-03 | 4.52E-03 |
| | | DAT model-Manufacturing jobs | -6.00E-02 | -6.00E-02 | -0.05 | 0.05 | 7.79E-01 | 3.89E-02 | -6.00E-03 | 6.00E-03 | 4.52E-03 | 4.52E-03 |
| | | Auto Drive model-Sales jobs | -6.00E-02 | -6.00E-02 | -0.05 | 0.05 | 7.79E-01 | 3.89E-02 | -6.00E-03 | 6.00E-03 | 4.52E-03 | 4.52E-03 |
| | | Passenger model-Sales jobs | -6.00E-02 | -6.00E-02 | -0.05 | 0.05 | 7.79E-01 | 3.89E-02 | -6.00E-03 | 6.00E-03 | 4.52E-03 | 4.52E-03 |
| E | Coefficient of travel time for | WAT model-General jobs | -3.11E-02 | -3.11E-02 | -0.025 | 0.025 | 8.36E-01 | 2.09E-02 | -3.11E-03 | 3.11E-03 | 2.71E-03 | 2.71E-03 |
| | | DAT model-General jobs | -3.11E-02 | -3.11E-02 | -0.025 | 0.025 | 8.36E-01 | 2.09E-02 | -3.11E-03 | 3.11E-03 | 2.71E-03 | 2.71E-03 |
| | | Auto Drive model-Manufacturing jobs | -2.50E-02 | -2.50E-02 | -0.025 | 0.025 | 8.36E-01 | 2.09E-02 | -2.50E-03 | 2.50E-03 | 2.18E-03 | 2.18E-03 |

Table B2 Selected parameters, their deviation limits, and the solution in the *second iteration* of the algorithm

| Factors | | Parameters | Calibrated Values (UCT) | Initially Estimated | Deviation bounds (SCTR-C&C) | | Solution (SCTR-C&C) | | Deviation bounds (SCT) | | Solution (SCT) | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Lower | Upper | deviation | calibrated | Lower | Upper | deviation | calibrated |
| | | Passenger model-Manufacturing jobs | -2.50E-02 | -2.50E-02 | -0.025 | 0.025 | 8.36E-01 | 2.09E-02 | -2.50E-03 | 2.50E-03 | 2.18E-03 | 2.18E-03 |
| | | WAT model-Sales jobs | -6.00E-02 | -6.00E-02 | -0.025 | 0.025 | 8.36E-01 | 2.09E-02 | -6.00E-03 | 6.00E-03 | 5.23E-03 | 5.23E-03 |
| | | DAT model-Sales jobs | -6.00E-02 | -6.00E-02 | -0.025 | 0.025 | 8.36E-01 | 2.09E-02 | -6.00E-03 | 6.00E-03 | 5.23E-03 | 5.23E-03 |
| F | Coefficient of travel cost for | Auto Drive model-General jobs | 4.41E+00 | 4.41E+00 | -1.5 | 1.5 | -3.03E-01 | -4.55E-01 | -4.41E-01 | 4.41E-01 | 3.42E-01 | 3.42E-01 |
| | | Passenger model-General jobs | 4.41E+00 | 4.41E+00 | -1.5 | 1.5 | -3.03E-01 | -4.55E-01 | -4.41E-01 | 4.41E-01 | 3.42E-01 | 3.42E-01 |
