School of Electrical Engineering, Computing and Mathematical Sciences

Performance Evaluation of Public Transport Networks and Its Optimal Strategies Under Uncertainty

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This thesis is presented for the Degree of
Doctor of Philosophy- Mathematics and Statistics
of
Curtin University

July 2023

Declaration

To the best of my knowledge and belief this thesis contains no material previously published by any other person except where due acknowledgement has been made.

This thesis contains no material which has been accepted for any other degree or diploma in any university.

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Abstract

Metropolitan areas around the world are dealing with urgent problems brought on by the use of personal vehicles and the environmental harm their use causes. Hence, the need for reliable networks of public transport (PT) is growing as it is essential for sustainable development. However, the management of PT via urban planning policies poses challenges in quantifying their effectiveness. Accurate assessment of PT performance is crucial for developing optimal solutions and informing future plans for governments, and both direct and external effects must be taken into account if the PT network is to operate more effectively. This study considers both direct and external effects on fundamental PT infrastructure, public transportation services, economic benefit, and sustainable development levels in order to enhance the performance of PT networks.

Further, in order to propose the optimal solutions for PT network performance under uncertainty, this study develops a novel framework to optimise the performance of public transportation under ambiguous circumstances at various levels of aspiration. The proposed methodology is exemplified and validated using three case studies from Australia—the cities of Stonnington, Bayswater, and Cockburn.

The model framework consists of the following three stages. In the first stage, we investigate the PT criteria that can influence PT network performance from basic PT infrastructure, service, economic benefit, and sustainable development aspects. To identify the indictors of each aspect, previous studies about the PT performance measurement systems are reviewed. Furthermore, multiple-criteria decision-making methods are compared and discussed. This study uses analytic hierarchy process (AHP) model and combines it with existing assessment and evaluation index systems. Then we establish a PT criteria matrix using an AHP. The developed method is utilised to weight 15

sub-criteria and four levels of criteria, and to measure PT network performance in the three case study cities.

The second stage is to propose a multi-aspiration-level goal programming (MALGP) approach to optimise the performance of the PT network based on the criteria weight and performance results. Improving on the original goal programming model, the proposed method includes a criteria aspiration level selection process for choosing criteria optimal values. The developed approach in this research offers an innovative way to select criteria aspiration levels for formulating objective functions to calculate optimal solutions among the three cases.

In the third stage, we analyse the probability of the best solution using Monte Carlo simulation to manage uncertainty. We investigate the criteria uncertainty level based on existing criteria risk rankings. In this study, it is assumed that decision makers have control over each criterion's performance and that each criterion's likelihood of occurring is between -5% and +10%. In addition, the Monte Carlo simulation process also shows that the criteria's most likely values are chosen during the optimisation process. The results of the Monte Carlo simulation demonstrate the most sensitive criterion during the optimisation process. The criteria impact on the optimisation outputs of all cities are also identified. For PT network planners and policymakers, the proposed models and results offer useful information and recommendations on how to improve public transportation in their cities.

Finally, the three-stage optimisation under the uncertainty framework is proposed to comprehensively optimise the PT network performance. The innovative framework can both generate the city PT performance reports and optimisation scenario by integrating MCDM, optimisation, and risk management methods. The results can be applied in MCDM for proposing PT performance optimisation solutions.

This thesis provides methodological and practical contributions to the field of PT performance optimisation under ambiguous circumstances. To optimise the performance of the public transportation network, a MALGP model, a PT criteria matrix-AHP model, and the incorporation of Monte Carlo simulation to examine the likelihood of optimal solutions are among the methodological contributions. The contributions to practical knowledge highlight the elements that affect the performance of the public transportation system and suggest the best options for the case study regions, while the results of the uncertainty analysis can be used to design strategies and plans for improving the performance of the public transportation system. The suggested framework gives decision makers a guide for allocating resources for improving the performance delivery of the public transportation network in accordance with governmental requirements.

Acknowledgements

I would like to take this opportunity to express my deepest appreciation to everyone who had contributed to the completion of this thesis.

I would like to express my deepest gratitude to my supervisors, A/Professor Honglei Xu, A/Professor Guanglu Zhou, and Dr Shaoli Wang, for their inspiration, direction, and encouragement throughout the entire PhD study journey. Your patience and encouragement enabled me to complete this thesis.

I appreciate my dear fellows in the School of Electrical Engineering, Computing and Mathematical Sciences at Curtin University sharing your knowledge and ideas. I have been very happy to study with all of them.

I also thank Dr Yongze Song, A/Professor Fan Zhang, Dr Junxiang Zhu, and Professor Conghua Lin, for their help and cooperation during my research.

Copyediting and proofreading services have been provided according to the guidelines laid out in the university-endorsed national "Guidelines for Editing Research Theses".

Finally, I would like to express my gratitude to my family, especially my parents Mr and Mrs Lin, for their unconditional support of me in all my endeavours.

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G. Lin, H. Xu, S. Wang, C. Lin, F. Zhang, & Zhu. J. Navigating uncertainty: A framework for optimising public transport network performance using multi-criteria decision analysis and multi-aspiration-level goal programming. (Under review)

Lin, G., Xu, H., Wang, S., Lin, C., & Huang, C. (2022). Performance optimisation of public transport networks using AHP-dependent multi-aspiration-level goal programming. *Energies*, *15*(17), 6479. (IF: 3.252)

Lin, G., Wang, S., Lin, C., Bu, L., & Xu, H. (2021). Evaluating performance of public transport networks by using public transport criteria matrix analytic hierarchy process models—Case study of Stonnington, Bayswater, and Cockburn public transport network. *Sustainability*, *13*(12), 6949. (IF: 3.889)

Chapter 1: Introduction

1.1 Background

The increasing use of private cars and the resulting environmental damage have been shown to be causing a number of urgent problems for metropolitan areas around the world (Loukopoulos et al., 2005). In response to these problems, utilising public transport (PT) is one important strategy, particularly in regard to sustainable development, and the need for effective and efficient PT networks is growing (Tumlin, 2012).

Both developing and developed nations have their own policies and strategies for sustainable development, particularly when it comes to promoting PT modes (UN-Habitat, 2015). However, UN-Habitat published a document in 2015 that serves as a roadmap for sustainable development. People are encouraged to use PT through a variety of urban planning policies and strategies.

To quantify the effectiveness of strategies and procedures, assessment of PT network performance requires accurate identification of the relevant criteria, and based on the evaluation, optimal solutions under uncertain conditions can be deduced and offered to stakeholders. Current research about providing governments with optimisation framework is, however, limited.

The formulation of a model framework, assessment of PT performance, and proposition of effective strategies amidst uncertainty constitute key stages in proposing optimal PT network strategies (Cyril et al., 2019; Cartenì et al., 2022). Each stage requires methods to enhance the performance of the PT network. Prior studies evaluating PT have predominantly focused on singular aspects, such as service quality, accessibility, and sustainability (De Ona et al., 2016; Fadaei & Cats, 2016; Curtis & Scheurer, 2017; Barabino et al., 2020; Tiznado-Aitken et al., 2021). While these assessments have been extensively utilised in evaluating urban PT performance, a critical need exists to extend this to proposing planning scenarios aimed at optimising PT performance under uncertain conditions. Achieving these objectives includes a comprehensive discussion of the existing literature, including resolving ambiguities in theoretical and methodological issues (Manzo et al., 2015; Cyril et al., 2019).

A comprehensive quantification and evaluation system to a operate PT network effectively is impacted by multiple factors. Daraio et al. (2016) stated that stakeholders are interested in both direct effects (level of economic benefit, quality, and efficiency of the PT service) as well as external effects (level of basic PT infrastructure, and level of sustainable development). Consequently, the identification of these criteria and their associated indicators has a wide potential to improve the performance evaluation process (Daraio et al., 2016).

From a multiple-criteria decision-making (MCDM) perspective, identifying criteria scores and providing performance reports are the key tasks for PT network performance evaluation (Nassereddine & Eskandari, 2017). As one of the main techniques for PT performance evaluation, analytical hierarchy process (AHP) is a MCDM technique that enables decision makers (DMs) to handle complex problems with subjective criteria and multiple conflicts (Saaty, 1977; Nosal & Solecka, 2014; Ryus, 2015; Daraio et al., 2016). Additionally, the model can also weight and score the criteria in conjunction with the determined grade level of the criteria (Cyril et al., 2019).

While MCDM methods have been extensively employed in PT evaluation, their utilisation for proposing optimal solutions based on the evaluation results remains somewhat constrained. The utilisation of AHP-based criteria optimisation via goal programming (GP) facilitates the optimisation of selection or evaluation, while accommodating relevant conditions or constraints (Tamiz et al., 1998; Lin et al., 2014; Cyril et al., 2019). However, the current GP method encounters limitations in resolving the optimisation involving criteria with multiple aspiration levels. Thus, the lack of a multi-aspiration-level selection process in the GP method can impact the identification of optimal strategies in practical applications.

Meanwhile, uncertainty frequently precipitates deviations from the initial anticipations or plans. A PT network comprises diverse PT modes, such as buses and trains. Improving the PT network entails uncertainty and risk, which will significantly impact the optimisation results. Schmidt et al. (2017) asserted that there are always incomplete or incorrect parameters, inaccurate data, and disturbances. Addressing these uncertainties necessitates the employment of optimisation algorithms (Schmidt et al., 2017).

In the pursuit of creating a comprehensive tool to optimise PT performance under ambiguous circumstances at various levels of aspiration, several important aspects of enhancing PT performance have been overlooked (Cyril et al., 2019; Schmidt et al., 2017). This study therefore aims to develop an appropriate optimisation framework for the performance of a variety of criteria with multiple aspiration levels in uncertain conditions for PT networks.

1.2 Research questions

The main research question is how can suitable mathematical models to assess and optimise PT network performance under uncertainty be established?

Four sub-research questions are listed as follows:

- What criteria need to be considered to evaluate PT network performance?
- How should the criteria of PT network performance be weighted?
- How can the performance of the PT network be optimised?
- How can the performance of the PT network be optimised under uncertainty?

1.3 Research objectives

The primary objective of this study is to develop a framework that integrates qualitative and quantitative techniques for comprehensive multi-criteria PT network performance evaluation and optimisation under uncertainty. In particular, the main tasks of this research include:

- Developing a PT criteria matrix for PT performance assessment at various areas of application.
- Ranking the PT performance by using a developed PT-criteria-matrix AHP model.
- Optimising the PT performance by using an integrated PT-criteria-matrix-AHP-MALGP model.
- Optimising the PT network performance under uncertainty by using MCS.
- Applying the developed evaluation and optimisation model to assess real world cases and offer advice and guidelines to relevant DMs.

1.4 Significance

The novelty of this thesis is threefold. First, this study develops a novel multi-level GP approach that is dependent on AHP and is used with PT networks. The second is the goal of developing the optimal strategy to improve the performance of PT, with multiple levels of aspiration, using PT criteria matrix-AHP (PTCM-AHP) models. Third, this study employs the Monte Carlo simulation (MCS) to enhance PT network performance in an uncertain environment.

1.5 Structure of the thesis

This thesis includes seven chapters, which are organised as follows.

Chapter 1 provides background for this research, introduces the research questions, objectives, and methods, and offers an overview of the thesis.

Chapter 2 examines the current literature on the PT evaluation model, the MCDM model, the GP model, and the risk management model. Their related concepts are also demonstrated.

Chapter 3 illustrates the AHP model formulation. The PTCM-AHP model is developed based on the existing PT evaluation index and indicators. The proposed model is then applied to three case study areas in Australia.

Chapter 4 investigates the formulation of the GP and multi-choice goal programming (MCGP) models. We improve on the existing models and then initiate a MALGP model. The developed model is used in all three cities and recommends the best solutions.

Chapter 5 studies the criteria's uncertainty level and establishes model inputs for three cities in MCS. For case study areas, sensitivity analysis, feature importance, and test accuracy are presented to optimise solutions under uncertain conditions.

Chapter 6 proposes a three-stage optimising process for PT network performance under uncertainty, and the process of each stage's model is demonstrated.

Finally, Chapter 7 summarises the thesis's major work and provides future research directions.

Chapter 2: Literature Review

2.1 General overview

In this chapter, we first evaluate current PT evaluation models to identify research gaps. Then we show the preliminary knowledge for this research, which includes six MCDM evaluating and weighing methods: AHP, data envelopment analysis (DEA), analytic network process (ANP), preference ranking organisation method for enrichment evaluations (PROMETHEE), technique for order preferences by similarity to ideal solutions (TOPSIS), and elimination and choice corresponding to reality (ELECTRE). Following that, we review the current literature on GP and MCGP, which are frequently used in conjunction with weighting methods to solve multi-criteria optimisation problems. Finally, a review of risk management applications in PT networks and MCS application areas is provided.

This chapter is organised as follows: Section 2.2 examines the current PT evaluation models. The introduction to MCDM and AHP is followed by an overview of the application areas in Section 2.3. Section 2.4 discusses the development of GP and MCGP. Section 2.5 reviews the various types of risk management tools and MCS, and Section 2.6 concludes this chapter.

2.2 Various PT evaluation models

In this section, we examine current PT evaluation and measurement systems. A performance measurement is required to improve the performance of the PT network. The current indicators used to assess PT performance are focused on the quality and network of PT services. In recent research, six indicators have been used: buses with high levels of service (BHLS), PT level-of-service (LOS), PT quality indicators, performance importance matrix, spatial network analysis for multimodal urban transport systems (SNAMUTS), and transit service indicators (TSIs). These PT evaluation and measurement systems are described in detail in the following subsections.

2.2.1 Buses with high level of service

The BHLS connects the quality and capacity of PT services. The model addresses the major factors influencing PT operation (Orth et al., 2012). This model can calculate the PT level of service score for a given set of PT elements. The score can provide a consistent evaluation framework across various levels of the evaluated PT network (Orth et al., 2012; Tiznado-Aitken et al., 2021). According to Orth et al. (2012), the developed capacity model computes actual capacity by reducing theoretical capacity based on operational influences. On-time performance, headway adherence, travel speed, and standing passenger density are indicators that affect transit service capacity and quality (Orth et al., 2012; Tiznado-Aitken et al., 2021).

2.2.2 PT level-of-service

The LOS model examines how various PT operational measures and design influence costs associated with fleet operations and passenger travel time reduction. According to Fadaei and Cats (2016), its automatic data collection model enables detailed performance monitoring and post-implementation evaluation. Moreover, operation policies and designs may have a significant impact on the costs incurred by numerous operators and passengers. The effect of such measures on vehicle scheduling and the ensuing operating costs is still largely unknown because of the inconsistent impact of the average vehicle travel time and its variability.

2.2.3 PT quality indicators

The performance of the transportation service is assessed based on the quality of its attribute. This index is the most complete and synthetic one. It is challenging to pinpoint the qualities of service quality because the indicator may be influenced by travel behaviour or customer preferences and includes different passenger perceptions (Dragu et al., 2013). The division of passenger transportation methods is also impacted by the standard of services offered, which determines a market share for the transport modes examined (Dragu et al., 2013; Barabino et al., 2020). The three components of this quality indicator are therefore a general description of the PT service, a detailed description of service achievement, and the effects on the environment (Dragu et al., 2013; Barabino et al., 2020).

2.2.4 Performance importance matrix

The PT sector is now competing with the private sector due to rapid economic growth and privatisation (Sezhian et al., 2011). As a result, the performance importance matrix considers both customer or passenger expectations and PT company aspects. For the PT company to continue providing high-quality services in the future, these are crucial considerations (Sezhian et al., 2011). The use of this technology will enhance important aspects of the services offered and boost client satisfaction (Sezhian et al., 2011). Performance importance matrix is a technology that is being developed to include managers' and customers' perspectives. Additionally, the performance importance matrix may contribute to higher customer satisfaction.

2.2.5 Spatial network analysis for multimodal urban transport systems

According to Curtis and Scheurer (2017), the SNAMUTS is a GIS-based tool for assessing the connectivity and centrality of urban PT networks in terms of land use and factoring in its market level when choosing multimodal transportation. SNAMUTS is dedicated to determining and visualising the benefits and drawbacks of the land-use PT system in terms of its capacity and effectiveness to link active nodes, network resilience in the face of future customer growth, geographic coverage, traveller flexibility to use the network for both planned and impromptu trips in metropolitan areas, and the strategic importance of network nodes and roads (Curtis & Scheurer, 2017). Various measures and indicators have been adopted based on the viewpoint of connectivity and centrality to study these geographic and configuration success factors more thoroughly. High centrality levels are geographically close to numerous and extensive urban activities. In the context of a transportation network, urban activities can be evaluated from a variety of angles depending on how they are distributed in urban areas, how they relate to activities, and how the movement patterns around edges and nodes are set up. The hierarchy of activity centres identified in the strategic planning document, the location and service standards of PT routes, and SNAMUTS are used to break down the land-use transportation system into a set of route segments and active nodes.

2.2.6 Transit service indicators

The TSIs integrates various performance indicators, including availability, accessibility, customer care, time, safety and security, comfort, and amenities, into a systematic framework. According to De Ona et al. (2016), TSIs recognises that the quality of service is a result of the interaction between supply and demand and considers temporal and spatial changes in travel demand. Design and condition variables affect TSIs. TSIs may be used in addition to or in place of current level of service methods (De Ona et al., 2016).

2.2.7 Summary

The six measurement systems are frequently used by academics and industry professionals to assess PT network performance; however, as shown above, each measurement system utilises different criteria to evaluate PT performance. The different measurement systems, their evaluation criteria, and their methods are shown in Table 1.

Table 1

List of measurement systems to evaluate PT

Measurement System	Evaluation Criteria	Method	Reference
PT level-of-service (LOS)	Travel speed, acceleration and braking, temporal spacing between vehicles, buffer times, space within vehicle, share of dedicated rights-of-way, type of road, type of transit stop, density within vehicle, on-time performance, headway adherence, service duration	Determine the score for PT LOS for PT elements. The score helps the DMs to evaluate the PT service.	(Orth et al., 2012), (Tiznado-Aitken et al., 2021)
Buses with high level of service (BHLS)	Vehicle running time and rest time, reliability, demand patterns, total vehicle trip time, layover and recovery times, passenger waiting time, passenger in-vehicle time, passenger travel time, monetary values, operator costs	Analyse the influence of a series of PT operational measures and design by assessing the impact of reliability on expenses associated with saving passenger travel time and fleet operations	(Fadaei & Cats, 2016)
PT quality indicators	Offer of services, accessibility, information, time, attention given to passengers, comfort, safety and security, effects on the environment	Evaluate the PT service quality and sustainable level	(Dragu et al., 2013) (Barabino et al., 2020)
Performance importance matrix	Bus punctuality, bus condition, new fleet addition, seating for elderly, ticket system, service system, bus facility, stopping bus at correct place, driver behaviour, information to passengers	Identify the strong and weak areas and general PT performance	(Sezhian et al., 2011)

SNAMUTS	Minimum service standard, activity nodes, travel impediment, weekday inter-peak	Assess the connectivity and centrality of urban PT networks in terms of land use and include its market level in the choice of multimodal transport.	(Curtis & Scheurer, 2017) (Curtis & Scheurer, 2019)
Transit service quality	Availability, accessibility, customer care, time, safety and security, comfort and amenities	Evaluate the transit system service quality	(De Ona et al., 2016)

Table 1 shows that operations and services are currently a major focus of PT evaluation research. However, the lack of a multi-standard framework in the research necessitates the consideration of numerous criteria, some subjective and competing, when PT networks are evaluated at various application levels. In addition, the comprehensive impact of other important factors, including development policies, energy and sustainability, and infrastructure and facilities, on the growth of urban transportation systems have not been fully considered.