| | | Carpool model-General jobs | 4.41E+00 | 4.41E+00 | -1.5 | 1.5 | -3.03E-01 | -4.55E-01 | -4.41E-01 | 4.41E-01 | 3.42E-01 | 3.42E-01 |
| | | WAT model-General jobs | 4.41E+00 | 4.41E+00 | -1.5 | 1.5 | -3.03E-01 | -4.55E-01 | -4.41E-01 | 4.41E-01 | 3.42E-01 | 3.42E-01 |
| | | DAT model-General jobs | 4.41E+00 | 4.41E+00 | -1.5 | 1.5 | -3.03E-01 | -4.55E-01 | -4.41E-01 | 4.41E-01 | 3.42E-01 | 3.42E-01 |
| | | Auto Drive model-Manufacturing jobs | 4.47E+00 | 4.47E+00 | -1.5 | 1.5 | -3.03E-01 | -4.55E-01 | -4.47E-01 | 4.47E-01 | 3.46E-01 | 3.46E-01 |
| | | Passenger model- Manufacturing jobs | 4.47E+00 | 4.47E+00 | -1.5 | 1.5 | -3.03E-01 | -4.55E-01 | -4.47E-01 | 4.47E-01 | 3.46E-01 | 3.46E-01 |
| | | Carpool model- Manufacturing jobs | 4.47E+00 | 4.47E+00 | -1.5 | 1.5 | -3.03E-01 | -4.55E-01 | -4.47E-01 | 4.47E-01 | 3.46E-01 | 3.46E-01 |
| | | WAT model- Manufacturing jobs | 4.47E+00 | 4.47E+00 | -1.5 | 1.5 | -3.03E-01 | -4.55E-01 | -4.47E-01 | 4.47E-01 | 3.46E-01 | 3.46E-01 |
| | | DAT model- Manufacturing jobs | 4.47E+00 | 4.47E+00 | -1.5 | 1.5 | -3.03E-01 | -4.55E-01 | -4.47E-01 | 4.47E-01 | 3.46E-01 | 3.46E-01 |
| | | Auto Drive model-Sales jobs | 4.50E+00 | 4.50E+00 | -1.5 | 1.5 | -3.03E-01 | -4.55E-01 | -4.50E-01 | 4.50E-01 | 3.49E-01 | 3.49E-01 |
| | | Passenger model- Sales jobs | 4.50E+00 | 4.50E+00 | -1.5 | 1.5 | -3.03E-01 | -4.55E-01 | -4.50E-01 | 4.50E-01 | 3.49E-01 | 3.49E-01 |
| | | Carpool model- Sales jobs | 4.50E+00 | 4.50E+00 | -1.5 | 1.5 | -3.03E-01 | -4.55E-01 | -4.50E-01 | 4.50E-01 | 3.49E-01 | 3.49E-01 |
| | | WAT model- Sales jobs | 4.50E+00 | 4.50E+00 | -1.5 | 1.5 | -3.03E-01 | -4.55E-01 | -4.50E-01 | 4.50E-01 | 3.49E-01 | 3.49E-01 |
| | | DAT model- Sales jobs | 4.50E+00 | 4.50E+00 | -1.5 | 1.5 | -3.03E-01 | -4.55E-01 | -4.50E-01 | 4.50E-01 | 3.49E-01 | 3.49E-01 |
| G | Coefficient of travel time for | Auto Drive model | -2.50E-02 | -2.50E-02 | -0.025 | 0.025 | 1.00E+00 | 2.50E-02 | -2.50E-03 | 2.50E-03 | 2.10E-03 | 2.10E-03 |