In conclusion, this section has offered a thorough analysis of the approaches currently being used to promote PT and the research being done on PT performance evaluation. The limitations of prior research have been identified and will be considered and responded to so as to create a matrix of PT performance criteria. The existing literature was found to have the following limitations:

- Current research lacks a multi-standard framework for PT network evaluation at multiple application levels, and multiple stakeholders are not considered.
- Most studies on PT effectiveness and performance assessment have concentrated on operations and services. The comprehensive impact of

other important factors (such as development policies, energy and sustainability, and infrastructure and facilities) on the growth of urban transportation systems have not been thoroughly investigated in previous studies.

- The existing research lacks adequate investigation in determining indicators or standards for different application levels.

This study aims to develop a thorough multi-criteria PT network performance evaluation model for various application levels to address these limitations. Additionally, the basic PT infrastructure level, PT service level, economic benefit level, and sustainable development level will be taken into consideration when choosing the evaluation model's criteria. The evaluation model's sub-criteria will be chosen based on the indicators and factors that will have an impact on the use of PT and will allocate limited resources in accordance with the priority of a particular urban PT problem.

2.3 Multiple-criteria decision-making in PT performance

The MCDM methods are the comprehensive tool that combine qualitative and quantitative aspects to evaluate complex problems and support DMs in making conclusive decisions (Khan & Ali, 2020). MCDM tools and applications have been used in numerous studies in the past to tackle a variety of area-specific problems, including, but not limited to, sustainability, material, environment, production management, construction and project management, energy, quality management, GIS, safety and risk management, technology and information management, manufacturing systems, operation research and soft computing, strategic management, tourism management, and supply chain management (Behzadian et al., 2010; Velasquez & Hester, 2013; Mardani et al., 2015; Kheybari et al., 2020). The main purpose of the MCDM tools is to rank, select, sort and evaluate alternatives or criteria (Behzadian et al., 2010; Mardani et al., 2015; Kheybari et al., 2020).

In the area of PT issues, MCDM methodologies are increasingly being used. According to Camargo Pérez et al. (2015), 58 different MCDM techniques have been used in the context of PT systems between 1982 and 2014, which ultimately led to the realisation that MCDM techniques have become a highly effective tool for assessing and making decisions pertaining to projects in PT systems in recent decades. As a result, MCDM has emerged as a crucial decision-making method that authorities, academics, and researchers use to assess how satisfied customers are with PT systems (Nassereddine & Eskandari, 2017).

Stochastic frontier analysis (SFA), AHP, and DEA are the three main MCDM techniques for evaluating the effectiveness of PT networks (Barnum et al., 2007; Holmgren, 2013; Boujelbene & Derbel, 2015). This research does not consider SFA in PT network evaluation, since SFA is not a weighting method (Hjalmarsson et al., 1996; Holmgren, 2013). Beside AHP and DEA, there are also another four MCDM methods for evaluating and weighting PT network performance considered: PROMETHEE, TOPSIS, ANP, and ELECTRE (Brans & Vincke, 1985; Olson, 2004; Saaty, 2004; Bojković et al., 2010; Greco et al., 2016; Nassereddine & Eskandari, 2017; Zhang et al., 2018; Lin et al., 2023). We arrived at the details of the six MCDM methods listed in Table 2 by referring to references related to assessing and weighting PT network performance.

Table 2

List of MCDM methods in evaluating and weighting PT network performance

Reference	Specific area	Weighting method
Cyril et al. (2019)	Assess the PT performance in quality, effectiveness, efficiency, and economic aspects.	AHP
Sheth et al. (2007)	Measure the PT service from the users, societal, and service providers perspectives.	DEA
Lin et al. (2023)	Measure the transit-oriented	ANP

	development performance degree within a zone.	
Nassereddine and Eskandari (2017)	Evaluate the PT service quality in different PT modes.	PROMETHEE
Zhang et al. (2018)	Evaluate the PT priority implementation based on overall development level, infrastructure construction, PT service level, and policy support.	TOPSIS
Bojković et al. (2010)	Assess transport sustainability at a macro level in terms of economic, environmental, and social aspects.	ELECTRE

2.3.1 Analytic hierarchy process model

As previously mentioned, the AHP model is a technique for MCDM that enables DMs to deal with complex problems involving a variety of subjective and conflicting criteria (Boujelbene & Derbel, 2015). The AHP breaks down the problem into different levels and provides a prioritised framework of choices, ranking them from most to least preferred (Jain et al., 2014). Level objectives are established using pairwise comparisons, and weights are given to each criterion. Pairwise comparisons are used to create the factors at each level, which calls for determining the relative weights of two criteria or sub-criteria (Jain et al., 2014). Additionally, AHP is the MCDM tool that is most frequently used to solve issues with multiple objectives (Pohekar & Ramachandran, 2004). The three main AHP processes are as follows (Nassereddine & Eskandari, 2017):

- Priority: Either least square analysis or eigenvectors are used to calculate the element priority weight at each level. This process will be repeated for each hierarchy level until the decision is made using the global weight (Saaty, 1994).
- Issue decomposition: The issue is broken down into elements (the elements are grouped at different levels to form a hierarchy chain), and

each factor is broken down further into sub-factors until the lowest hierarchy level (Sadeghi & Ameli, 2012).

- Comparison analysis: A pairwise comparison process is used to calculate each factor's relative weight at a specific level. The DMs produce a numerical value for the importance of each factor using a rating scale.

Furthermore, AHP allows DMs to handle complex issues involving multiple conflicts and subjective criteria. In terms of PT, stakeholders are concerned with both direct and indirect effects (Daraio et al., 2016), and AHP addresses the financial benefit, the quality and effectiveness of the PT service, the foundational infrastructure of PT, and the degree of sustainable development. Given these areas of application, the AHP model can assist governments in more effectively monitoring and enhancing the performance of PT networks.

Despite its frequent use, AHP has been criticised for inconsistencies between criteria and ranking reversal, which can, however, be managed by testing consistency during calculations and limiting the number of criteria (Konidari & Mavrakis, 2007; Velasquez & Hester, 2013). One other issue though is the need for AHP to consider setting criteria before calculation to handle interdependence among them (Velasquez & Hester, 2013).

2.3.2 Data envelopment analysis model

DEA is often used to evaluate the efficiency of a set of decision-making units (DMUs) or alternatives (Farrell, 1957; Charnes et al., 1978; Sheth et al., 2007). DEA handles multiple inputs and outputs without needing the explicit specification of relationships among the performance criteria (Izadikhah et al., 2021). In addition, the criteria efficiency can be quantified and analysed (Velasquez & Hester, 2013; Izadikhah et al., 2021).

However, a critical limitation of the DEA model involves its inability to handle imprecise data, operating under the assumption of precise knowledge for all input and output variables (Velasquez & Hester, 2013; Izadikhah et al., 2021). Real-world scenarios often deviate from this assumption, potentially impacting result sensitivity based on varying inputs and outputs. Consequently, this model's reliance on precise information for all parameters can pose challenges in practical applications.

2.3.3 Analytic network process model

ANP is a more generalized model of AHP, catering to the interdependency among criteria within a hierarchical structure due to criteria interactivity (Saaty, 2004). In terms of merits, the model establishes a network structure where criteria, sub-criteria, and alternatives interact, allowing comprehensive communication and feedback among all network elements, and enabling interconnection between nodes (clusters) (Saaty, 2004; Kheybari et al., 2020). While ANP significantly encompasses relationships, it is not without limitations, including the necessity for exhaustive brainstorming sessions in attribute identification, the time-intensive nature of data acquisition, the higher computational requirements compared to AHP process, and the neglect of subjectivity in comparisons (Yellepeddi et al., 2006).

2.3.4 PROMETHEE model

PROMETHEE is an outranking technique designed to rank and select among conflicting criteria within a finite set of alternative actions (Brans & Vincke, 1985). The PROMETHEE model contains several versions, and PROMETHEE I and II are often used to weight and rank criteria (Behzadian et al., 2010; Nassereddine & Eskandari, 2017).

The method offers ease of use and does not need to assume proportionality among criteria (Velasquez & Hester, 2013). However, it lacks a definitive approach for assigning weights and requires value assignments without providing a clear methodology for this purpose (Velasquez & Hester, 2013). Hence, the weighting results of criteria may be negative (Nassereddine & Eskandari, 2017).

2.3.5 TOPSIS model

TOPSIS is a multi-criteria evaluation method for pinpointing an alternative closest to the ideal solution and farthest from the negative ideal solution within a multi-dimensional computational space (Velasquez & Hester, 2013; Zhang et al., 2018). Criteria weights are the inputs of the TOPSIS model (Olson, 2004). Its advantages include a straightforward process, user-friendliness, programmability, and a consistent number of steps irrespective of attribute count (Velasquez & Hester, 2013). However, a drawback emerges from its reliance on Euclidean distance, neglecting attribute correlations (Velasquez & Hester, 2013). Additionally, challenges arise in attribute weighting and maintaining judgment consistency, particularly with an increased number of attributes (Olson, 2004; Velasquez & Hester, 2013).

2.3.6 ELECTRE model

ELECTRE is an outranking method which is similar to PROMETHEE. ELECTRE includes several versions, such as the ELECTRE I for a choice problem, the ELECTRE II, III and IV for dealing with ranking, and the ELECTRE TRI for a sorting problem (Bojković et al., 2010). The criteria associated weights are mostly determined by DMs (Bojković et al., 2010; Greco et al., 2016). The advantage of the method is its consideration of vagueness and uncertainty during the process (Velasquez & Hester, 2013). However, the model outcome's results can be difficult to explain in simple terms (Velasquez & Hester, 2013). Additionally, the outranking method hinders the direct identification of strengths and weaknesses within alternatives, consequently impeding the verification of both results and impacts (Konidari & Mavrakis, 2007).

Table 3

Summary of MCDM evaluating and weighting methods

Method	Advantages	Limitations
Analytic hierarchy process	• User-friendly interface • Scalability • Flexible hierarchy structure adaptable to various problem sizes • Low data intensity	• Criteria interdependence • Ranking reversal • Inconsistency between judgment and criteria
Data envelopment analysis	• Handle multiple inputs and outputs adeptly • Allow analysis and quantification of efficiency	• Does not accommodate imprecise data • Operates under the assumption of precise knowledge for all inputs and outputs
Analytic network process	• Handle interdependence between criteria • Scalability • Considers criteria network structure	• Needs extensive brainstorming sessions for criteria identification • Consumes significant time in data acquisition • ANP involves more calculations compared to AHP • Neglects the subjectivity in comparisons
PROMETHEE	• User-friendly interface • Eliminates the need for assuming proportionate criteria	• Lack of a clear method for assigning weights
TOPSIS	• Simple process • User-friendly and programmable • Consistent number of steps regardless of attribute number	• Challenging to maintain consistent judgment and weight allocation
ELECTRE	• Considers uncertainty and vagueness	• Complex to explain results in simple terms • Outranking obscures direct identification of strengths and weaknesses

Table 3 summarises the advantages and limitations of the current PT performance MCDM evaluation and weighting methods. PROMETHEE lacks a clear criterion weighting method. For TOPSIS and ELECTRE, the weighting process does not contain a consistency test. Furthermore, most DEA application in PT consider the efficiency of PT network performance. In addition, the evaluation model needs to produce criteria weighting results for the optimisation process. Although AHP and ANP can manage to evaluate and weight PT network performance criteria, ANP needs to spend more time for data acquisition and calculations. ANP is used to handle criteria interdependence, compared with AHP.

In conclusion, this section has provided a detailed consideration of current MCDM methods in PT network performance. As mentioned before, the current research seeks to attain performance reports and criteria weights for the optimisation of the PT process. Consequently, AHP has been chosen to be used to assess and balance the PT network performance criteria.

2.4 PT performance optimisation

Numerous mathematical models have been applied to optimise PT performance in recent literature. To reduce transfer waiting times, a model for optimising PT timetables has been created (Wong et al., 2008). Many researchers have used this optimisation model with various criteria, while modifying the bus line offset (Cevallos & Zhao, 2006; Hadas & Ceder, 2010; Petersen et al., 2013). A PT timetable optimisation model was developed further by Niu and Zhou (2013) by considering the situation of boarding passengers at a crowded station. An optimisation model was put forth by Guihaire and Hao (2010) to maximise both the quantity and quality of passenger transfer opportunities. A bi-level timetable optimisation model was used by Parbo et al. (2014) to optimise the PT schedule from the viewpoints of the users. In order to optimise PT routes, Heyken Soares et al. (2019) scaled down the network using genetic algorithms (GA). The GA model has also been utilised to suggest a zone-based PT route optimisation method (Heyken Soares, 2021). A Markov-chain-based model to maximise a PT network's effectiveness was described by Faizrahnemoon et al. (2015). But each of these PT optimisation models concentrated on a single factor, such as the schedule, the PT route, or the effectiveness. There are not many studies that take complete PT network performance optimisation into account.

In the following section, we introduce the concepts of GP and MCGP models that we will further develop in this research.

2.4.1 Goal programming

GP and AHP are frequently combined to support decision-making, address MCDM issues, and find the best solutions, (Larbani & Aouni, 2011; Hamurcu & Eren, 2018). The objective function criteria priority of GP is determined using the AHP process' outputs, and GP is used to optimise the selection or evaluation, incorporating conditions or constraints that need to be dealt with as they arise (Tamiz et al., 1998; Lin et al., 2014; Cyril et al., 2019). By choosing the criteria aspiration value from a large number of criterion input values, the model minimises the objective function (Ignizio, 1983; Tamiz et al., 1998; Cyril et al., 2019). AHP results can manage the limitation of GP, which is unable to weight the coefficients (Zeleny, 1981; Velasquez & Hester, 2013). Establishing the optimal objective value for each objective is the best solution for DMs' multi-objective problems (Jadidi et al., 2015). According to Zeleny (1981), the criticism of GP is that the goal levels setting is too arbitrary. Additionally, the goals' lower and upper levels setting are difficult (Zeleny 1981). However, this issue can be managed by considering and determining goals using government policies and documentation (Cyril et al., 2019).

GP and fuzzy GP approaches are two widely used techniques for resolving multi-objective issues (Jadidi et al., 2015). When using the GP objective function to optimise the scenario, the weights for the criteria can be assigned using the AHP (Cyril et al., 2019). Furthermore, the GP model has been combined with the weighting approach to enhance PT (Hamurcu & Eren, 2018; Cyril et al., 2019).

According to Cyril et al. (2019), GP is an optimisation process that minimises the objective function by choosing inputs from a range of input values. According to Chang (2007) and Larbani and Aouni (2011), GP aids DMs in resolving MCDM problems and identifying a range of workable solutions. According to Chang (2007) and Larbani and Aouni (2011), the goal of GP is to reduce the gap between aspirational levels and actual goal achievement. GP can be applied to numerous user-defined criteria priorities as well as many criteria goals specified by DMs (Chen & Xu, 2012; Hamurcu & Eren, 2018; Cyril et al., 2019).

Governments often establish a target level or goal for a criterion rather than pursuing the optimal solution. By allowing DMs to optimise the performance of the criteria, GP aims to suggest a solution that best satisfies their objectives (Chen & Xu, 2012). In addition, GP can offer DMs solutions to put into practise. The primary benefit of GP is that it gives DMs optimal processes and control over their preferences (Jadidi et al., 2015).

The most recent GP research has been used to optimise budget scenarios, choose projects, and choose suppliers (Jadidi et al., 2015). On the optimisation of PT performance, few studies have been conducted. In order to choose the best rail system project in Istanbul, the AHP and GP models were used (Hamurcu et al., 2017; Hamurcu & Eren, 2018). An AHP-GP model was put forth by Cyril et al. (2019) with the goal of improving PT performance in terms of both operational and user-related factors. It is noteworthy that the study only used one aspiration value for the optimisation of the criteria, though.

Therefore, to address optimisation issues involving multiple aspiration level criteria, the researchers improved the GP model and built the MCGP model. The details of the MCGP model are described below.

2.4.2 Multiple choice goal programming

To manage the multiple aspiration level criteria issue, MCGP is proposed. A model that allows DMs to address multiple goals or aspiration levels per criterion is further developed by MCGP, which is based on GP (Chang, 2007; Chang, 2008; Chang, 2011; Jadidi et al., 2015). The fundamental idea behind MCGP is that criteria should have multiple aspiration levels because each goal may have multiple desired target values for each criterion (Hocine et al., 2020). During the optimisation process in MCGP modelling, these aspiration levels offer numerous options for locating a suitable solution set (Hocine et al., 2020).

The MCGP approach enables DMs to specify a series of values rather than a single scalar target level or select multiple aspiration levels for each criterion (Chang, 2007; Ho et al., 2013; Jadidi et al., 2015). Because the DMs can select multiple aspiration levels or goals for each criterion, this approach is preferable to GP (Ho et al., 2013; Jadidi et al., 2015).

Multi-criteria problems have previously been resolved using MCGP and the criteria weighting method. Ho et al. (2013) proposed the AHP and MCGP models to address the housing location selection problem. AHP and MCGP were combined by Lin et al. (2014) to help DMs choose the best online IT tools. Furthermore, MCGP is utilised to manage the site selection process for renewable energy sources (Hocine et al., 2020).

For each criterion, the majority of studies on improving PT performance have taken into account a single level of aspiration; however, in reality these criteria frequently involve multiple goals and levels of aspiration. DMs can set multiple levels of aspiration or goals for each criterion of the suggested MCGP model (Chang, 2007, 2008, 2011). The model addresses the issue of multiple aspiration levels, but the aspiration level of the criteria may be required to select between various aspiration-level cases in PT performance optimisation.

2.5 Risk management

Few MCDM and GP methods have been integrated in optimising PT performance to satisfy DMs' goals and requirements even though MCDM and GP methods offer a variety of frameworks (Ngossaha et al., 2017; Cyril et al., 2019). To solve multicriteria optimisation problems, the AHP and GP approach are frequently combined (Cyril et al., 2019). It can be challenging for DMs to deliver an optimal solution in some situations because of uncertainty that arises during the optimisation process.

Previous studies have not examined uncertainty pertaining to criteria uncertainty. Furthermore, risk and uncertainty are closely related to the optimisation of the PT network performance and can have a big impact on the results of optimisation. This section describes how risk management is implemented in PT networks, including how the risk management tool MCS is used.