Table B2 Selected parameters, their deviation limits, and the solution in the *second iteration* of the algorithm

| Factors | Parameters | | Calibrated Values (UCT) | Initially Estimated | Deviation bounds (SCTR-C&C) | | Solution (SCTR-C&C) | | Deviation bounds (SCT) | | Solution (SCT) | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Lower | Upper | deviation | calibrated | Lower | Upper | deviation | calibrated |
| | Student in | Passenger model | -2.50E-02 | -2.50E-02 | -0.025 | 0.025 | 1.00E+00 | 2.50E-02 | -2.50E-03 | 2.50E-03 | 2.10E-03 | 2.10E-03 |
| H | Coefficient of travel time for Student in | WAT model | -2.50E-02 | -2.50E-02 | -0.025 | 0.025 | 8.29E-02 | 2.07E-03 | -2.50E-03 | 2.50E-03 | 1.84E-03 | 1.84E-03 |
| | | DAT model | -2.50E-02 | -2.50E-02 | -0.025 | 0.025 | 8.29E-02 | 2.07E-03 | -2.50E-03 | 2.50E-03 | 1.84E-03 | 1.84E-03 |
| J | Coefficient of travel cost for Student in | Auto Drive model | 4.14E+00 | 4.14E+00 | -1.5 | 1.5 | -1.75E-01 | -2.63E-01 | -4.14E-01 | 4.14E-01 | -1.91E-01 | -1.91E-01 |
| | | Passenger model | 4.14E+00 | 4.14E+00 | -1.5 | 1.5 | -1.75E-01 | -2.63E-01 | -4.14E-01 | 4.14E-01 | -1.91E-01 | -1.91E-01 |
| | | Carpool model | 4.14E+00 | 4.14E+00 | -1.5 | 1.5 | -1.75E-01 | -2.63E-01 | -4.14E-01 | 4.14E-01 | -1.91E-01 | -1.91E-01 |
| | | WAT model | 4.14E+00 | 4.14E+00 | -1.5 | 1.5 | -1.75E-01 | -2.63E-01 | -4.14E-01 | 4.14E-01 | -1.91E-01 | -1.91E-01 |
| | | DAT model | 4.14E+00 | 4.14E+00 | -1.5 | 1.5 | -1.75E-01 | -2.63E-01 | -4.14E-01 | 4.14E-01 | -1.91E-01 | -1.91E-01 |
| K | Coefficient of travel time for Non-worker students in | Auto Drive model | -4.28E-02 | -4.28E-02 | -0.04 | 0.04 | -8.56E-02 | -3.43E-03 | -4.28E-03 | 4.28E-03 | -1.13E-04 | -1.13E-04 |
| | | Passenger model | -4.28E-02 | -4.28E-02 | -0.04 | 0.04 | -8.56E-02 | -3.43E-03 | -4.28E-03 | 4.28E-03 | -1.13E-04 | -1.13E-04 |
| L | Coefficient of travel time for Non-worker students in | WAT model | -4.44E-02 | -4.44E-02 | -0.04 | 0.04 | 1.00E+00 | 4.00E-02 | -4.44E-03 | 4.44E-03 | 2.50E-07 | 2.50E-07 |
| | | DAT model | -4.44E-02 | -4.44E-02 | -0.04 | 0.04 | 1.00E+00 | 4.00E-02 | -4.44E-03 | 4.44E-03 | 2.50E-07 | 2.50E-07 |
| M | Coefficient of travel cost for Non-worker students in | Auto Drive model | 2.52E+00 | 2.52E+00 | -1 | 1 | -8.14E-01 | -8.14E-01 | -2.52E-01 | 2.52E-01 | 1.09E-06 | 1.09E-06 |
| | | Passenger model | 2.52E+00 | 2.52E+00 | -1 | 1 | -8.14E-01 | -8.14E-01 | -2.52E-01 | 2.52E-01 | 1.09E-06 | 1.09E-06 |
| | | Carpool model | 2.52E+00 | 2.52E+00 | -1 | 1 | -8.14E-01 | -8.14E-01 | -2.52E-01 | 2.52E-01 | 1.09E-06 | 1.09E-06 |
| | | WAT model | 2.52E+00 | 2.52E+00 | -1 | 1 | -8.14E-01 | -8.14E-01 | -2.52E-01 | 2.52E-01 | 1.09E-06 | 1.09E-06 |
| | | DAT model | 2.52E+00 | 2.52E+00 | -1 | 1 | -8.14E-01 | -8.14E-01 | -2.52E-01 | 2.52E-01 | 1.09E-06 | 1.09E-06 |
| N | Coefficient of Auto travel time in the Destination Choice Model for Market purpose | | -2.00E-01 | -2.00E-01 | -0.1 | 0.1 | 9.95E-01 | 9.95E-02 | -2.00E-02 | 2.00E-02 | 2.56E-07 | 2.56E-07 |
| O | Coefficient of transit constant in the Destination Choice Model for | | -3.20E+00 | - | -1 | 1 | 9.03E-01 | 9.03E-01 | -3.20E-01 | 3.20E-01 | 4.29E-06 | 4.29E-06 |

Table B2 Selected parameters, their deviation limits, and the solution in the *second iteration* of the algorithm