2.5.1 Uncertainty and risks in PT networks

The delivery of optimised results is, in practise, impacted by the uncertainty of events. Uncertainty and variation are problematic when trying to optimise PT network performance. According to Altieri et al. (2017), PT is a complex system whose quality analysis is challenging because it must consider the risks and uncertainties associated with human reasoning. Additionally, there are numerous risks and uncertainties associated with user demand, operations, and traffic conditions that must be considered when PT performance improvement is being considered (Cats & Gkioulou, 2017). So, whenever a PT optimisation model is developed to replicate a complex system, its output will always be uncertain.

Uncertainty is usually related to risk, which is defined as the influence of uncertainty on objectives or criteria (PMI, 2000; Aven, 2016; Hopkin, 2018).

Appropriate identification of major sources of risk can eliminate or at least reduce the probability of discovering new sources of uncertainty during the modelling process (Manzo et al., 2015). Thus, the uncertainty or risk identification process of the criteria is needed to deliver the project results. Risk management is the tool that provides methods for mitigating project risk.

Risk management employs both qualitative and quantitative techniques. Budzynski et al. (2021) examined PT's response to hazards using a qualitative method, risk registers. Similarly, Dalmau (2022) used risk management to forecast the likelihood of airspace user rerouting, which will aid the flow manager in air traffic flow management. To model the likelihood of project objectives, this study employs a quantitative risk management tool.

In the PT sector, risk management models have already been used to model the input and model uncertainty (Fowkes, 1995; De Jong et al., 2007), and recent optimisation under uncertainty problems in PT frequently employ quantitative risk management methods, which assist DMs in determining the probability of the optimal solution (Schmidt et al., 2017; Liang et al., 2019).

2.5.2 Monte Carlo simulation for managing uncertainty

Uncertainty cannot be fully investigated due to limited knowledge or the randomness of some model components. MCS is a quantitative risk analysis method based on a probabilistic model that employs probability distributions to model uncertainty (Fishman, 1995; Zito et al., 2011). The results assist the DMs in managing risk and uncertainty to complete the project.

MCS is a risk management tool that is widely used in many fields, including medicine and project management. For example, MCS is used in medicine to assess the likelihood of viral transmission (Liu et al., 2021). Yang et al. (2020) employed MCS to model uncertainty in a project to assess the health of land ecosystems. Kannan et al. (2021) used MCS to analyse the sensitivity of

VIKOR and grey relational analysis in a sustainable location of solar site selection project. MCS is also used to improve the reliability of assessment results in a lake eutrophication level evaluation project (Lin et al., 2020). In most cases, MCS is used to assess the likelihood of project outcomes.

MCS is frequently used in cost management to determine the feasibility of project costs. After the project feasibility stage, MCS is applied in public and private partnership (PPP) projects to optimise capital structure, which balances the interests of the public and private sectors (Feng et al., 2017). Similarly, to address revenue uncertainty in transportation PPP projects, Liu et al. (2020) used MCS in the proposed optimisation model to improve dynamic capital structure adjustment, with the research beginning with the PT project to optimise the capital structure.

MCS has attracted the interest of PT researchers in recent years. For instance, Manzo et al. (2015) used MCS to analyse uncertainty in a four-stage transport model. Conway et al. (2018) utilised MCS to account for variation and uncertainty in accessibility metrics when planning PT sketches. Furthermore, Pencheva et al. (2021) applied MCS to determine the waiting time of passenger vehicles in PT areas. Previous research has concentrated on mitigating the impact of PT model inputs and outputs as well as evaluating PT performance. Despite the advantages of MCS, a limitation of this model is that it is difficult to identify the maximum and minimum values of each input variable, and the researchers have to investigate and assess the level of risk associated with each input variable (Raychaudhuri, 2008).

To the best of our knowledge, little research has been conducted on PT optimisation under uncertain conditions. To fill the gap, the current research aims to develop a new framework for optimising PT network performance in the presence of uncertainty.

2.6 Conclusion

This chapter has reviewed current PT measurement systems, as well as methodologies and methods for solving MCDM in PT, optimising, and managing uncertainty. Previous research has not thoroughly investigated the impact of other key factors on the development of urban transportation systems (such as development policies, energy/sustainability, and infrastructure/facilities).

MCDM and GP methods provide a variety of frameworks, and a few MCDM and GP methods have been integrated in optimising PT performance to meet the goals and requirements of DMs. To solve multicriteria optimisation problems, the AHP is an MCDM method that is frequently combined with the GP approach. The current GP method is incapable of addressing the issue of multiple criteria aspiration levels. To solve this problem in practise, a multi-aspiration level GP method combined with a criterion weighting method that assigns weights to multiple criteria and combines them is required.

In some cases, DMs fail to deliver an optimal solution due to uncertainty that arises during the optimisation process. Previous research has lacked a closer look of the uncertainty associated with criteria uncertainty. By performing MCS, probabilistic analysis is a commonly used technique for addressing evaluation-based issues in project management. MCS is also used in mitigating uncertainty related to model inputs and outputs in various application areas. Despite its effectiveness in addressing project management issues, little research has used MCS to address the problem of optimising PT network performance. The current study only looks at one aspect of physical performance. In the PT network performance optimisation problems, the probability of a scenario (scenario analysis) is thus required.

This study proposes a three-stage approach for optimising PT network performance under uncertain conditions. The models optimise four levels of criteria with uncertainty to achieve the DMs' PT network optimisation goals. The primary goal of this study is to determine the level of criteria uncertainty, and a sensitivity analysis is performed to guide the optimisation process. MCS results can be used to assist DMs in making PT network optimisation decisions, as well as to precisely indicate the probability of uncertainty rate when delivering criteria outcomes.

Chapter 3: Performance Evaluation of PT Networks by Using PT Criteria Matrix Analytic Hierarchy Process Models

3.1 General overview

In this chapter, we develop a transport criteria matrix AHP model for monitoring and evaluating the performance of a PT network. To evaluate the performance of a PT network, evaluation criteria must first be chosen. This study proposes a PT criteria matrix based on existing indicators, which includes the basic PT infrastructure level, PT service level, economic benefit level, and sustainable development level. Then, a PT criteria matrix AHP model is established to evaluate the performance of PT networks. Based on existing performance standards, the established model selects appropriate evaluation criteria. It is used to investigate the Stonnington, Bayswater, and Cockburn PT networks, which represent a variety of land use and transportation policy backgrounds.

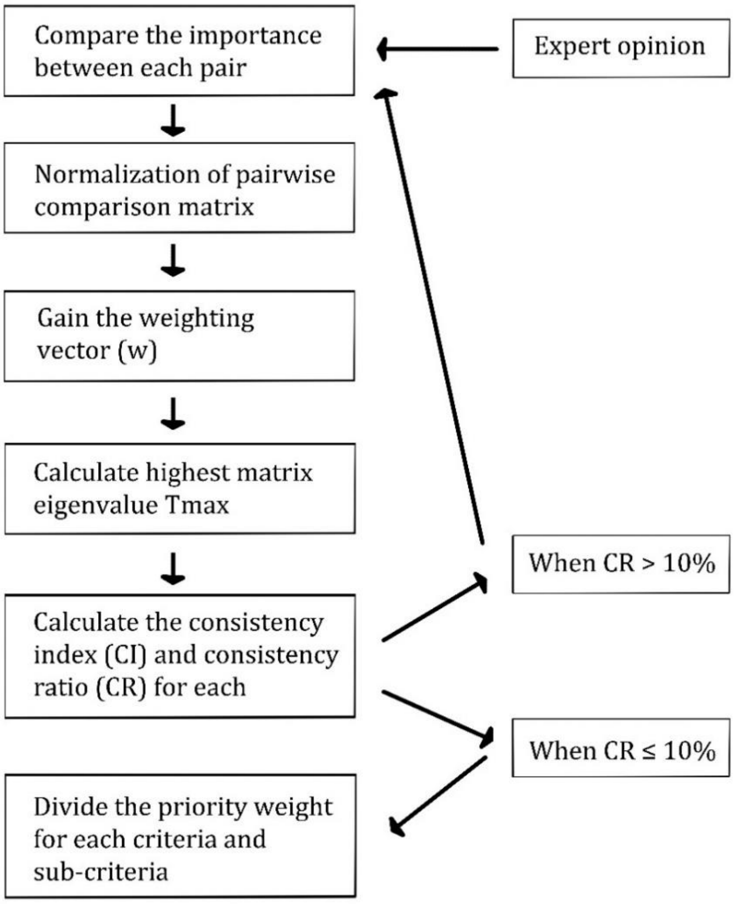
This chapter is organised as follows: Section 3.2 introduces the AHP model calculation process. In Section 3.3, we develop the PT criteria matrix AHP model. Section 3.4 discusses the motivation and characteristics of the three case study areas. Section 3.5 identifies the results of using the established model to evaluate the PT network performance of the three case study areas, and Section 3.6 concludes this chapter.

3.2 Analytic hierarchy process model formulation

We demonstrate the AHP model process and each process formulation in this section. The AHP model is used in this study to evaluate the performance of the PT network and calculate the criteria weights. It has five major processes for dividing the criterion weights. Figure 1 depicts the AHP model computation process. The formulations for each process are shown below.

Figure 1

AHP model calculation process (Yedla & Shrestha, 2003; Sadeghi & Ameli, 2012)



1. Comparison of the importance between each pair:

The value (c_{ig}) is assigned to represent the importance (from 1 to 9) for attribute (i) and attribute (g); additionally, $c_{ig} = 1/c_{gi}$. Next, a decision matrix is created, which is matrix C = (c_{ig}).

2. Normalisation of pairwise comparison matrix:

The pairwise comparison matrix needs to be normalized using the normalised arithmetic averages method (Saaty, 1977). After the normalization, matrix C is transformed into matrix D = (d_{ig}). The formula of matrix D is shown as follows:

$$d_{ig} = \frac{c_{ig}}{\sum_{i=1}^{n} C_{ig}} \qquad (1)$$

3. Obtaining the weighting vector (w):

The prioritisation vector (w) is gained by calculating the arithmetic averages from the normalized comparison matrix (d_{ig}) row. The calculation of vector w is calculated as below:

$$w = \frac{\sum_{g=1}^{n} d_{ig}}{n} \qquad (2)$$

4. Calculation of the highest matrix eigenvalue T_{max}:

Next, the highest matrix eigenvalue is calculated. The highest eigenvalue T_{max} is satisfied by:

$$Cw = T_{max}w \text{ and } T_{max} \approx T = \frac{\sum_{i=1}^{n} T_i}{n} \qquad (3)$$

5. Calculation of the consistency index (CI) and consistency ratio (CR) for each comparison matrix C:

The researcher tests that the ratings given by the experts are consistent. T_{max} is the highest eigenvalue of the matrix, n is the number of objects which are compared, RI (Table 4) is the random index, and n is the matrix dimension. The RI is shown as below:

Table 4

Random Index (RI) (Saaty, 1987)

Matrix Size	1	2	3	4	5	6	7	8	9
Random consistency index	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45

Furthermore, the calculation details of CI and CR for each comparison

$$CI = \frac{T_{max} - n}{n - 1} \tag{4}$$

$$CR = \frac{CI}{RI} \tag{5}$$

When CR ≤ 10%, the comparisons are considered as internally coherent; otherwise, it would be considered that inconsistency was present during the comparison process.

This study uses the AHP model to develop a comprehensive multi-criteria PT network performance evaluation model for various application levels. The source of the standards and criteria explanation of the PTCM-AHP model are demonstrated in the following section.

3.3 PT criteria matrix AHP model

As mentioned in Chapter 2, this study selects the criteria and standards of the proposed model based on four levels, which are the economic benefit level, the quality and efficiency of the PT service level, the basic PT infrastructure level, and the sustainable development level. Based on the above considerations, the criteria are selected from the *Evaluation Index System of Public Transportation City Assessment* (Ministry of Transport, 2014), the *Code for Transport Planning on Urban Road GB50220-1995* (Ministry of Construction, 1995), the *Passenger Transport Services for Bus/Trolleybus GB/T22484-2008* (Ministry of Housing and Urban-Rural Development, 2018), *GBT 22484-2016,* the *Passenger Transport Services Specifications for Urban Bus/Trolleybus* (Ministry of Transport, 2016), and the *Urban Road Traffic Management Evaluation Index System* (2012 edition) (Ministry of Transport, 2012).

Following these criteria, the model divides the criteria into two levels, which are (1) the urban level, and (2) the company operation level. In particular, the model makes the following definitions:

(1) Urban level: PT is considered at the urban level to evaluate the urban PT management and infrastructure establishment. The detailed expression of each criterion is described as follows:

- The PT network ratio refers to the proportion of the length of the PT network to the length of the urban road network, which reflects the service capacity and scope of urban PT.
- The PT coverage ratio reflects the convenience of using the PT system for residents. It refers to the ratio of the urban PT service area to the urban land area.
- The harbour-type bus stop setting ratio indicates the capacity of buses and the government's guarantees of bus priority. It considers the number of stations with bus stop bays on the expressways, main roads, and secondary roads in the city and accounts for the proportion of the total number of stops on the expressways, main roads, and secondary roads in the city.
- The PT priority lane setting ratio shows the proportion of the road length of PT priority lanes in relation to the total length of the urban main roads in the city. The length of the roads with PT priority lanes refers to the length of the centre line of the roads with PT priority lanes in the city. This is an important indicator that needs to be monitored to improve the traffic conditions of urban PT vehicles, and it reflects the level of a city's emphasis on PT priority policies.
- The PT land area per capita refers to the ratio of the area of PT roads to the total urban population. This represents land use for PT.
- The PT utiliation rate refers to the degree of coincidence between land used for PT and planned land use in the same period. This criterion is expressed

as the ratio of the number of jobs in PT to the total number of jobs during the same period. It reflects the consistency of PT with the city's master plan.

- The green PT vehicle rate is the proportion of green PT vehicles to total PT vehicles during the statistical period. Green PT vehicles include subways, light rail vehicles, trams, new energy vehicles, trolleybuses, liquid petroleum gas vehicles, etc. It reflects the important indicators of energy conservation and environmental protection of urban PT systems.
- The PT energy intensity is the ratio of the total energy consumption of urban PT to the volume of passenger transport of urban PT. It reflects the energy consumed to complete a unit of passenger turnover. This indicator reflects the energy conservation and environmental protection of an urban PT system. This indicator has a high correlation with the number and type of energy of vehicles employed.

(2) Company operation level: This level considers PT from the company level to evaluate the PT operators. The detailed information for each criterion is shown as follows:

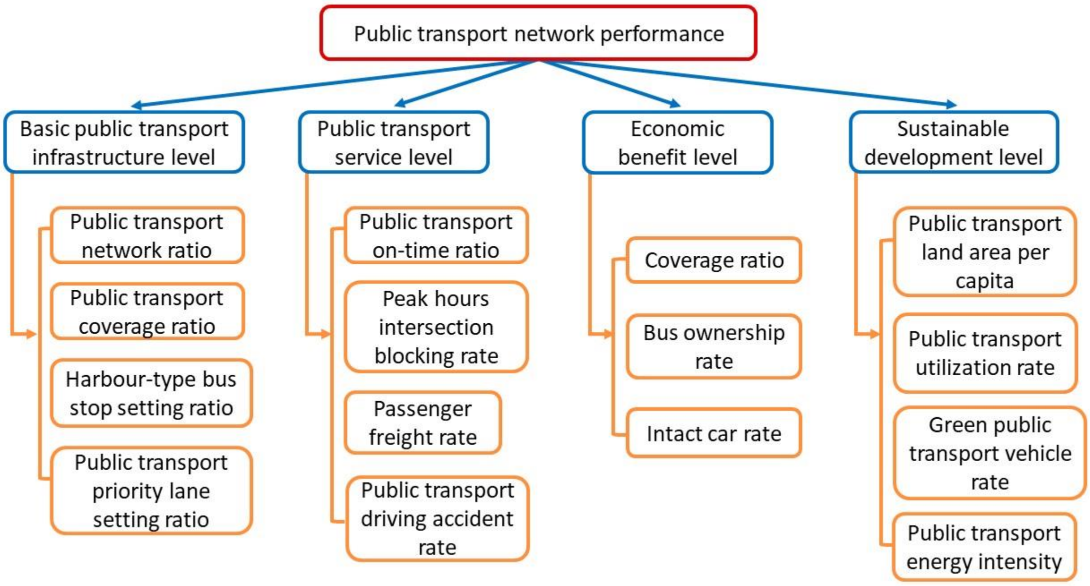
- The PT on-time rate indicates the average of buses' on-time rates and rail transit's on-time rates. The departure time of a bus is the first departure time of the bus. If the actual departure time is less than 2 minutes later than the planned departure time, it will be recorded that the departure time is punctual. The arrival time at the last station means that the actual arrival time at the last station is within the range of being 2 minutes earlier than the planned schedule or less than 5 min late, which is recorded as the arrival time at the last station. This is recorded as a delay when a rail transit train leaves or arrives at the terminal at the departure station greater than or equal to 2 minutes later compared to the planned time of the train schedule.
- The intersection blocking rate during peak hours is an indicator that measures the saturation of the entire road network. A periodically blocked intersection is frequently blocked for a certain period, such as in the AM and

PM peaks (and the blocked intersections are not caused by accidents). This is also a basis for checking the effects of traffic management, the development of traffic demand management measures, and proposing intersection reconstruction planning.

- The passenger freight rate is the ratio of the cost of PT paid by an ordinary passenger per month to the average city salary for that month. This index can reflect the rationality and affordability of ticket prices.
- The PT driving accident rate is the number of accidents per million kms travelled by PT vehicles in a year. This is an important criterion to reflect the safety performance of the PT system and has a high correlation with the use and maintenance of PT vehicles.
- The coverage rate refers to the rate of total commercial revenue of the last year to the total operating expenses of the last year. It shows the users' financial contributions and the economic sustainability of the operators.
- The bus ownership rate refers to the number of bus stations per 10,000 people in the statistical period. It reflects the distribution of traffic structure.
- The intact car rate is the ratio of intact vehicle days to operating vehicle days during the statistical period. It shows the maintenance level of PT.

Figure 2

PT network performance criteria hierarchy structure



As demonstrated above, the creation of the PTCM-AHP model is based on these urban and company operation levels of criteria. According to Figure 2, the PTCM-AHP model criteria are classified into four levels: PT infrastructure level, sustainable development level, PT service level, and economic benefit level. Furthermore, Figure 2 displays the PT network performance criteria hierarchy structure of the PTCM-AHP model. The model includes four levels of criteria, and 15 sub-criteria.

An overview of the formula for the sub-criteria and level grade for all sub-criteria can be found in Appendixes A and B. It can be seen from Appendix B that level A shows the best performance regarding the criteria, and level E means ordinary performance. The process for measuring the city score is indicated as follows:

- First, data for each criterion need to be collected from the relevant planning and PT departments.
- Second, the calculated data are ranked according to established performance standards.