| Factors | Parameters | | Calibrated Values (UCT) | Initially Estimated | Deviation bounds (SCTR-C&C) | | Solution (SCTR-C&C) | | Deviation bounds (SCT) | | Solution (SCT) | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Lower | Upper | deviation | calibrated | Lower | Upper | deviation | calibrated |
| | Market purpose | | | 3.20E+00 | | | | | | | | |
| P | Coefficient of transit boarding in the Destination Choice Model for Market purpose | | -1.99E-01 | -1.99E-01 | -0.1 | 0.1 | 5.23E-01 | 5.23E-02 | -1.99E-02 | 1.99E-02 | -4.33E-03 | -4.33E-03 |
| Q | Coefficient of Auto travel time in the Destination Choice Model for Other purpose | | -2.00E-01 | -2.00E-01 | -0.1 | 0.1 | 9.40E-02 | 9.40E-03 | -2.00E-02 | 2.00E-02 | 1.91E-07 | 1.91E-07 |
| R | Coefficient of transit constant in the Destination Choice Model for Other purpose | | -3.20E+00 | - 3.20E+00 | -1 | 1 | 9.77E-02 | 9.77E-02 | -3.20E-01 | 3.20E-01 | -4.67E-03 | -4.67E-03 |
| S | Coefficient of transit boarding in the Destination Choice Model for Other purpose | | -1.04E-02 | -1.04E-02 | -0.05 | 1.04E-02 | -2.99E-01 | -2.88E-02 | -1.04E-03 | 1.04E-03 | 2.76E-04 | 2.76E-04 |
| T | Coefficient of Auto travel time in the Destination Choice Model for Work-based business purpose | | -2.00E-01 | -2.00E-01 | -0.1 | 0.1 | -7.54E-01 | -7.54E-02 | -2.00E-02 | 2.00E-02 | 9.22E-08 | 9.22E-08 |
| U | Coefficient of transit constant in the Destination Choice Model for Work-based business purpose | | -3.20E+00 | - 3.20E+00 | -1 | 1 | -2.95E-02 | -2.95E-02 | -3.20E-01 | 3.20E-01 | 1.52E-04 | 1.52E-04 |
| V | Coefficient of transit boarding in the Destination Choice Model for Work-based business purpose | | -1.26E-02 | -1.26E-02 | -0.05 | 1.26E-02 | 1.00E+00 | 1.26E-02 | -1.26E-03 | 1.26E-03 | 2.83E-08 | 2.83E-08 |
| W | Coefficient of aivtt in Access station model | AM | -1.69E-01 | -1.69E-01 | -0.1 | 0.1 | -4.08E-01 | -4.08E-02 | -1.69E-02 | 1.69E-02 | -9.30E-03 | -9.30E-03 |
| | | MD | -1.69E-01 | -1.69E-01 | -0.1 | 0.1 | -4.08E-01 | -4.08E-02 | -1.69E-02 | 1.69E-02 | -9.30E-03 | -9.30E-03 |
| | | PM | -1.69E-01 | -1.69E-01 | -0.1 | 0.1 | -4.08E-01 | -4.08E-02 | -1.69E-02 | 1.69E-02 | -9.30E-03 | -9.30E-03 |
| | | EV | -1.69E-01 | -1.69E-01 | -0.1 | 0.1 | -4.08E-01 | -4.08E-02 | -1.69E-02 | 1.69E-02 | -9.30E-03 | -9.30E-03 |
| X | Coefficient of perceived transit time in Access station model | AM | -2.30E-02 | -2.30E-02 | -0.05 | 2.30E-02 | 1.00E+00 | 2.30E-02 | -2.30E-03 | 2.30E-03 | -1.01E-07 | -1.01E-07 |
| | | MD | -2.30E-02 | -2.30E-02 | -0.05 | 2.30E-02 | 1.00E+00 | 2.30E-02 | -2.30E-03 | 2.30E-03 | -1.01E-07 | -1.01E-07 |

Table B2 Selected parameters, their deviation limits, and the solution in the *second iteration* of the algorithm

| Factors | Parameters | Calibrated Values (UCT) | Initially Estimated | Deviation bounds (SCTR-C&C) | | Solution (SCTR-C&C) | | Deviation bounds (SCT) | | Solution (SCT) | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | Lower | Upper | deviation | calibrated | Lower | Upper | deviation | calibrated |
| | PM | -2.30E-02 | -2.30E-02 | -0.05 | 2.30E-02 | 1.00E+00 | 2.30E-02 | -2.30E-03 | 2.30E-03 | -1.01E-07 | -1.01E-07 |
| | EV | -2.30E-02 | -2.30E-02 | -0.05 | 2.30E-02 | 1.00E+00 | 2.30E-02 | -2.30E-03 | 2.30E-03 | -1.01E-07 | -1.01E-07 |

Table B3 Selected parameters and their levels in the first iteration of the algorithm

| Code | Parameters | | Estimated value | Adjusted value | Level 1 | Level 2 | Level 3 | Best level |
|---|---|---|---|---|---|---|---|---|
| A | Constant of Drive Access Transit model for students | | -7.2317 | -6.7317 | -7.2317 | -6.7317 | | Level 2 |
| B | Constants of Walk Access Transit models for | Professional jobs | -0.8071 | 0.9929 | -0.8071 | 0.9929 | | Level 1 |
| | | General jobs | -2.2294 | -0.4294 | -2.2294 | -0.4294 | | |
| | | Sales jobs | 0.4702 | 2.2702 | 0.4702 | 2.2702 | | |
| | | Manufacturing jobs | -1.5462 | 0.2538 | -1.5462 | 0.2538 | | |
| | | Non-worker students | -2.7999 | -0.9999 | -2.7999 | -0.9999 | | |
| C | Constant of Walk Access Transit model for students | | 0.0223 | 1.5223 | 0.0223 | 1.5223 | | Level 2 |
| D | Constant of Carpool model for professional jobs | | -2.9014 | -3.6014 | -2.9014 | -3.6014 | | Level 2 |
| E | Constants of Carpool models for | General jobs | 0.0000 | -1.0000 | 0.0000 | -1.0000 | | Level 2 |
| | | Sales jobs | -3.0000 | -4.0000 | -3.0000 | -4.0000 | | |
| | | Manufacturing jobs | -3.0000 | -4.0000 | -3.0000 | -4.0000 | | |
| | | Students | -2.9949 | -3.9949 | -2.9949 | -3.9949 | | |
| | | Non-worker students | -1.2510 | -2.2510 | -1.2510 | -2.2510 | | |
| F | Constants of Walk models for | Professional jobs | 2.2620 | 1.7620 | 2.2620 | 1.7620 | | Level 1 |
| | | General jobs | 1.8429 | 1.3429 | 1.8429 | 1.3429 | | |
| | | Sales jobs | 0.0000 | -0.5000 | 0.0000 | -0.5000 | | |
| | | Manufacturing jobs | 0.0008 | -0.4992 | 0.0008 | -0.4992 | | |
| | | Students | 2.4034 | 1.9034 | 2.4034 | 1.9034 | | |
| | | Non-worker students | 0.0000 | -0.5000 | 0.0000 | -0.5000 | | |
| G | Constants of Bicycle models for | Professional jobs | -3.9999 | -2.6999 | -3.9999 | -2.6999 | | Level 1 |
| | | General jobs | -3.2545 | -1.9545 | -3.2545 | -1.9545 | | |

Table B3 Selected parameters and their levels in the first iteration of the algorithm

| Code | Parameters | | Estimated value | Adjusted value | Level 1 | Level 2 | Level 3 | Best level |
|---|---|---|---|---|---|---|---|---|
| | | Sales jobs | -3.8620 | -2.5620 | -3.8620 | -2.5620 | | |
| | | Manufacturing jobs | -3.8139 | -2.5139 | -3.8139 | -2.5139 | | |
| | | Students | -3.4941 | -2.1941 | -3.4941 | -2.1941 | | |
| | | Non-worker students | -4.0000 | -2.7000 | -4.0000 | -2.7000 | | |
| | | Professional jobs | 3.8190 | 2.4190 | 3.8190 | 2.4190 | | |
| | | General jobs | -3.9978 | -5.3978 | -3.9978 | -5.3978 | | |
| | | Sales jobs | 4.0000 | 2.6000 | 4.0000 | 2.6000 | | |
| H | Constants of Passenger models for | Manufacturing jobs | 4.0000 | 2.6000 | 4.0000 | 2.6000 | | Level 1 |
| | | Students | 4.0000 | 2.6000 | 4.0000 | 2.6000 | | |
| | | Non-worker students | 0.2357 | -1.1643 | 0.2357 | -1.1643 | | |
| J | Coefficient of # of full-time Manufacturing jobs in Market model (Location Choice) | | 0.2000 | 0.2000 | 0.2000 | 0.1600 | | Level 2 |
| K | Coefficient of # of full-time Manufacturing jobs in Other model (Location Choice) | | 2.26E-6 | 2.1E-6 | 2.1E-6 | 2.26E-6 | | Level 2 |
| L | Coefficient of # of full-time Manufacturing jobs in Work Based Business model (Location Choice) | | 1.305E-4 | 1.661E-4 | 1.661E-4 | 1.305E-4 | | Level 2 |
| M | Coefficient of auto travel time in Market model (Location Choice) | | -0.2000 | -0.2000 | -0.1800 | -0.2000 | -0.2200 | Level 2 |
| N | Coefficient of auto travel time in Other model (Location Choice) | | -0.2000 | -0.2000 | -0.1800 | -0.2000 | -0.2200 | Level 1 |
| O | Coefficient of auto travel time in Work Based Business model (Location Choice) | | -0.2000 | -0.2000 | -0.1800 | -0.2000 | -0.2200 | Level 3 |
| P | Coefficient of Closest Station in Access Station Model for AM | | 1.2037 | 1.2037 | 1.0833 | 1.2037 | 1.3241 | Level 2 |
| Q | Coefficient of Closest Station in Access Station Model for MD | | 3.9757 | 3.9757 | 3.5781 | 3.9757 | 4.3733 | Level 2 |
| R | Coefficient of Closest Station in Access Station Model for PM | | 0.0024 | 0.0024 | 0.0021 | 0.0024 | 0.0026 | Level 3 |
| S | Coefficient of Cost in Market model (Location Choice) | | -2.0000 | -2.0000 | -1.8000 | -2.0000 | -2.2000 | Level 1 |