- Third, the global weight for each sub-criterion is calculated as the weight of the criteria (main criteria prioritisation) multiplied by the sub-criteria weight (sub-criteria prioritisation).
- Finally, based on the established PT network performance score levels, the PT performance grade for a city can be measured.

To identify the process of the proposed model, this research applies the PTCM-AHP model to three case studies of Australian cities. The details of the case study areas are shown in the next section.

3.4 Case study areas: Stonnington, Bayswater, and Cockburn PT Network

In this section, the evaluation model described in the previous section was applied to the three Australian case study areas — (1) the City of Stonnington, (2) the City of Bayswater, and (3) the City of Cockburn — to examine the PTCM-AHP model.

Before we examine the process of the PTCM-AHP model, we give a brief introduction of the case study areas. Stonnington's location is close to Melbourne's Central Business District (CBD), and Bayswater's location is adjacent to Perth's CBD. Cockburn is in the southern part of the Perth CBD. The population densities of Bayswater, Cockburn, and Stonnington are 19.94 persons per hectare, 6.98 persons per hectare, and 46.27 persons per hectare, respectively. The main designation of these three cities is residential. The length of Bayswater's PT network is approximately 62 km, Cockburn's is 148 km, and Stonnington's is approximately 75 km. The details of three case studies are shown in Table 5.

Table 5

Details of the three case studies

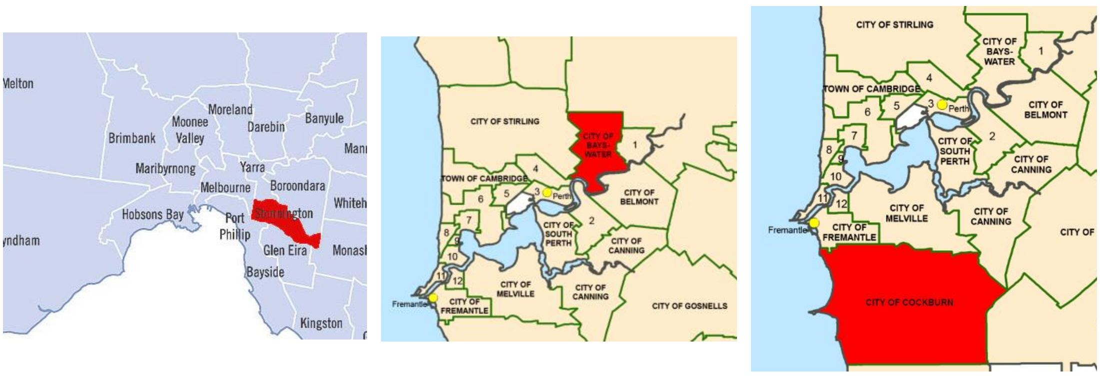
City	Bayswater	Cockburn	Stonnington

Population density	19.94 persons per hectare	6.98 persons per hectare	46.27 persons per hectare
Length of PT network	61.9117 km	147.9874 km	74.7598 km
Predominant purpose of case study area	Residential	Residential	Residential
Main type of PT	Bus and train	Bus and train	Bus and train

Overall, all of the case study areas have a well-established PT network. As can be seen from Table 3, the main types of PT in the three cities are buses and trains. As the population of the three case study cities continues to grow, the government requires an assessment of the existing PT networks. All three governments have created new strategies and plans to promote PT, but car ownership in Melbourne and Perth continues to increase. This is the main motivation for a comparison study of the three cities. The city boundaries of the three case study areas are shown in Figure 3.

Figure 3

(a) City boundary of Stonnington; (b) city boundary of Bayswater; (c) city boundary of Cockburn



(a) (b) (c)

Note. From *Metropolitan councils map* (https://www.viccouncils.asn.au/find-your-council/council-map) and *PERTH METRO REGION* (https://library.dpird.wa.gov.au/rd_maps/13/)

Next, we calculate the score and level of sub-criteria, and determine the city PT network performance score of Stonnington, Bayswater, and Cockburn.

3.5 Findings

In this section, the proposed PTCM-AHP model is applied to the PT network performance of the case study areas in terms of the basic PT infrastructure level, PT service level, economic benefit level, and sustainable development level.

Before we evaluate the case study areas PT network performance, we define and calculate the weights of the criteria and sub-criteria. The pairwise comparison matrix was defined by studying the polices of the local councils and state governments in the case study areas. The details of the preference matrix, prioritisation, CI, and CR for the four main criteria and 15 sub-criteria are listed in Appendix C.

Table C1 presents the preference matrix of the four main criteria, taking the overall weight for the basic PT infrastructure level as 41%, for the PT service level as 19%, for the economic benefit level as 11%, and for the sustainable development level as 29%. The local weights for the sub-criteria (sub-criteria prioritisation) are shown in Tables C2–5. Based on the weights for the criteria and sub-criteria, the global weight for each sub-criterion is shown in Table C6. Subsequently, the score and rating for each criterion in the case study areas can be determined using the original data of the cities.

Table 6 illustrates the original data and achieved grade of the PT network performance for Bayswater, Cockburn, and Stonnington. The results show that Stonnington has the highest level in terms of the PT network ratio, PT coverage ratio, PT priority lane setting ratio, intersection blocking rate during peak hours, and coverage rate. All of the cities achieve level A for the passenger freight rate, intact car rate, PT utilisation rate, and green PT vehicle rate. Compared to

Stonnington, both Bayswater and Cockburn achieve higher levels for the PT on-time rate, PT driving accident rate, PT land area per capita, and PT energy intensity. Moreover, all three case study areas only achieve level D for the bus ownership rate. Bayswater has the lowest level of PT coverage ratio and intersection blocking rate during peak hours.

Table 6

Original data and achieved grades for the PT network performance criteria for Stonnington, Bayswater, and Cockburn

Criteria		Original Data and Achieved Grade		
		Bayswater	Cockburn	Stonnington
Basic PT infrastructure level	PT network ratio	17.64 = Level D	19.21 = Level D	60.78 = Level A
	PT coverage ratio	46.82 = Level C	50.42 = Level B	83.72 = Level A
	Harbour-type bus stop setting ratio	19.04 = Level C	9.2 = Level D	26.71 = Level B
	PT priority lane setting ratio	0 = Level E	0.31 = Level E	25.38 = Level A
PT service level	PT on-time rate	91.03 = Level B	91.03 = Level B	84.68 = Level C
	Intersection blocking rate during peak hours	21 = Level E	8.1 = Level D	1.5 = Level A
	Passenger freight rate	1.75 = Level A	1.75 = Level A	2.33 = Level A
	PT driving accident rate	2.38 = Level C	2.38 = Level C	4.54 = Level E

Economic benefit level	Coverage rate	98.8 = Level D	98.8 = Level D	101.5 = Level B
	Bus ownership rate	7 = Level D	7 = Level D	7.36 = Level D
	Intact car rate	100 = Level A	100 = Level A	100 = Level A
Sustainable development level	PT land area per capita	20.47 = Level A	26.23 = Level A	9.28 = Level B
	PT utilisation rate	0.8 = Level A	0.8 = Level A	0.78 = Level A
	Green PT vehicle rate	100 = Level A	100 = Level A	100 = Level A
	PT energy intensity	25.45 = Level A	25.45 = Level A	83.59 = Level C

According to the standard scoring interval (see Appendix B), we divided each city's PT network performance into five levels (see Table 7). We calculated the scores for PT performance for all of the criteria and summed the performance over all criteria, as indicated in Table 8. The results show that Stonnington's PT network, at 82.45, scores higher than Cockburn and Bayswater, while Cockburn's PT network scores 66.61, which is higher than Bayswater's score of 63.55. The analysis shows us that the area with the best practice in terms of PT network performance is Stonnington.

Table 7

City PT evaluation result classification standard

	Level A	Level B	Level C	Level D	Level E
Index value evaluation range	90–100	80–90	70–80	60–70	0–60

Table 8

Comparative analysis of Bayswater, Cockburn, and Stonnington

	Criteria	Global Weight		
		Bayswater	Cockburn	Stonnington
Basic PT infrastructure level	PT network ratio	3.03	3.3	12.98
	PT coverage ratio	10.52	11.56	14.3
	Harbour-type bus stop setting ratio	2.97	1.66	3.5
	PT priority lane setting ratio	0	0.15	7.17
PT service level	PT on-time rate	5.46	5.46	4.99
	Intersection blocking rate during peak hours	0	2.91	4.26
	Passenger freight rate	5.3	5.3	5.3
	PT driving accident rate	2.01	2.01	0.76
Economic benefit level	Coverage rate	3.34	3.34	3.86
	Bus ownership rate	1	1	1.06
	Intact car rate	1.9	1.9	1.9
Sustainable development level	PT land area per capita	7.8	7.8	6.62
	PT utilisation rate	2.99	2.99	3
	Green PT vehicle rate	9	9	9
	PT energy intensity	8.23	8.23	5.5
	Total	63.55	66.61	82.45

According to the classification standard, the outcome of the city score in Table 8 shows that Stonnington is classified as level B, while Cockburn's and Bayswater's PT networks' performances are both rated as level D.

The outcomes of the case study areas reveal the criteria that governments should consider in future optimization efforts to enhance the PT network performance of cities.

3.6 Conclusion

In this chapter, we investigated the performance of PT networks at the basic PT infrastructure level, PT service level, economic benefit level, and sustainable development level. The research established a new AHP-based model to provide weights for the criteria and sub-criteria. Based on the existing standards for each sub-standard, the new evaluation model gives a score for a city's PT network performance, and the results show the aspects that the governments should consider improving in the future.

Moreover, we collected a series of indicators across three sample cities, representing a series of land use and transport policy backgrounds, and these indicators can help researchers determine numerous standards, so as to potentially inspire any city that wants to improve the future performance of its PT network. Results of the model show that all three cities have high levels of sustainable development. By providing indicators that can be used to evaluate specific PT policy issues, this research has made a significant contribution to PT network performance evaluation. The findings of this chapter are as follows:

- The PT network ratio and PT coverage ratio are the most important criteria for the basic PT infrastructure level, whereas for the PT service level, the PT on-time rate has the highest weighting. For the economic benefit level, the coverage rate is the most important criterion. The green PT vehicle rate and PT energy intensity have the highest weighting in the area of sustainable development.
- The results of the three case study areas indicate that both Bayswater and Cockburn should consider their PT infrastructure level, PT service level, and economic level more closely in their plans and strategies. Stonnington

should improve its sustainable development level, PT service level, and economic benefit level.

Chapter 4: Performance Optimisation by Multi-Aspiration-Level Goal Programming

4.1 General overview

In this chapter, we propose an optimisation approach to improve multiple-criteria aspiration-level PT performance by combining PTCM-AHP models and MALGP. The approach uses the PTCM-AHP to calculate the system weights of PT network performance criteria. Based on the criteria weight values, the approach combines the multi-aspiration goal-level selection process in three different ways. The proposed approach was used to optimise PT networks in Bayswater, Cockburn, and Stonnington, Australia, to demonstrate the PT network performance optimisation process. By controlling the criteria goal value interval, this new approach combines decision-making plans and strategies to optimise various scenarios.

The remainder of this chapter is organised as follows: in Section 4.2, the mathematical formulations for the GP and MCGP models is explained. Section 4.3 proposes the multi-aspiration-level GP approach dependent on PTCM-AHP models, followed by three examples in Section 4.4. Section 4.5 discusses the results of three case study areas and the application of the model. Section 4.6 presents conclusions.

4.2 Model formulation

The PTCM-AHP model's criteria weighting results are used as coefficient values in this study to calculate the optimal solution. Section 4.2.1 introduces the basic formulation of the GP model before we develop and construct AHP-dependent MALGP models. Section 4.2.2 also presents the concept and formulation of MCGP development.

4.2.1 Goal programming

As we have mentioned in Chapter 2, the GP often combines with the AHP model for solving optimisation problems. Thus, we use the PTCM-AHP model criteria weighting results as coefficients of the objective function to model PT network performance optimisation process (Cyril et al., 2019). Details of the objective function and constraints are presented below.

We define the following notations:

i: number of goals, $i = 1, 2, \dots n$,

s: number of criteria, $s = 1, 2, \dots\ e$,

R_i: ith priority,

x_s: sth criteria,

b_{is}: coefficient of the ith goal and sth criteria,

d_i: goal value for goal i,

p_i: positive deviation,

q_i: negative deviation.

The optimisation problem of the PT network performance can be formulated as follows:

$$\text{Min } \sum_{i=1}^{n} R_i\,(p_i + q_i) \tag{6}$$

subject to

$$\sum_{s=1}^{e} b_{is}\, x_s - p_i + q_i = d_i, \tag{7}$$

$$p_i,\ q_i,\ x_s \geq 0, \tag{8}$$

where R_i is the rating and value of the ith decision variable.

The GP method cannot manage a goal which contains multiple choice aspiration level. To solve this problem, Chang (2007) developed the MCGP model to manage multiple choice optimal process. The details of the MCGP model formulation are presented below.

4.2.2 Multiple choice goal programming

The GP optimisation approach relies on choosing a goal at a single aspiration level. However, a goal may involve multiple choice aspiration levels (Chang, 2007; Ho et al., 2013). According to Chang (2007), the author identifies a situation where DMs aim to address a problem with a specific goal achievable through multiple aspiration levels, noting that current GP approaches do not offer a solution for this scenario.

The original GP method cannot solve multiple choice aspiration-level issues; thus, MCGP was proposed to solve this problem. The details of the MCGP model consists of the objective function (6) and the constraints are shown as follows:

$$\sum_{s=1}^{e} b_{is}\, x_s - p_i + q_i = \sum_{j=1}^{m} g_{ij} S_{ij}(B), \tag{9}$$

$$S_{ij}(B) \in R_i(x), \; p_i, q_i, x_s \geq 0, \tag{10}$$

where g_{ij} is the jth aspiration level of the ith objective, $g_{ij-1} \leq g_{ij} \leq g_{ij+1}$, and $S_{ij}(B)$ represents a binary serial function attached to multiple aspiration levels for each objective and is based on the restriction $R_i(x)$ (Chang, 2007; Jadidi et al., 2015). $S_{ij}(B)$ ensures that each objective selects one of the multiple goals (Chang, 2007; Jadidi et al., 2015).

In practical scenarios, the criteria used often involve multiple goals and levels of aspiration. While the model solves the problem of multiple aspiration levels, selecting the appropriate aspiration level for a set of criteria may be necessary for optimising PT performance. Therefore, this research proposes an AHP-Dependent MALGP model that can effectively choose an appropriate aspiration level for a given set of criteria, which may consist of multiple levels. The proposed AHP-Dependent MALGP model is explained in detail below.

4.3 AHP-dependent multi-aspiration-level goal programming

As we have stated in Chapter 2, AHP is often combined with GP models to solve performance optimisation issues. In a real situation, the model has multiple choices for each criterion. However, the criteria aspiration level may have different aspiration-level cases. The DMs require the model to be able to select an aspiration level among different cases. The current MCGP model in PT performance optimisation lacks consideration in the selection process of different aspiration level cases. Therefore, in this section, we propose an AHP-Dependent MALGP model to address this issue. In this chapter we use PTCM-AHP model criteria weighting results as coefficient values from which to calculate the criteria optimal solution. The details of the model are as follows.

The proposed model consists of three steps:

(1) As mentioned in Sections 3.2 and 3.3, the PT network performance criteria weights for the model are obtained from the PTCM-AHP model.

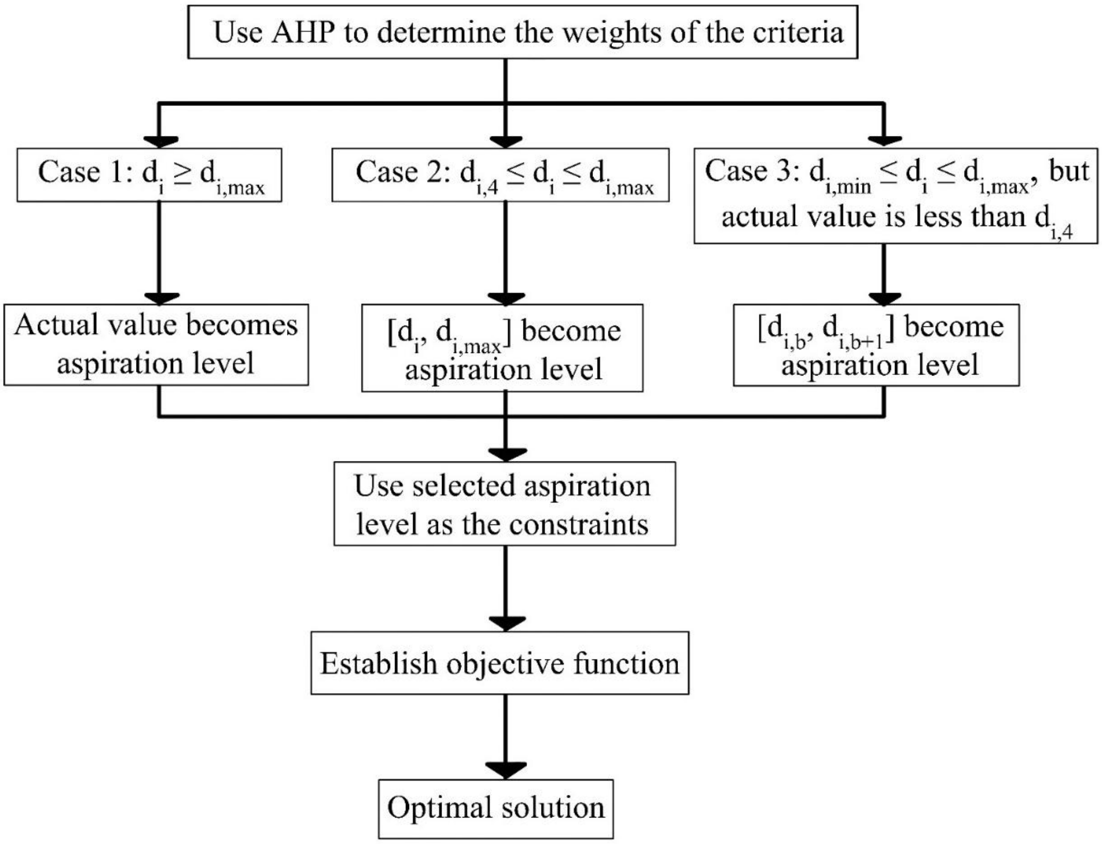
(2) The formulated constraints consider the upper and lower bounds of the criteria by assigning positive and negative deviations in the form of inequalities. The model considers three cases for the aspiration level selection criterion.

(3) The model uses the selected aspiration levels as constraints to establish the objective function and calculate the optimal solution.

Overall, the proposed model applies the PTCM-AHP model to determine the weights of the criteria. The model identifies the weights by studying the local council policies of the case study areas. Based on the AHP, the PTCM-AHP model considers the basic PT infrastructure, PT services, economic benefits, and sustainable development levels. These criteria are further divided into 15 factors. Details of the 15 sub-criteria can be found in Section 3.3. The 15 decision variables are the PT network ratio (X_1), PT coverage ratio (X_2), green PT vehicle rate (X_3), PT energy intensity (X_4), PT priority lane setting ratio (X_5), PT land area per capita (X_6), PT on-time rate (X_7), passenger freight rate (X_8), coverage rate (X_9), peak hours intersection blocking rate (X_{10}), harbour-type bus stop setting ratio (X_{11}), bus ownership rate (X_{12}), PT utilisation rate (X_{13}), PT driving accident rate (X_{14}), and intact car rate (X_{15}). Based on the established AHP model, the weights for the criteria are used in the multi-aspiration-level GP objective function. The weights for each sub-criterion are listed in Table C6.

Figure 4

Flowchart of AHP-dependent multi-aspiration-level GP model



Upon completion of the criteria weights determination process using the PTCM-AHP model, the proposed AHP-Dependent MALGP model incorporates the aspiration level selection process to optimise the performance of the PT network for DMs. This approach minimises the sum of deviations between optimal values and goal values. Subsequently, the optimal solutions for the case study area can be determined.

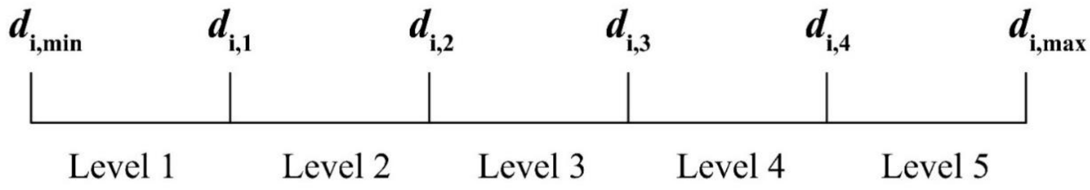
As shown in Figure 4, the flowchart of the AHP-Dependent MALGP model contains serval major steps. The details of criteria aspiration-level case selection and MALGP formulation establishment process are presented in the following subsections.

4.3.1 Criteria aspiration-level case selection

Criterion case selection was based on the criterion of aspiration levels and the actual value of the case study area. Table B1 presents the level grades for all the sub-criteria. This study utilises Levels 1–5 to represent Levels E–A. The aspiration level selection for the cases is listed in Figure 5.

Figure 5

Sub-criteria grade level



Case 1:

If the actual value of the ith criterion is higher than $d_{i,\max}$, then the actual value becomes the ith criterion aspiration goal value.

Case 2:

If the ith criterion's actual value is higher than $d_{i,4}$ but less than $d_{i,\max}$, the ith criterion's aspiration goal value should be higher than the actual value but less than $d_{i,\max}$.

Case 3:

If the ith criterion's actual value belongs to levels 1, 2, 3, or 4, the aspiration level of the ith criterion becomes the $(i+1)$th goal level. After the case selection process, the formulas for the three cases are as given in the next section.

4.3.2 Establishing multi-aspiration-level goal programming

This model focuses on the criteria index value interval selection that enables the government to control the optimisation process. The proposed model formulation also includes Eq. (6)-(8).

Let d_i be the ith criterion grade level, $i = 1, 2 \dots 5$. The new multi-aspiration-level GP is described below.

Case 1: When the goal value is greater than $d_{i,\max}$,

$$d_i \geq d_{i,\max}, \tag{11}$$

where the aspiration level of d_i is the actual value of the criterion.

Case 2: When the goal value is less than $d_{i,\max}$ but higher than $d_{i,4}$,

$$d_{i,4} \leq d_i \leq d_{i,\max}, \tag{12}$$

where the constraints of d_i are selected between the actual value of the criterion and $d_{i,\max}$.

Case 3: When the goal value is less than $d_{i,\max}$ but the actual value is less than $d_{i,4}$,

$$d_{i,\min} \leq d_i \leq d_{i,\max}, \tag{13}$$

where the constraints of d_i are selected from the next level of the criterion goal value. For example, if the actual value of d_i achieves goal 1, then goal 2 should be the aspiration level for d_i.

In the next section, we use three cities to illustrate the MALGP process.

4.4 Illustrative example

In this section, to explain the process and outcome of the proposed model, this research used the PTCM-AHP model-based MALGP model on the three case studies. The details of the case study areas can be found in Section 4.3. The case studies were used to explain how the multi-aspiration-level GP model is able to optimise PT network performance in three cities in Australia, considering basic PT infrastructure, PT services, economic benefits, and sustainable development levels. The goal value of the case study areas is to choose the selection process of the aspiration level for optimisation based on the actual value.

The formulated constraints were different for each of the three case study areas. As detailed in subsection 4.3.1, the constraints of the objective function were established according to the selection of the criteria-level grades (for more information, refer to Table B1). Subsequently, the objective function for the case study area can be formulated.

This study assumed the conditions for the three case studies in which the DMs optimise the performance based on the criteria aspiration level case selection. The details of the actual values and goals are listed in Tables 9–11. Referring to the goals for case study areas, the formulations are as follows:

Table 9

Bayswater's actual and goal values for decision variables

Variable	Criteria	Actual Value	Goal Value
X_1	PT network ratio	17.64	50–55
X_2	PT coverage ratio	46.82	50–55
X_3	Green PT vehicle rate	100	100
X_4	PT energy intensity	25.45	0–25.45
X_5	PT priority lane setting ratio	0	10–15
X_6	PT land area per capita	20.47	20.47
X_7	PT on-time rate	91.03	95–100
X_8	Passenger freight rate	1.75	1.75
X_9	Coverage rate	98.8	100

X_{10}	Peak hours intersection blocking rate	21	8–11
X_{11}	Harbour-type bus stop setting ratio	19.04	25–35
X_{12}	Bus ownership rate	7	18–19
X_{13}	PT utilisation rate	0.8	0.8–2
X_{14}	PT driving accident rate	2.38	1.5–2
X_{15}	Intact car rate	100	100

Using Table 9, we construct the objective function and constraints for Bayswater as follows.

The objective function for Bayswater:

Min $14.3p_1 + 14.3q_1 + 14.3p_2 + 14.3q_2 + 9p_3 + 9q_3 + 7.9p_4 + 7.9q_4 + 6.5p_5 + 6.5q_5 + 5.5p_6 + 5.5q_6 + 5.05p_7 + 4.6p_8 + 4.6q_8 + 4.5p_9 + 4.5q_9 + 4.3p_{10} + 4.3q_{10} + 2.25p_{11} + 2.25q_{11}$

Constraints for Bayswater:

Constraint 1: Improve PT network ratio

$$X_1 + p_1 = 55$$

$$X_1 - q_1 = 50$$

Constraint 2: Increase PT coverage ratio

$$X_2 + p_2 = 55$$

$$X_2 - q_2 = 50$$

Constraint 3: Minimise PT energy intensity and increase green PT vehicle rate

$$X_3 + X_4 + p_3 = 125.45$$

$$X_3 + X_4 - q_3 = 100$$

Constraint 4: Maximise PT priority lane setting ratio

$$X_5 + p_5 = 15$$

$$X_5 - q_5 = 10$$

Constraint 5: Improve PT on-time rate

$$X_7 + p_5 = 100$$

$$X_7 - q_5 = 95$$

Constraint 6: Improve PT utilisation rate and increase PT land area per capita

$$X_6 + X_{13} + p_6 = 22.47$$

$$X_6 + X_{13} - q_6 = 21.27$$

Constraint 7: Optimise financial resources by decreasing passenger freight rate and increasing coverage rate

$$X_8 + X_9 + p_7 = 101.75$$

Constraint 8: Reduce peak hours intersection blocking rate

$$X_{10} + p_8 = 11$$

$$X_{10} - q_8 = 8$$

Constraint 9: Increase harbour-type bus stop setting ratio

$$X_{11} + p_9 = 35$$

$$X_{11} - q_9 = 25$$

Constraint 10: Maximise bus ownership rate

$$X_{12} + p_{10} = 19$$

$$X_{12} - q_{10} = 18$$

Constraint 11: Maximise intact car rate and reducing PT driving accident rate

$$X_{14} + X_{15} + p_{11} = 102$$

$$X_{14} + X_{15} - q_{11} = 101.5$$

Table 10

Cockburn's actual and goal values for decision variables

Variable	Criteria	Actual Value	Goal Value
X_1	PT network ratio	19.21	50–55
X_2	PT coverage ratio	50.42	55–100
X_3	Green PT vehicle rate	100	100
X_4	PT energy intensity	25.45	0–25.45
X_5	PT priority lane setting ratio	0.31	10–15
X_6	PT land area per capita	26.23	26.23
X_7	PT on-time rate	91.03	95–100
X_8	Passenger freight rate	1.75	1.75
X_9	Coverage rate	98.8	100
X_{10}	Peak hours intersection blocking rate	8.1	5–8
X_{11}	Harbour-type bus stop setting ratio	9.2	15–25
X_{12}	Bus ownership rate	7	18–19
X_{13}	PT utilisation rate	0.8	0.8–2
X_{14}	PT driving accident rate	2.38	1.5–2

X_{15}	Intact car rate	100	100

Using Table 10, we construct objective function and constraints for Cockburn as below.

The objective function for Cockburn is the same as that of Bayswater.

Constraints for Cockburn:

Constraints 1, 3, 4, 5, 7, 10, and 11 are the same as those for Bayswater.

Constraint 2: Increase PT coverage ratio

$$X_2 + p_2 = 100$$

$$X_2 - q_2 = 55$$

Constraint 6: Improve PT utilisation rate and increase PT land area per capita

$$X_6 + X_{13} + p_6 = 28.23$$

$$X_6 + X_{13} - q_6 = 27.03$$

Constraint 8: Reduce peak hours intersection blocking rate

$$X_{10} + p_8 = 8$$

$$X_{10} - q_8 = 5$$

Constraint 9: Increase harbour-type bus stop setting ratio

$$X_{11} + p_9 = 25$$

$$X_{11} - q_9 = 15$$

Table 11

Stonnington's actual and goal values for decision variables

Variable	Criteria	Actual Value	Goal Value
X_1	PT network ratio	60.78	60.78–70
X_2	PT coverage ratio	83.72	83.72
X_3	Green PT vehicle rate	100	100
X_4	PT energy intensity	83.59	30–80
X_5	PT priority lane setting ratio	25.38	25.38–30
X_6	PT land area per capita	9.28	11–14
X_7	PT on-time rate	84.68	85–95
X_8	Passenger freight rate	2.33	2.33
X_9	Coverage rate	101.5	150–200
X_{10}	Peak hours intersection blocking rate	1.5	0–1.5
X_{11}	Harbour-type bus stop setting ratio	26.71	35–100
X_{12}	Bus ownership rate	7.36	18–19
X_{13}	PT utilisation rate	0.78	0.78–2
X_{14}	PT driving accident rate	4.54	2.5–3
X_{15}	Intact car rate	100	100

Using Table 11, we construct objective function and constraints for Stonnington as follows.

The objective function for Stonnington:

Min $14.3p_1 + 14.3q_1 + 9p_2 + 9q_2 + 7.9p_3 + 7.9q_3 + 7.8p_4 + 7.8q_4 + 6.5p_5 + 6.5q_5 + 5.05p_6 + 5.05q_6 + 4.6p_7 + 4.6q_7 + 4.5p_8 + 4.5q_8 + 4.3p_9 + 4.3q_9 + 3.2p_{10} + 3.2q_{10} + 2.25p_{11} + 2.25q_{11}$

Constraints for Stonnington:

Constraint 1: Maximise accessibility by improving PT network and coverage ratios

$$X_1 + X_2 + p_1 = 153.72$$

$$X_1 + X_2 - q_1 = 144.5$$

Constraint 2: Minimise PT energy intensity and increase green PT vehicle rate

$$X_3 + X_4 + p_2 = 180$$

$$X_3 + X_4 - q_2 = 130$$

Constraint 3: Maximise PT priority lane setting ratio

$$X_5 + p_3 = 30$$

$$X_5 - q_3 = 25.38$$

Constraint 4: Increasing PT land area per capita

$$X_6 + p_4 = 14$$

$$X_6 - q_4 = 11$$

Constraint 5: Improve PT on-time rate

$$X_7 + p_5 = 95$$

$$X_7 - q_5 = 85$$

Constraint 6: Optimise financial resources by decreasing passenger freight rate and increasing coverage rate

$$X_8 + X_9 + p_6 = 202.33$$

$$X_8 + X_9 - q_6 = 152.33$$

Constraint 7: Reduce peak hours intersection blocking rate

$$X_{10} + p_7 = 1.5$$

$$X_{10} - q_7 = 0$$

Constraint 8: Increase harbour-type bus stop setting ratio

$$X_{11} + p_8 = 100$$

$$X_{11} - q_8 = 35$$

Constraint 9: Maximise bus ownership rate

$$X_{12} + p_9 = 19$$

$$X_{12} - q_9 = 18$$

Constraint 10: Improve PT utilisation rate

$$X_{13} + p_{10} = 2$$

$$X_{13} - q_{10} = 0.78$$

Constraint 11: Maximise intact car rate and reducing PT driving accident rate

$$X_{14} + X_{15} + p_{11} = 103$$

$$X_{14} + X_{15} - q_{11} = 102.5$$

Based on the formulations and constraints listed above for the case study areas, the results of the MALGP process are discussed in the next section.

4.5 Results and discussions

The optimisation results were obtained using MATLAB to obtain the optimal solution for the case study areas, which are shown in Tables D1–D3. These scenarios indicate that the criteria performances significantly improved, including the PT network ratio, PT coverage ratio, PT energy intensity, PT priority lane setting ratio, PT on-time rate having a higher priority than coverage rate, peak hours intersection blocking rate, harbour-type bus stop setting ratio, bus ownership rate, and PT driving accident rate.

The optimal solutions for Bayswater are listed in Table D1. At the basic PT infrastructure level, an increase of 183.34, 6.79, and 31.3% in the PT network, PT coverage, and harbour-type bus stop setting ratios, respectively, would improve the PT network performance for Bayswater. Reducing the peak hours intersection blocking rate by 61.9%, decreasing the PT driving accident rate by 36.97%, and improving the PT on-time rate by 4.36% would improve the PT service level in Bayswater. Improving the coverage rate by 1.21% and bus ownership rate by 157.14% would optimise Bayswater's economic benefit level.

Table D2 shows that increasing the PT network, PT coverage, and harbour-type bus stop setting ratios by 160.28, 9.08, and 63.04%, respectively, would improve Cockburn's basic PT infrastructure level. In terms of Cockburn's PT service level, increasing the PT on-time rate to 95%, decreasing the peak hours intersection blocking rate by 1.23%, and reducing the PT driving accident rate to 1.5 times per million kilometres would help to achieve the optimal PT service level scenario. Increasing the coverage rate to 100% and bus ownership rate to 18 cars per 10,000 people would improve Cockburn's economic benefit level. Both Bayswater and Cockburn's optimal solutions suggest decreasing the PT energy intensity to 0 g standard coal per person-kilometre and improving the PT priority lane setting ratio to 10%.

The optimal solutions for Stonnington are listed in Table D3. In terms of the PT infrastructure level, increasing the harbour-type bus stop setting ratio by 31.03% would improve PT network performance. An increase in the PT on-time rate of 0.37% and a reduction of 44.93% in the PT driving accident rate would improve Stonnington's PT service level. The optimal solution was achieved with an intersection blocking rate of 0% during peak hours. Increasing the coverage rate by 47.78% and bus ownership rate by 144.56% would improve the economic benefit level. A reduction of 64.11% in PT energy intensity and an increase of 18.53% in PT land area per capita would improve the optimal value for the sustainable development level.

Tables D1-3 also highlight that PT energy intensity and PT priority lane setting ratio are the most sensitive criteria in Bayswater and Cockburn optimisation solution. In the case of Stonnington, the criterion showing the highest sensitivity is the peak hours intersection blocking rate.

Overall, all case study areas show that the optimal solutions have a significant increase in the harbour-type bus stop setting ratio, and the bus ownership rate. The optimisation model results also recommend the DMs to propose a management plan to reduce the PT driving accident rate. Additionally, plans and strategies are also needed to optimise the most sensitive criteria in the case study areas.

4.6 Conclusion

In this chapter, we established and formulated a multi-aspiration-level GP model for PT network performance optimisation. The proposed model is a further development of the GP and MCGP models. The criteria for optimising a PT network's performance often contains multiple aspiration levels. Hence, this model considered optimising the PT network performance with criteria with multiple aspiration levels. The multi-aspiration-level GP approach involves three steps. First, the DM's criteria preferences are implemented to express each criterion weight, which are gained from the PTCM-AHP model. Subsequently, the DMs grade the criteria performance based on the level grade for all sub-criteria and find each criterion aspiration level for performance optimisation. Finally, the multi-aspiration-level GP method is used to optimise the city's PT network performance and provide an optimal solution.

Compared to the GP and MCGP approaches, this model combined the multi-aspiration goal-level selection process in three different situations to create a PTCM-AHP model-based multi-aspiration-level GP approach. The three examples illustrated the PT network performance optimisation process. The optimal solutions obtained in all case study areas indicate a substantial rise in the ratio of harbour-type bus stop settings and bus ownership rates, while the optimisation model also suggests the need for a management plan to address the issue of PT driving accidents.

Chapter 5: Uncertainty Analysis of PT Networks Performance Optimisation Using Monte Carlo Simulation

5.1 General overview

In this chapter, we use MCS to analyse the probability of the optimal solution to manage uncertainty. Probabilistic analysis is a commonly used technique and addresses evaluation-based issues in project management by performing MCS. Based on different application areas, MCS is also used in mitigating uncertainty related to the model inputs and outputs. Despite its effectiveness in addressing project management concerns, there has been little research that has utilised MCS to tackle the problem of optimising PT network performance. The current research only considers a single specific aspect of PT performance. The probability of the scenario analysis is thus required in the PT network performance optimisation problems.

In some cases, DMs have difficulty to deliver an optimal solution due to uncertainty that arises during the optimisation process. Previous research has lacked an examination of the uncertainty associated with criteria uncertainty. To fill the gap, the models optimise four levels of criteria with uncertainty in order to achieve the DMs' PT network optimisation goals. This chapter's main task is to determine the level of criteria uncertainty, and a sensitivity analysis is performed to guide the optimisation process in three case study areas. MCS results can be used to help DMs make decisions about PT network optimisation and to precisely indicate the probability of uncertainty rate when delivering criteria outcomes.

The remainder of this chapter is structured as follows: Section 5.2 describes the MCS process. The input data for three case study areas are presented in

Section 5.3. Section 5.4 discusses the findings of the three case study areas as well as the conclusion. Finally, Section 5.5 presents the chapter's conclusion.