Table B3 Selected parameters and their levels in the first iteration of the algorithm

| Code | Parameters | Estimated value | Adjusted value | Level 1 | Level 2 | Level 3 | Best level |
|---|---|---|---|---|---|---|---|
| T | Coefficient of Cost in Other model (Location Choice) | -0.1999 | -0.1999 | -0.1799 | -0.1999 | -0.2199 | Level 1 |
| U | Coefficient of Cost in Work Based Business model (Location Choice) | -2.0000 | -2.0000 | -1.8000 | -2.0000 | -2.2000 | Level 2 |
| V | Coefficient of Transit Boarding in Market model (Location Choice) | -0.1985 | -0.1985 | -0.1787 | -0.1985 | -0.2184 | Level 3 |
| W | Coefficient of Transit Boarding in Other model (Location Choice) | -0.0104 | -0.0104 | -0.0094 | -0.0104 | -0.0115 | Level 1 |
| X | Coefficient of Transit Boarding in Work Based Business model (Location Choice) | -0.0126 | -0.0126 | -0.0114 | -0.0126 | -0.0139 | Level 2 |

Table B4 Selected parameters and their levels in the second iteration of the algorithm

| Code | Selected parameters | | Estimated value | Adjusted value | Level 1 | Level 2 | Level 3 | Best level |
|---|---|---|---|---|---|---|---|---|
| A | Coefficient of Auto Travel Time in Other model (Location Choice) | | -0.2000 | -0.2000 | -0.1800 | -0.1600 | | Level 2 |
| B | Coefficient of # of full-time General jobs in Other model (Location Choice) | | 9.57E-10 | 3.89E-09 | 9.57E-10 | 3.89E-09 | | Level 2 |
| C | Coefficient of # of full-time General jobs in Work Based Business model (Location Choice) | | 1.5E-4 | 1.478E-3 | 1.5E-4 | 1.478E-3 | | Level 2 |
| D | Coefficient of # of full-time General jobs in Market model (Location Choice) | | 0.0197 | 0.0034 | 0.0197 | 0.0034 | | Level 2 |
| E | Coefficient of # of full-time Professional jobs in Work Based Business model (Location Choice) | | 1.15E-4 | 2.22E-05 | 1.15E-4 | 2.22E-05 | | Level 2 |
| F | Coefficient of # of full-time Sales jobs in Work Based Business model (Location Choice) | | 0.0000 | 6.62E-12 | 0.0000 | 6.62E-12 | | Level 2 |
| G | Coefficient of Transit Boarding in Other model (Location Choice) | | -0.0104 | -0.0104 | -0.0094 | -0.0080 | | Level 2 |
| H | Constants of passenger models for | Professional jobs | 3.8190 | 2.4190 | 3.8190 | 4.8190 | | Level 1 |
| | | General jobs | -3.9978 | -5.3978 | -3.9979 | -2.9979 | | |
| | | Sales jobs | 4.0000 | 2.6000 | 4.0000 | 5.0000 | | |
| | | Manufacturing jobs | 4.0000 | 2.6000 | 4.0000 | 5.0000 | | |
| | | Students | 4.0000 | 2.6000 | 0.2357 | 1.2357 | | |
| | | Non-worker students | 0.2357 | -1.1643 | 4.0000 | 5.0000 | | |
| J | Constant of Walk Access Transit models for | Sales jobs | 0.4702 | 2.2702 | -0.5298 | 0.4702 | | Level 1 |
| | | Manufacturing jobs | -1.5462 | 0.2538 | -2.5462 | -1.5462 | | |
| K | Constant of Walk Access Transit models for | Professional jobs | -0.8071 | 0.9929 | -1.8071 | -0.8071 | | Level 1 |
| | | General jobs | -2.2294 | -0.4294 | -3.2294 | -2.2294 | | |
| | | Non-worker students | -2.7999 | -0.9999 | -3.7999 | -2.7999 | | |
| L | Constant of Walk Access Transit model for | Students | 0.0223 | 1.5223 | -0.9777 | 0.0223 | | Level 1 |
| M | Professional Time Factor for | Auto Drive mode | -0.0592 | -0.0592 | -0.0651 | -0.0592 | -0.0533 | Level 2 |

Table B4 Selected parameters and their levels in the second iteration of the algorithm

| Code | Selected parameters | | Estimated value | Adjusted value | Level 1 | Level 2 | Level 3 | Best level |
|---|---|---|---|---|---|---|---|---|
| | | Passenger mode | -0.0592 | -0.0592 | -0.0651 | -0.0592 | -0.0533 | |
| | | Carpool mode | -0.0600 | -0.0600 | -0.0660 | -0.0600 | -0.0540 | |
| | | WAT mode | -0.0540 | -0.0540 | -0.0594 | -0.0540 | -0.0486 | |
| | | DAT mode | -0.0540 | -0.0540 | -0.0594 | -0.0540 | -0.0486 | |
| N | Professional Travel Cost Factor for | Auto Drive mode | 2.3077 | 2.3077 | 2.0769 | 2.3077 | 2.5385 | Level 1 |
| | | Passenger mode | 2.3077 | 2.3077 | 2.0769 | 2.3077 | 2.5385 | |
| | | Carpool mode | 2.3077 | 2.3077 | 2.0769 | 2.3077 | 2.5385 | |
| | | WAT mode | 2.3077 | 2.3077 | 2.0769 | 2.3077 | 2.5385 | |
| | | DAT mode | 2.3077 | 2.3077 | 2.0769 | 2.3077 | 2.5385 | |
| O | General Time Factor for | Auto Drive mode | -0.0589 | -0.0589 | -0.0648 | -0.0589 | -0.0530 | Level 2 |
| | | Passenger mode | -0.0589 | -0.0589 | -0.0648 | -0.0589 | -0.0530 | |
| | | Carpool mode | -0.1474 | -0.1474 | -0.1621 | -0.1474 | -0.1326 | |
| | | WAT mode | -0.0311 | -0.0311 | -0.0342 | -0.0311 | -0.0280 | |
| | | DAT mode | -0.0311 | -0.0311 | -0.0342 | -0.0311 | -0.0280 | |
| P | General Travel Cost Factor for | Auto Drive mode | 4.4116 | 4.4116 | 3.9704 | 4.4116 | 4.8528 | Level 2 |
| | | Passenger mode | 4.4116 | 4.4116 | 3.9704 | 4.4116 | 4.8528 | |
| | | Carpool mode | 4.4116 | 4.4116 | 3.9704 | 4.4116 | 4.8528 | |
| | | WAT mode | 4.4116 | 4.4116 | 3.9704 | 4.4116 | 4.8528 | |
| | | DAT mode | 4.4116 | 4.4116 | 3.9704 | 4.4116 | 4.8528 | |
| Q | Sales Time Factor for | Auto Drive mode | -0.0600 | -0.0600 | -0.0660 | -0.0600 | -0.0540 | Level 1 |
| | | Passenger mode | -0.0600 | -0.0600 | -0.0660 | -0.0600 | -0.0540 | |

Table B4 Selected parameters and their levels in the second iteration of the algorithm