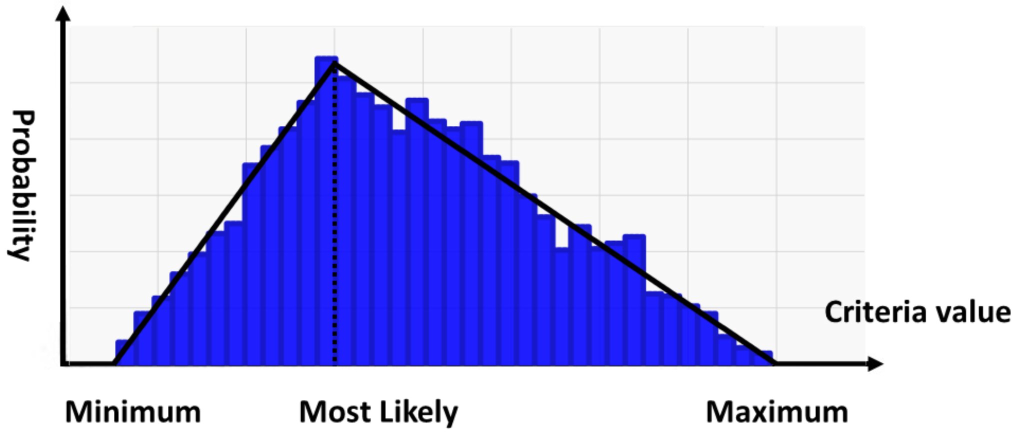
5.2 Monte Carlo simulation process

In this chapter, we use MCS to model the probability of optimal scenario delivery. The MCS is used to determine the likelihood of finding the best solution. The proposed method is used to calculate the possibility of an optimal solution. MCS performs calculations, allowing for multiple simulations of a project. The process is used to quantitatively analyse project risk and identify the probability of the best solution by randomly selecting criteria values (Zhou et al., 2020; Landau & Binder, 2021). MCS analyses risk and uncertainty using probability distribution. The details of the MCS process are shown below.

5.2.1 Criteria probability distribution identification

Figure 6

Triangular distribution



Before we begin simulating the optimisation results, we must first determine the probability of the criteria. The types of criteria probability distributions must be chosen during the identification process. According to Figure 6, the criteria sampling process uses a triangular probability distribution because the minimum, most likely, and maximum values can be estimated. The MALGP process outputs are used as the most likely value of criteria in the MCS process. Table 12 shows the criteria ratings for the uncertainty level, which can be used to calculate the minimum and maximum values of the criteria. The level of uncertainty is divided into five categories: very high, high, medium, low, and very low.

Table 12

Uncertainty level (Oracle, n.d.)

Uncertainty level	Min	Most likely	Max
Very high	50%	100%	200%
High	75%	100%	150%
Medium	85%	100%	125%
Low	90%	100%	115%
Very low	95%	100%	110%

Thus, the criteria risk and uncertainty level need to be identified. To determine the input of criteria, the uncertainty and risk level of the criterion are selected based on the risk rating recommendation and existing risk ratings for the criteria. The current PT risk assessment shows that the risk level of PT driving accident rates is high (Weldon, 2021). Based on existing risk ratings, the uncertainty level of the intersection blocking rate during peak hours, coverage rate, PT land area per capita, and PT utilisation rate are medium (CCOHS, 2022). Other criteria uncertainty levels are very low since the optimisation process can be controlled under the government implementation plan. After the criteria uncertainty level have been identified, the results are utilised in the sampling process. During the criteria sampling, the sampling model needs to be selected. The details of the sampling model selection are shown in following subsection.

5.2.2 Sampling model selection

MCS uses a random sampling process. Sampling is the process of selecting criteria values from the criteria input probability distribution in a model. Monte Carlo (MC) sampling and Latin Hypercube sampling (LHS) are the two major sampling model used in MCS. LHS is a method that partitions the probability distribution by segmenting the cumulative curve into uniform intervals and randomly selecting one value from each interval. Consequently, LHS can effectively represent the distribution with a low number of samples (Manzo et al., 2015).

MC sampling can recreate the full input distribution by making random selections across the entire probability distribution with large iterations (Montemanni et al., 2018). With high iteration, the model results are closer to the actual situation (Montemanni et al., 2018). Hence, this study uses MCS performed by means of MC sampling. After the sampling model is selected, the optimisation results of the PT network performance in the case study areas can be simulated to model the uncertainty. The details of the case study areas' model input for the criteria are described in Section 5.3.

5.3 Case study

As previously stated, the analysis was implemented in three study areas in Australia: the City of Bayswater, the City of Cockburn, and the City of Stonnington. The details of case study areas can be found in Section 3.4.

The MCS is conducted to analyse the likelihood of achieving PT network performance optimisation goals. The input data for the three case study areas are derived from AHP and MALGP outputs. As demonstrated in Section 4.3, the PTCM-AHP model calculates the criteria weights that are later utilised in MALGP for the optimisation process. The criteria weights are presented in

Table C6. The mean value of the criteria for MCS are extracted from the MALGP criteria optimising results, and the details can be found in Table D1-3.

The sources of uncertainty for the optimisation process of PT network performance have not been fully investigated. Thus, the degree of uncertainty for each criterion is defined based on the existing risk rating, which is discussed in Section 5.2.1. This analysis focuses on the uncertainty of the implementation criteria of the optimisation results. The risk level of criteria is defined based on an existing risk assessment of the uncertainty level.

According to the risk rating description, the uncertainty level is medium for the intersection blocking rate during peak hours, coverage rate, PT land area per capita, and PT utilisation rate. Based on existing PT risk assessments, the uncertainty level of the PT driving accident rate is high. The criteria mean values are each criterion's optimal value. The remaining criteria have very low uncertainty levels. Thus, the minimum and maximum values for the criteria can be calculated.

The type of probability distribution for all criteria sampling is assumed to be triangularly distributed since the minimum, most likely, and maximum values can be estimated. The list of the model inputs in MCS for the three case study areas is shown in Table E1-3. The sampling result is more likely to display the distribution accurately with a high number of draws. Thus, the criteria use 5,000 draws by applying MC sampling.

Sensitivity analyses on three case study areas are implemented. Each PT criteria performance is calculated on 5,000 model runs. To explore the criteria model outputs uncertainty, criteria uncertainty is investigated via criteria coefficient value, criteria optimising value impact on model output, and the criteria probability for reaching the DMs' optimisation goals. The details of the model's results and sensitivity analyses are shown in the next section.

5.4 Results and discussions

In this section, sensitivity analyses were implemented in the three case study areas. The most likely values for the criteria during the optimisation process were also determined. This study assumed that the DMs must control each criterion's performance and the criteria probability of being within a range of -5%/+10%. The model outcomes were analysed to identify the probability and confidence level for achieving the goals. Finally, the results reveal the critical sensitive criteria that governments must take into account to manage uncertainty for future optimisation plans and strategies of the case study areas. Section 5.4.1 identifies the most sensitive criteria and the criteria's most likely value during the optimisation process. Section 5.4.2 shows the most important criteria of the MCS model output for the study areas. Section 5.4.3 determines the probability of sensitive criteria to achieve the government requirement.

5.4.1 Sensitivity analysis

We first examine the likelihood of achieving the optimal solution and identify the most sensitive criterion. According to Table F1-3, all cities' outputs are influenced by the on-time rate. Based on the output of the probability distribution for the case study areas, three cities have a 50th percentile chance of achieving the performance optimisation goals for each criterion. Except for the on-time rate, other criteria have at least a 60% likelihood of achieving the optimising solution.

Figure 7

Bayswater PT network performance criteria coefficient value

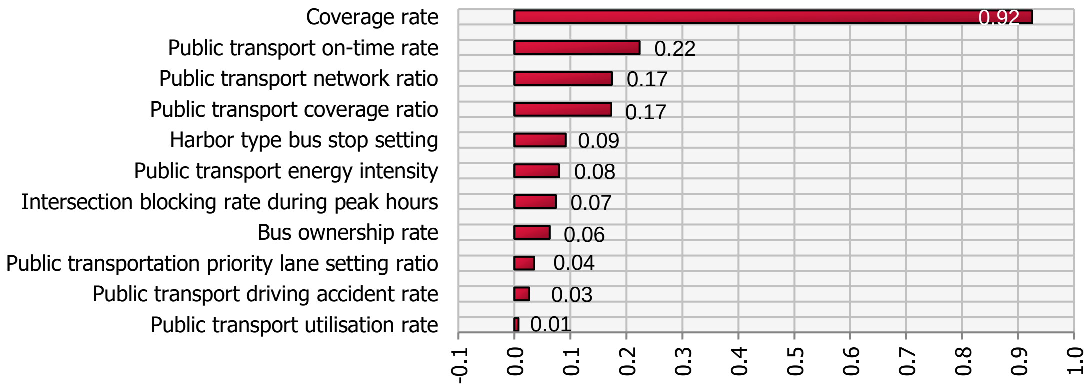


Figure 8

Cockburn PT network performance criteria coefficient value

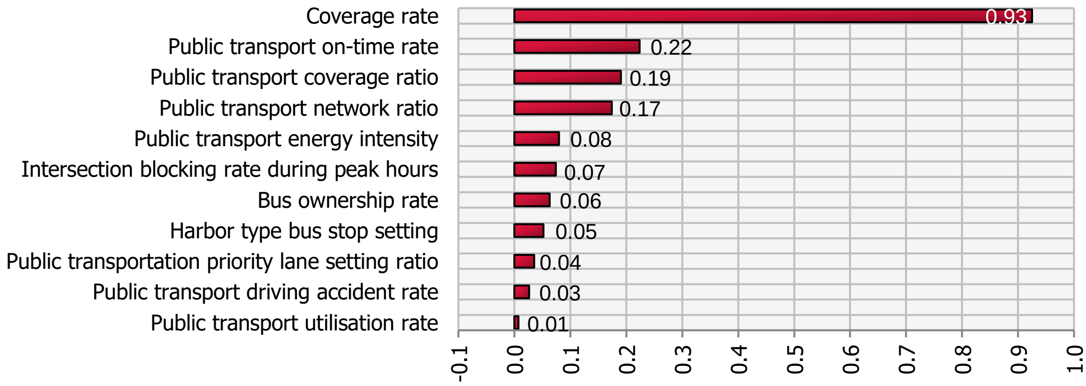
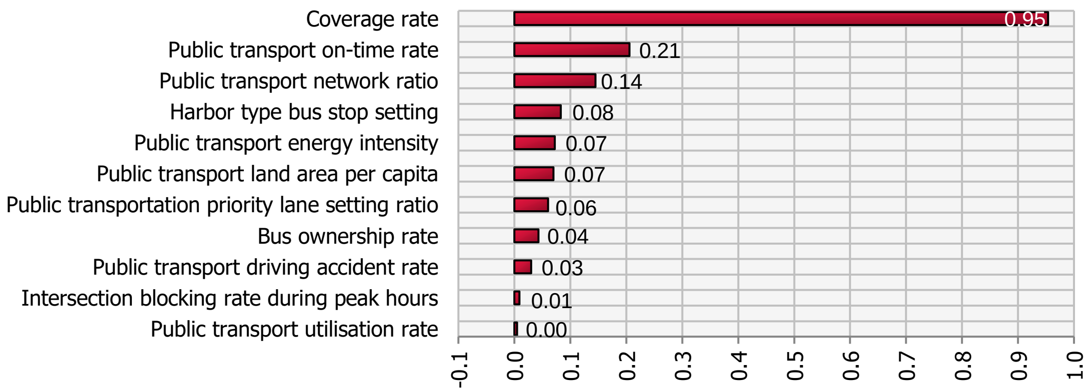


Figure 9

Stonnington PT performance criteria coefficient value



Figures 7-9 show the coefficient values of the criteria for the three case study areas. The y-axis displays the names of the criteria from top to bottom in order of sensitive influence to the criteria. The x-axis indicates the coefficient value of the associated criteria.

According to the results, the most sensitive criterion for all cities is coverage rate. This criterion coefficient value is over 0.9 for the three cities. According to Tables G1 and G2, Bayswater and Cockburn's most likely value is 103.33%. The two cities' minimum and maximum values are 85.08% and 124.5%, respectively. Table G3 suggests that the most likely value for Stonnington is 155%. The Stonnington minimum and maximum values are 127.76% and 186.52%, respectively. To control and minimise the uncertainty of this most sensitive criterion optimisation process, the DMs should consider improving the PT service commercial revenue and reducing the operating expenses for all cities optimisation scenario.

Figures 7-9 effectively offer an overall interpretation of the model based on each criterion. However, the relative importance of the criteria on model output has not been discovered. For this reason, Figures 10-12 show the criteria optimising inputs' impact on MCS output in the next subsection.

5.4.2 Features importance

Next, we investigate the effect of the criteria optimal value on model output. Figures 10-12 show the impact of the three cities' criteria for optimising the value on the model results. The y-axis demonstrates the name of the criteria based on importance magnitude from top to bottom. The x-axis indicates the criteria impact on the model output. The line colour shows the impact of the criteria on the model output, which supports the DMs in analysing the criteria impact on the city optimisation solution.

Figure 10

Bayswater criteria optimising value impact on model output

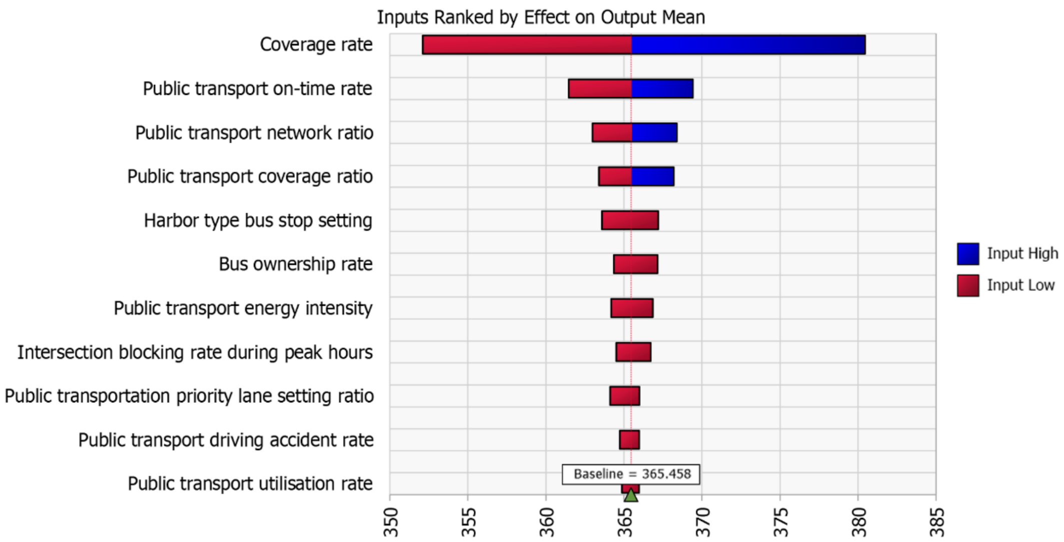


Figure 11

Cockburn criteria optimising value impact on model output

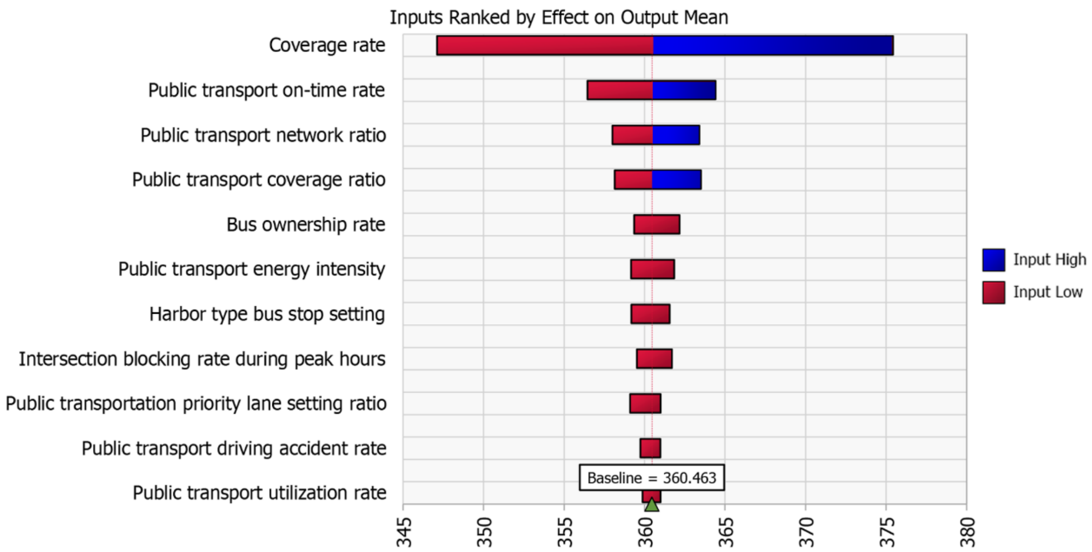
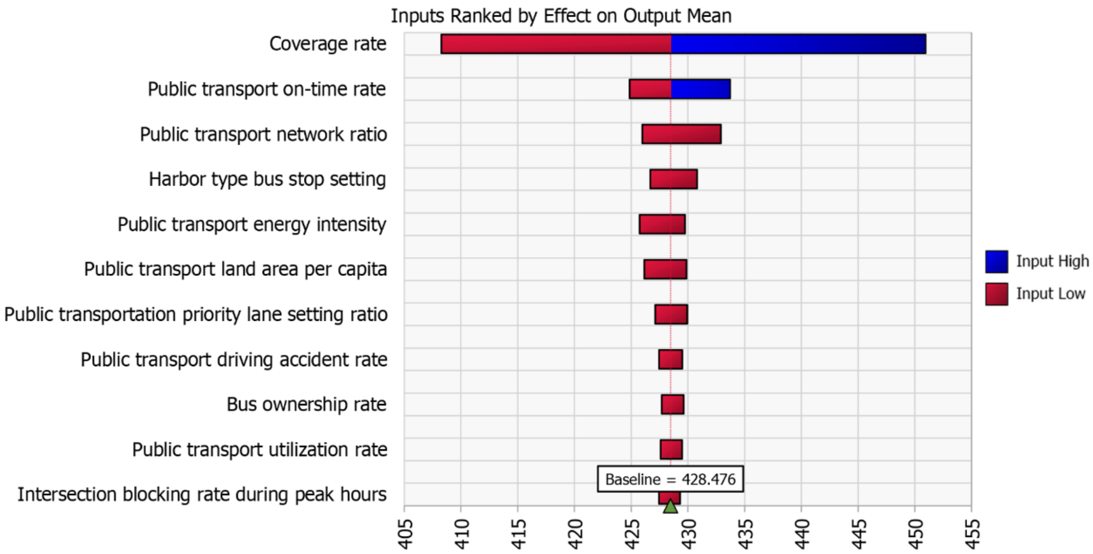


Figure 12

Stonnington criteria optimising value impact on model output



Figures 10-12 show that the coverage rate has the highest impact on the model output of the three case study areas. Furthermore, the higher the coverage rate value is, the greater the influence on the model output. However, this criterion suggests a baseline result when the coverage rate input is low. For Bayswater, other criteria, such as the PT on-time rate, the PT network ratio, and the PT coverage ratio, also have a high impact on the output (as shown in Figure 10).