| Code | Selected parameters | | Estimated value | Adjusted value | Level 1 | Level 2 | Level 3 | Best level |
|---|---|---|---|---|---|---|---|---|
| | | Carpool mode | -0.1950 | -0.1950 | -0.2145 | -0.1950 | -0.1755 | |
| | | WAT mode | -0.0600 | -0.0600 | -0.0660 | -0.0600 | -0.0540 | |
| | | DAT mode | -0.0600 | -0.0600 | -0.0660 | -0.0600 | -0.0540 | |
| | | Auto Drive mode | 4.5000 | 4.5000 | 4.0500 | 4.5000 | 4.9500 | |
| | | Passenger mode | 4.5000 | 4.5000 | 4.0500 | 4.5000 | 4.9500 | |
| R | Sales Travel Cost Factor for | Carpool mode | 4.5000 | 4.5000 | 4.0500 | 4.5000 | 4.9500 | Level 3 |
| | | WAT mode | 4.5000 | 4.5000 | 4.0500 | 4.5000 | 4.9500 | |
| | | DAT mode | 4.5000 | 4.5000 | 4.0500 | 4.5000 | 4.9500 | |
| | | Auto Drive mode | -0.0250 | -0.0250 | -0.0275 | -0.0250 | -0.0225 | |
| | | Passenger mode | -0.0250 | -0.0250 | -0.0275 | -0.0250 | -0.0225 | |
| S | Manufacturing Time Factor for | Carpool mode | -0.0821 | -0.0821 | -0.0903 | -0.0821 | -0.0739 | Level 2 |
| | | WAT mode | -0.0600 | -0.0600 | -0.0660 | -0.0600 | -0.0540 | |
| | | DAT mode | -0.0600 | -0.0600 | -0.0660 | -0.0600 | -0.0540 | |
| | | Auto Drive mode | 4.4676 | 4.4676 | 4.0208 | 4.4676 | 4.9143 | |
| | | Passenger mode | 4.4676 | 4.4676 | 4.0208 | 4.4676 | 4.9143 | |
| T | Manufacturing Travel Cost Factor for | Carpool mode | 4.4676 | 4.4676 | 4.0208 | 4.4676 | 4.9143 | Level 2 |
| | | WAT mode | 4.4676 | 4.4676 | 4.0208 | 4.4676 | 4.9143 | |
| | | DAT mode | 4.4676 | 4.4676 | 4.0208 | 4.4676 | 4.4676 | |
| | | Auto Drive mode | -0.0250 | -0.0250 | -0.0275 | -0.0250 | -0.0225 | |
| U | Student Time Factor for | Passenger mode | -0.0250 | -0.0250 | -0.0275 | -0.0250 | -0.0225 | Level 2 |
| | | Carpool mode | -0.0600 | -0.0600 | -0.0660 | -0.0600 | -0.0540 | |

Table B4 Selected parameters and their levels in the second iteration of the algorithm

| Code | Selected parameters | | Estimated value | Adjusted value | Level 1 | Level 2 | Level 3 | Best level |
|---|---|---|---|---|---|---|---|---|
| | | WAT mode | -0.0250 | -0.0250 | -0.0275 | -0.0250 | -0.0225 | |
| | | DAT mode | -0.0250 | -0.0250 | -0.0275 | -0.0250 | -0.0225 | |
| V | Student Travel Cost Factor for | Auto Drive mode | 4.1363 | 4.1363 | 3.7227 | 4.1363 | 4.5499 | Level 3 |
| | | Passenger mode | 4.1363 | 4.1363 | 3.7227 | 4.1363 | 4.5499 | |
| | | Carpool mode | 4.1363 | 4.1363 | 3.7227 | 4.1363 | 4.5499 | |
| | | WAT mode | 4.1363 | 4.1363 | 3.7227 | 4.1363 | 4.5499 | |
| | | DAT mode | 4.1363 | 4.1363 | 3.7227 | 4.1363 | 4.5499 | |
| W | Non-worker Student Time Factor for | Auto Drive mode | -0.0428 | -0.0428 | -0.0471 | -0.0428 | -0.0385 | Level 2 |
| | | Passenger mode | -0.0428 | -0.0428 | -0.0471 | -0.0428 | -0.0385 | |
| | | Carpool mode | -0.1867 | -0.1867 | -0.2054 | -0.1867 | -0.1680 | |
| | | WAT mode | -0.0444 | -0.0444 | -0.0489 | -0.0444 | -0.0400 | |
| | | DAT mode | -0.0444 | -0.0444 | -0.0489 | -0.0444 | -0.0400 | |
| X | Non-worker Student Travel Cost Factor for | Auto Drive mode | 2.5186 | 2.5186 | 2.2668 | 2.5186 | 2.7705 | Level 2 |
| | | Passenger mode | 2.5186 | 2.5186 | 2.2668 | 2.5186 | 2.7705 | |
| | | Carpool mode | 2.5186 | 2.5186 | 2.2668 | 2.5186 | 2.7705 | |
| | | WAT mode | 2.5186 | 2.5186 | 2.2668 | 2.5186 | 2.7705 | |
| | | DAT mode | 2.5186 | 2.5186 | 2.2668 | 2.5186 | 2.7705 | |