Similarly, Figure 11 demonstrates that these three criteria have a high influence on the model output for Cockburn. The conclusion of coverage rate also applies to these three criteria.

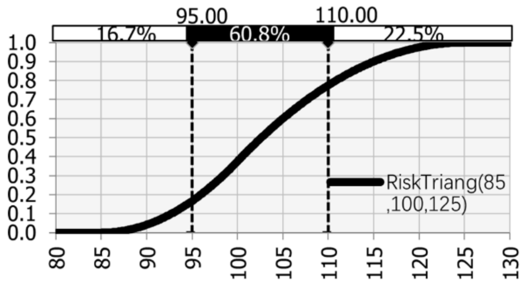
Finally, Figure 12 suggests that the higher the PT on-time rate requirement is, the higher the impact on the model optimisation result for Stonnington. Except for the criteria mentioned above, other criteria inputs have a low influence on the model optimisation output for the three cities. The results shown in the figure also validate the criteria weighting results of the PTCM-AHP model. The PT network ratio and PT coverage ratio, PT on-time rate, and coverage rate are the most important variables for the basic PT infrastructure level, PT service level, and economic benefit level, respectively (see Table C6).

Figures 10-12 provide a way to analyse the effect of each criterion on the model outputs. However, DMs often have government requirements to control the optimisation process. It is necessary to identify the probability of criteria that meet the government requirements.

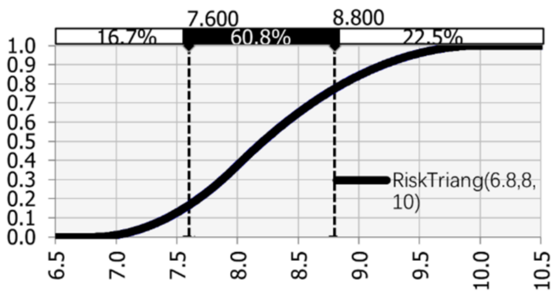
5.4.3 Test accuracy

Figure 13

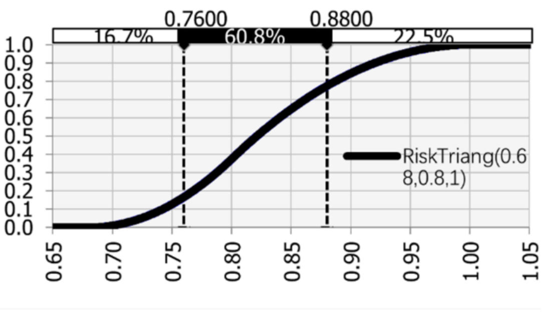
Bayswater and Cockburn criterion probability distribution for reaching DMs' optimising goal



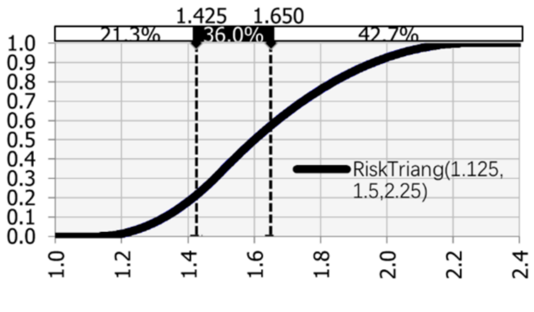
(a) Coverage rate probability distribution



(b) Intersection blocking rate during peak hours probability distribution



(c) PT utilisation rate probability distribution



(d) PT driving accident rate probability distribution

Finally, we determine the criteria probability distribution in the PT network performance optimisation process. The following section identifies the probability of the criterion that meets the DMs' requirements. DMs require the criteria probability of being within a range of -5%/+10%. Figures 13-14 show the probability of the criteria reaching the requirement for the three cities. The y-axis displays the probability of achieving the criterion optimising value. The x-axis indicates the input value of the associated criteria.

Since the uncertainty level of most criteria is very low, most criteria have a 100% probability of meeting the government requirement. For Bayswater and Cockburn, there are four criteria uncertainty levels that are higher than very low, including coverage rate, intersection blocking rate during peak hours, PT utilisation rate, and PT driving accident rate. The details of the criteria probability distribution for Bayswater and Cockburn are shown in Figure 13. Five criteria for Stonnington have an uncertainty level higher than the 'very low' level. Figure 14 shows the probability distribution of these five criteria, including PT land area per capita, coverage rate, intersection blocking rate during peak hours, PT utilisation rate, and PT driving accident rate.

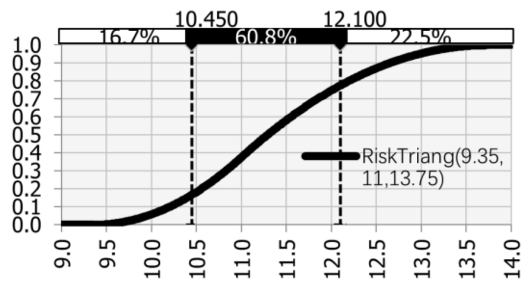
For Bayswater and Cockburn, Figure 13(a) shows that the coverage rate of 60.8% reaches the government goal. According to Table C6, this criterion has the highest weight in the economic benefit level. Hence, when cities implement the optimisation scenario for economic benefit level, DMs are suggested to plan ahead, applying a management plan during the optimisation process to mitigate the uncertainty.

Figures 13(b) and 13(c) show that both cities have a probability of 60.8% of achieving the requirement for intersection blocking rate during peak hours and PT utilisation rate. Table C6 shows that these two criteria have low priority. Hence, DMs only need to monitor and control to deliver optimisation scenarios.

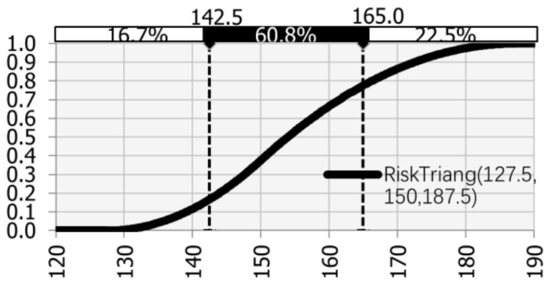
Figure 13(d) shows that the PT driving accident rate has a low probability, that is, 36%, of achieving the government requirement. According to Table C6, although the priority of this criterion is low, the government still needs a management plan for the optimisation scenario. Since this criterion has a high uncertainty level, the delivery of the optimising solution will be influenced.

Figure 14

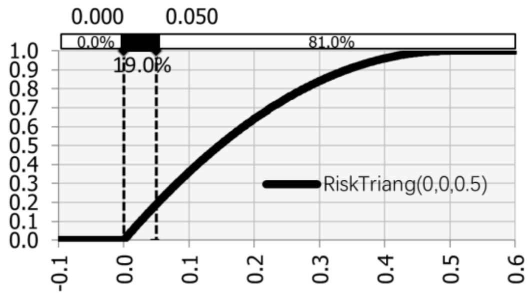
Stonnington criterion probability distribution for reaching the DMs' optimising goal



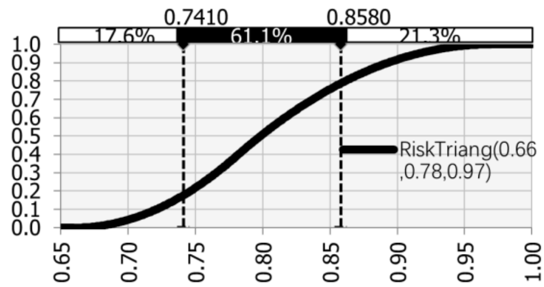
(a) PT land area per capita probability distribution



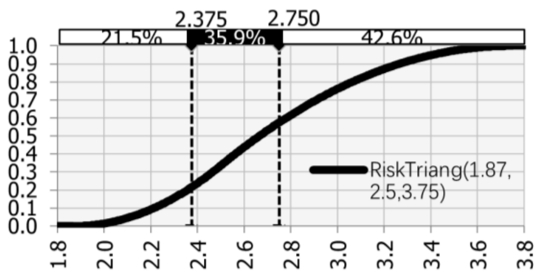
(b) Coverage rate probability distribution



(c) Intersection blocking rate during peak hours probability distribution



(d) PT utilisation rate probability distribution



(e) PT driving accident rate probability distribution

For Stonnington, Figure 14(a) and Figure 14(b) show that both criteria have a probability of 60.8% of fulfilling the government's requirements. The criterion of PT land area per capita is not the highest importance in sustainable development level, but the weight is higher than the coverage rate. The coverage rate is the most important criterion in the economic benefit level for which the government needs to apply management plans to optimise PT network performance. Hence, DMs are also suggested to implement management action to achieve an optimising solution.

According to Figure 14(c), although Stonnington only has a probability of 19% of achieving the DMs' requirement for the criterion of the intersection blocking rate during peak hours, the evaluation results show that the actual value achieved the highest level, which is level A. Since the criterion performance is difficult to further improve and is achieving optimising results, the DMs only need to focus on maintaining the current performance and keep control of and optimise the criterion performance.

Figure 14(d) shows that there is a probability of 61.1% of achieving the government requirement for the PT utilisation rate. Since the weight of this criterion is low, DMs are suggested to monitor and control during the optimisation process.

According to Figure 14(e), the probability of Stonnington's PT driving accident rate is similar to the other two case study areas, which is 35.9%. The criterion uncertainty level is high. Thus, in Stonnington it is also suggested to implement actions to mitigate the risks during the optimisation process.

Figures 13-14 are useful for analysing the probability distribution of each criterion to fulfill the governments' requirements. It helps governments allocate resources for delivering case study area optimisation solutions.

5.5 Conclusion

In this chapter, we investigated the probability distribution and sampling type of the model criteria. To mitigate the risk involved in the process of optimising PT network performance, we use MCS to analyse the PT network performance optimised solutions under criteria uncertainty. Then, we implement MCS to analyse the sensitive criteria, discover the optimal solution under criteria uncertainty, and identify the likelihood of criteria optimisation based on DMs' requirements for three case study areas.

Finally, our research results indicate that the coverage rate is the most sensitive criterion for these three cities. Furthermore, a higher coverage rate and PT on-time rate requirement will lead to a higher impact on the model optimising result for all cities. Last, although the PT driving accident rate has a low priority and probability of achieving the DMs' requirements, this criterion has a high level of risk. Governments still need to implement management plans to achieve optimised solutions.

Chapter 6: A Unified Optimised Framework for PT Network Performance Under Uncertainty

6.1 General overview

In this chapter, we combine the PTCM-AHP, MALGP, and MCS models into a three-stage framework to optimise PT network performance under uncertain conditions. PT networks face significant challenges in achieving optimal outcomes due to the presence of risk and uncertainty. Despite the importance of optimising PT network performance, there has been limited research that applies risk management tools to tackle this issue. In response, this research presents a three-stage framework to optimise PT network performance under uncertain conditions. First, we use the established PT network criteria matrix. Second, we propose a MALGP approach to optimise PT network performance based on the weight results. To manage uncertainty, we use MCS to analyse the probability of the optimal solution. In the previous chapters, we have applied the three-stage framework to three case study areas in Australia to validate our approach. The results of this research offer significant insights into identifying the likelihood of criteria optimisation scenarios, thereby assisting DMs in allocating resources for optimising the delivery of PT network performance solutions in according with government requirements.

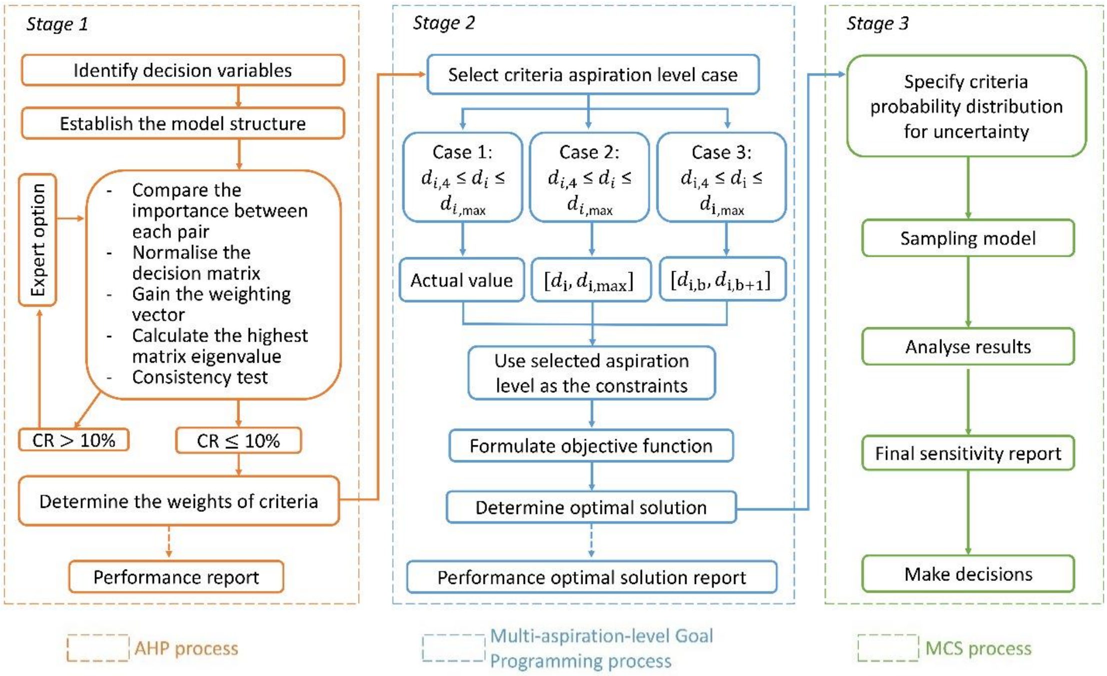
The rest of this chapter is organised as follows: Section 6.2 introduces the model process framework of proposed three-stage optimising PT network performance under uncertain process. Then we demonstrate AHP process in Section 6.3. The MALGP process are described in Section 6.4. Section 6.5 identifies the major tasks of MCS, and Section 6.6 conclude this chapter.

6.2 Model process framework

In this section, we develop a three-stage framework for optimising PT network performance under uncertain conditions based on the model introduced in the previous chapters. Figure 15 depicts a three-stage approach for optimising the uncertain PT network performance, which includes an AHP process, a MALGP process, and an MCS process. The following sections go over the specifics of each stage.

Figure 15

The proposed three-stage optimising PT network performance under uncertainty



6.3 AHP process

In the AHP process (stage 1), the PTCM-AHP model of Chapter 3 is applied. In this process, there are three major tasks to determine the weight of criteria. Furthermore, a city's PT network performance report is created, which includes scores for PT performance across all criteria and a summed performance through all criteria. The following subsections go over the specifics of the AHP process.

6.3.1 Decision variable identification and establishment of the PTCM-AHP model structure

The decision variables of the AHP model have been described in Section 3.3. Additional details of the PT network performance criteria can be found in Table A1. The criteria are selected from existing PT evaluation assessments and indices (Ministry of Construction, 1995; Ministry of Transport, 2012; Ministry of Transport, 2014; Ministry of Transport, 2016; Ministry of Housing and Urban–Rural Development, 2018). These criteria are used to determine the PTCM-AHP model structure.

The PTCM-AHP model is based on four levels: the basic PT infrastructure level, the PT service level, the economic benefit level, and the sustainable development level. As mentioned in Section 3.3, Figure 2 presents the hierarchy of the PT network performance criteria of the PTCM-AHP model. The model includes four levels of criteria and 15 sub-criteria.

- The PT infrastructure level includes the harbour-type bus stop setting ratio, PT coverage ratio, PT priority lane setting ratio, and PT network ratio.
- The PT service level contains four sub-criteria: passenger freight rate, PT on-time ratio, PT driving accident rate, and peak hours intersection blocking rate.
- The economic benefit level contains the intact car rate, coverage ratio, and bus ownership rate.
- The level of sustainable development considers the PT utilisation rate, PT energy intensity, PT land area per capita, and green PT vehicle rate.

Once the PTCM-AHP model structure is established, the process of determining criteria weights is undertaken to test and calculate the results of the weightings. The details of weighting process are shown as follow.

6.3.2 Criteria weight determination

In Section 3.2, we illustrate the process and formulation of the AHP (see Eqs. (1)-(5)). The major steps for determining the weights of criteria are described below.

1) Construct the problem in a hierarchical structure and comprise the criteria and sub-criteria.

2) Create the decision matrix and pairwise comparison between criteria and sub-criteria, which is between 1 and 9 given by experts.

3) Normalise the decision matrix.

4) Calculate the arithmetic mean of normalised decision matrix rows to obtain the prioritisation vector.

5) Calculate and find the highest matrix eigenvalue.

6) Calculate the criteria weight and verify the CR of the results.

7) Repeat steps 2-6 until $CR \leq 10\%$. When $CR \leq 10\%$, the model result is deemed internally coherent.

Hence, we can eventually identify the weight of the PTCM-AHP model criteria and sub-criteria, which are used as coefficient values in the MALGP process. The case study area performance report is also created to identify the city PT network performance score and show each criterion performance score, which is calculated based on the case study areas' criteria actual value. The results of the city performance report will be used to determine the criteria aspiration level used in the calculation of criteria goal values in the MALGP process.

6.4 Multi-aspiration-level goal programming process

The MALGP model is created and used to optimise the PT network performance in the MALGP process (stage 2). The implementation of MALGP assists DMs in selecting different aspiration levels to solve the PT network performance optimisation problem. The model considers the criteria aspiration level selection to assist DMs in performance optimisation. The second stage consists of three tasks that must be completed in order to calculate the best solution for the city. The MALGP process is described in detail below.

6.4.1 Criteria aspiration level case selection

As mentioned before, the MALGP model includes the criterion case selection process. The aspiration level criterion is selected based on the actual value of the criteria. The details of the criteria level grades can be found in Table B1. Each criteria divide the performance grade into 5 levels. According to Figure 15, the process contains the following three cases.

Case 1: The actual value is the aspiration value for the ith criterion when the ith criterion actual value is greater than d_i,max.

Case 2: The aspiration value of criterion ith is less than d_i,max but greater than the actual value when the actual value for criterion ith is less than d_i,max but greater than $d_{i,4}$.

Case 3: The aspiration value of criterion ith is the $(i+1)$th aspiration level when the actual value level for criterion ith is level 1, 2, 3, or 4.

Then, the criteria aspiration level case of the model can be identified. In the calculation step, the conditions of the objective function formulation are based on the criteria aspiration level selection results.

The details of the optimisation objective function formulation are described in the next subsection.

6.4.2 Objective function formulation

After the criteria aspiration level case selection process, we establish the objective function formulation PT network performance optimisation process.

The MALGP model uses criteria weights as coefficients in the model objective function (Cyril et al., 2019). The notations and formulation for the MALGP objective function are shown in Section 4.3. The goal value for goal i is selected, which is based on three different criteria aspiration-level cases selection processes. The MALGP model formulation also includes Eqs. (6)-(8) and (11)-(13). The details of the three cases are shown as follow.

In the first case, if the constraint of d_i is the actual value of the criterion, then the d_i is greater than or equal to $d_{i,\max}$.

In the second case, if the constraint of d_i is chosen between the criterion actual value and $d_{i,\max}$, then the d_i is less than or equal to $d_{i,\max}$, and greater than or equal to $d_{i,4}$.

In the third case, if the criterion actual value is less than $d_{i,4}$ and the criterion goal value is less than $d_{i,\max}$, then the d_i is less than or equal to $d_{i,\max}$, and greater than or equal to $d_{i,\min}$.

After the calculation, we determine the optimal results of the city PT network performance. Then, the case study area performance optimal solution report is created to identify the city PT network performance optimisation scenario. In the last stage, the results of the PT performance optimisation report will be utilised in the MCS process. During the optimisation process, the uncertain conditions and risks of the criteria are not fully investigated. The criteria optimal results are used as input for simulation in the MCS process.

6.5 MCS process

The MCS is used in the last step to model the probability of the PT network performance, as stated in Chapter 5. It is used in this study to simulate the criteria optimal results and analyse the uncertainty and risks related to the criteria optimal solution by randomly selecting criteria values. We analyse the probability of the optimal solution using MCS results, which include criteria sensitive analysis, criteria optimal solution under uncertain condition discovery, and the likelihood of optimal criteria results based on DM requirements identification. The MCS process details are shown in the following subsections.

6.5.1 Input probability distributions and uncertainty

The first step in the MCS process is to identify the probability distribution type of the simulation criteria. The underlying characteristics of the criterion, which can be either continuous or discrete, influence the choice of probability distribution type. Notably, our approach is limited to optimising the performance of PT networks under uncertain conditions by taking into account continuous probability distributions. Following that, we specify the appropriate continuous probability distribution type for each criterion based on its relevant information.

Furthermore, once the type of criteria probability distribution is chosen, the input probability distributions should be assigned to each criterion. The parameters for criteria probability distributions are obtained by clarifying reasons for criteria minimum, maximum, and most likely values. Once the model inputs are defined, the sampling model that will be used to simulate the results can be determined.

6.5.2 Sampling model identification

After determining the type of criteria probability distribution, we choose a random number generator to sample values from the criteria input distribution. MCS employs a stochastic sampling process in which criteria values are chosen from the model's input probability distribution. There are two methods for randomly sampling during the sampling process: Monte Carlo (MC) sampling and Latin Hypercube sampling.

MC sampling, a popular method in MCS, allows for the recreation of the entire input distribution via random sampling across the entire probability distribution over a large number of iterations. A greater number of iterations results in more accurate model results that are more in line with actual conditions. Thus, MCS is used in this study's three-stage framework for optimising the PT network under uncertain conditions, which is implemented using MC sampling.

Finally, MCS is used to simulate the probability distribution inputs of the PT network performance criteria optimisation solution. After the simulation, a sensitivity analysis is performed to identify and analyse the most sensitive criteria as well as the criteria with the most likely values during the optimisation process. Furthermore, the most important MCS model output criteria for the study areas are identified, as is the probability of sensitive criteria meeting the government requirement. Following that, DMs can use the sensitivity analysis results, criteria weighting results, and performance report to make informed decisions about future PT network performance optimisation solutions.

6.6 Conclusion

This chapter established a three-stage optimisation model for optimising PT network performance under uncertain conditions to mitigate the risk involved in the process of optimising PT network performance. First, the PTCM-AHP model is developed to determine the weights of the model criteria and to assess the PT network performance of the case study areas. The AHP process assesses and weights for four levels of PT network performance criteria as well as 15 sub-criteria. The obtained weights are then used in the second model, the MALGP model, to propose PT network performance optimisation solutions for the case study areas. The city's performance optimal solution report is completed during the MALGP process. Following that, MCS is used to analyse the sensitive criteria, discover the optimal solution under criteria uncertainty, and identify the likelihood of criteria optimisation based on DMs' requirements for the case study areas.

Finally, DMs can incorporate the results of the sensitivity analysis, criteria weighting outcomes, and performance report into their decision-making processes, allowing them to make well-informed decisions for future optimal solutions to improve the performance of the PT network.

Chapter 7: Summary and Future Research

7.1 Summary

In this thesis, we propose a three-stage approach to optimising PT network performance in an uncertain process using the PTCM-AHP model-based MALGP approach and MCS. To the best of our knowledge, current research concentrates solely on one aspect of PT performance optimisation. Furthermore, little research has used MCS to address the problem of optimising PT network performance under uncertain conditions. We obtain optimal solutions to PT network performance optimisation problems by implementing a three-stage optimisation framework. The effectiveness of the proposed models is evaluated using three case study areas. The main research findings are summarised below.

1. The PTCM-AHP model results for the three case study areas show that all cities have a high level of sustainable development. The primary criteria for basic PT infrastructure level are the PT network ratio and coverage ratio, while the PT on-time rate is the most important for PT service level. Furthermore, the coverage rate is critical for the level of economic benefits, and the green PT vehicle rate and energy intensity are critical for the level of sustainable development. Based on the findings of the case study, Bayswater and Cockburn should prioritise PT infrastructure, service, and economic benefit levels in their plans and strategies. Meanwhile, Stonnington must prioritise sustainable development, PT service, and economic benefit.

2. The optimal solutions derived from the three case studies demonstrate a significant increase in the ratio of harbour-type bus stop settings and bus ownership rates, indicating the need for a management plan to address the issue of PT driving accidents.

3. According to the MCS results, the coverage rate is the most sensitive criterion in all case study areas, and a higher coverage rate and PT on-time rate requirement have a significant impact on the optimisation model results for all cities, whereas the PT driving accident rate carries a high level of risk despite having a low priority and probability of meeting DMs' requirements.

7.2 Revisiting the research questions

The four research questions listed in Chapter 1 are revisited as follows.

7.2.1 What criteria need to be considered to evaluate PT network performance?

This first question has been answered by reviewing the current PT network performance measuring systems. Subsequently, a PT criteria matrix for PT performance assessment at various areas of application is developed. The criteria are selected from basic PT infrastructure, PT service, economic benefit, and sustainable development aspects.

7.2.2 How should the criteria of PT network performance be weighted?

This second question has been satisfactorily addresses by developing the PTCM-AHP model. Following the development of the PTCM-AHP model, the weights of criteria and subcriteria are allocated via the AHP process. The criteria weights are identified based on the government and UN-Habitat documents.

7.2.3 How can the performance of the PT network be optimised?

The third research question has been answered by developing the MALGP model to optimise PT network performance. The model enables the DM to select subcriteria goal levels from multiple aspiration levels, which are based on the AHP process subcriteria weighting and grading results.

7.2.4 How can the performance of the PT network be optimised under uncertainty?

MCS is used to answer this last research question. The optimal results are the most likely value for each subcriterion. Based on the existing criteria risk descriptions, this research identifies the risk levels for the subcriteria. The model uses MC sampling to simulate the PT network performance under uncertain conditions. The approach explores the sensitivity criteria and proposes the optimal solution along with its probability. Based on the weighted results, it assists the DMs in allocating the resources to optimise the PT network performance.

7.3 Research contributions

This thesis contains methodological and practical knowledge contributions to the optimisation of PT network performance under uncertain conditions. The major contributions are listed below.

Methodological contributions:

1. The PTCM-AHP model provides a comprehensive framework for evaluating the performance of a city's PT network. The model generates a quantifiable performance score by assigning appropriate weights to the criteria at each level. This score allows PT planners to gain insights into the current PT system's strengths and weaknesses, facilitating evidence-based decision-making for future improvements.

2. A novel MALGP model is developed to optimise PT network performance using PTCM-AHP model criteria weights. The MALGP model proposes an optimisation solution for cities by integrating the criteria weights and the government's performance criteria goals. The proposed PT performance optimisation model provides an optimal solution that the government can effectively implement. The model provides guidelines for optimising PT

network performance scenarios by incorporating the DM's plans and strategies, taking into account multi-aspiration levels or interval goals, and accounting for the relative importance of criteria. This allows DMs to adjust and modify the importance of the criteria and the aspiration-level selection process, ensuring that the PT network performance is optimised based on their specific needs.

3. This research establishes a solid framework for optimising PT network performance in the face of uncertainty. The combination of the PTCM-AHP model, the MALGP model, and MCS enables DMs to make informed decisions based on criteria weights while optimising the PT network and accounting for uncertainty. The findings of this study help to advance PT network optimisation methodologies and provide practical advice for improving urban transportation systems. DMs gain insights into the relative importance of criteria, propose optimal solutions, and assess the probability of criteria optimisation in uncertain environments by integrating the PTCM-AHP model, the MALGP model, and MCS.

Contributions of practical knowledge to PT network performance optimisation under uncertain conditions:

1. Key factors influencing PT network performance are demonstrated to DMs and city planners at the basic PT infrastructure, PT service, economic benefit, and sustainable development levels.

2. The criteria for case study areas that need to be improved are investigated, and optimal solutions for cities are proposed. The uncertain analysis results aid in the development of PT network performance optimisation plans and strategies.

7.4 Future research directions

The primary aim of this thesis is to develop a three-stage model framework for optimising PT network performance in uncertain environments. The proposed model framework is both practical and efficient in that it allows DMs to create PT network performance optimisation plans that are aligned with governmental requirements and demands, while also taking the likelihood of the proposed plans into account. We also present new models, such as the PTCM-AHP and MALGP models. Despite innovations in the three-stage optimisation framework design, the models and theories used in this thesis still have scope for improvement. Future research should consider overcoming the relevant limitations.

In terms of calculating city performance score, AHP has been used to calculate the weighting and score results of criteria in each case study area. However, it is time consuming to handle and calculate the city criteria score results in the PTCM-AHP process. Thus, the programming of this process can potentially be further developed.

In terms of the optimisation process, similar to the PTCM-AHP process, the process of conducting optimal results necessitates collaboration with statistical programming software to enhance efficiency.

The following suggestions for future research directions are given:

1. The MALGP model can add new requirements and constraints to control the PT network performance optimisation, which is based on the DMs' requirements and demands. The model criteria and constraints are not currently fully investigated. Future work would include more appropriate performance optimisation criteria and sub-criteria that align with actual requirements in order to tailor the model framework for its application to various other cities.

2. From a theory aspect, the three-stage model ignores actual risk events and risk treatments. The framework can add qualitative risk management methods to proposed associate risk treatments. As a result, additional work can be done beyond risk analysis to optimise performance. Future research should consider risk information obtained from other subject sources.

3. This research has been applied to a limited number of cities. The model framework should be integrated with an intelligent and geospatial model for analysing urban planning issues. To model PT network performance and optimal solutions for large-scale urban areas, the model framework can be combined with deep learning, machine learning, and GeoAI techniques.

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Appendix A

Table A1

Formula for sub-criteria

Criteria	Variables	Mode of Computation	Unit
Public transport network ratio	A1: Length of public transport network B1: Length of urban road network	(A1/B1) × 100	%
Public transport coverage ratio	A2: A 300 m radius of urban public transportation service area within an urban built area (for a circle with a radius of 300 m and a center of public transportation station, the intersection part shall not be counted twice) B2: The area of urban built zone	(A2/B2) × 100	%
Harbour-type bus stop setting ratio	A3: The number of bus stops of bay type B3: Total number of stops	(A3/B3) × 100	%
Public transportation priority lane setting ratio	A4: The road length of the public transport priority lane is set on the main road of the city. B4: Total main road length	(A4/B4) × 100	%
Public transport on-time rate	A5: Bus on-time rate B5: Rail transport on-time rate A5: ((∑(the number of departure on time + the number of arrive last station on time)/∑the number of schedule departure × 2) × 100% B5: ((∑(the number of departure on time + the number of arrive last station on time)/∑the number of schedule departure × 2) × 100%	(A5 + B5)/2	%

Intersection blocking rate during peak hours	A6: Number of periodically severely blocked intersections on arterial roads in built-up areas B6: Total arterial road intersections	(A6/B6) × 100	%
Passenger freight rate	A7: The cost of public transportation paid by passengers per month B7: The city's monthly average salary	(A7/B7) × 100	%
Public transport driving accident rate	A8: The total number of public transport accidents in one year B8: Total mileage of public transport vehicles operated in one year	A8/B8	Times/million kilometers
Coverage rate	A9: Last year's total commercial revenue B9: Last year's total operating expenses	(A9/B9) × 100	%
Bus ownership rate	A10: The number of working buses in the statistical period B10: The number of urban area population in case study city	A10/B10	Car/ten thousand
Intact car rate	A11: Intact car day B11: Operating vehicle-days	(A11/B11) × 100	%
Public transport land area per capita	A12: The area of roads served by public transport B12: Total urban population	A12/B12	m2/person

Public transport utilisation rate	A13: The number of jobs in public transportation B13: Total number of positions for the same period (the number of jobs in public transportation, urban planning and land use)	A13/B13	Null
Green public transport vehicle rate	A14: Number of green public transport vehicles B14: Total number of public transport vehicle	(A14/B14) × 100	%
Public transport energy intensity	A15: Total public transport energy consumption B15: Public transport passenger turnover	A15/B15	g standard coal/person-km

Appendix B

Table B1

Level grade for all sub-criteria

	Level Grade	Level A	Level B	Level C	Level D	Level E
Public transport network ratio (unit: %)	Index value interval	[60, 70]	[55, 60)	[50, 55)	[0, 50)	—
	Score interval	[90, 100]	[75, 90)	[60, 75)	[0, 60)	—
Public transport coverage ratio (unit: %)	Index value interval	≥55	[50, 55)	[45, 50)	[35, 45)	<35
	Score interval	[90, 100]	[80, 90)	[70, 80)	[60, 70)	[0, 60)
Harbour-type bus stop setting ratio (unit: %)	Index value interval	[35, 100)	[25, 35)	[15, 25)	[0, 15)	—
	Score interval	[90, 100]	[75, 90)	[60, 75)	[0, 60)	—
Public transport priority lane setting ratio (unit: %)	Index value interval	≥ 25	[20, 25)	[15, 20)	[10, 15)	[0, 10)
	Score interval	[90, 100]	[80, 90)	[70, 80)	[60, 70)	[0, 60)
Public transport on-time rate (unit: %)	Index value interval	[95, 100]	[85, 95)	[70, 85)	[0, 70)	—
	Score interval	[90, 100]	[75, 90)	[60, 75)	[0, 60)	—
Peak hours intersection blocking rate (unit: %)	Index value interval	[0, 2]	(2, 5]	(5, 8]	(8, 11]	>11
	Score interval	[90, 100]	[80, 90)	[70, 80)	[60, 70)	[0, 60)
Passenger freight rate	Index value interval	<3.5	[3.5, 4.5)	[4.5, 5.5)	[5.5, 6.5)	≥6.5

(unit: %)	Score interval	[90, 100]	[80, 90)	[70, 80)	[60, 70)	[0, 60)
Public transport driving accident rate (unit: times /million kilometres)	Index value interval	[0, 1.5]	[1.5, 2)	[2, 2.5)	[2.5, 3)	>3
	Score interval	[90, 100]	[80, 90)	[70, 80)	[60, 70)	[0, 60)
Coverage rate (unit: %)	Index value interval	>150	(100, 150]	= 100	[50, 100)	<50
	Score interval	[90, 100]	[80, 90)	[70, 80)	[60, 70)	[0, 60)
Bus ownership rate (unit: car/10,000)	Index value interval	[20, 25]	[19, 20)	[18, 19)	[0, 18)	—
	Score interval	[90, 100]	[75, 90)	[60, 75)	[0, 60)	—
Intact car rate (unit: %)	Index value interval	≥ 92	[88, 92)	[84, 88)	[80, 84)	<80
	Score interval	[90, 100]	[80, 90)	[70, 80)	[60, 70)	[0, 60)
Public transport land area per capita (unit: m2/person)	Index value interval	≥11	[8, 11)	[6, 8)	[4, 6)	<4
	Score interval	[90, 100]	[80, 90)	[70, 80)	[60, 70)	[0, 60)
Public transport utilisation rate (unit: %)	Index value interval	[0.17, 2)	[0.14, 0.17)	[0.11, 0.14)	[0.08, 0.11)	<0.08
	Score interval	[90, 100]	[80, 90)	[70, 80)	[60, 70)	[0, 60)
Green Public transport vehicle rate (unit: %)	Index value interval	≥ 95	[95, 92)	[88, 92)	[85, 88)	<85
	Score interval	[90, 100]	[80, 90)	[70, 80)	[60, 70)	[0, 60)
Public transport	Index value interval	[0, 30)	[30, 80)	[80, 130)	[130, 200)	—

energy intensity (unit: g standard coal/person-km)	Score interval	[90, 100]	[75, 90)	[60, 75)	[0, 60)	—

Appendix C

Table C1

Preference matrix, prioritisation, CI, and CR for the four main criteria

	Basic public transport infrastructure level	Public transport service level	Economic benefit level	Sustainable development level
Basic public transport infrastructure level	1	2	3	2
Public transport service level	1/2	1	2	1/2
Economic benefit level	1/3	1/2	1	1/3
Sustainable development level	1/2	2	3	1
Prioritisation	41%	19%	11%	29%
CI	2.72%			
CR	3.02%			

Table C2

Preference matrix, prioritisation, CI, and CR for basic public transport infrastructure level

	Public transport network ratio	Public transport coverage ratio	Harbour-type bus stop setting ratio	Public transportation priority lane setting ratio
Public transport network ratio	1	1	3	2
Public transport coverage ratio	1	1	3	2
Harbour-type bus stop setting ratio	1/2	1/2	1	1/2
Public transportation priority lane setting ratio	1/3	1/3	2	1
Prioritisation	35%	35%	11%	19%
CI	0.27%			
CR	0.3%			

Table C3

Preference matrix, prioritisation, CI, and CR for public transport service level

	Public transport on-time rate	Intersection blocking rate during peak hours	Passenger freight rate	Public transport driving accident rate
Public transport on-time rate	1	2	1	2
Intersection blocking rate during peak hours	1/2	1	1	2
Passenger freight rate	1	1	1	2
Public transport driving accident rate	1/2	1/2	1/2	1
Prioritisation	34%	24%	28%	14%
CI	2.18%			
CR	2.42%			

Table C4

Preference matrix, prioritisation, CI, and CR for economic benefit level

	Coverage rate	Bus ownership rate	Intact car rate
Coverage rate	1	1	3
Bus ownership rate	1	1	2
Intact car rate	1/3	1/2	1
Prioritisation	44%	39%	17%
CI	0.91%		
CR	1.57%		

Table C5

Preference matrix, prioritisation, CI, and CR for sustainable development level

	Public transport land area per capita	Public transport utilisation rate	Green public transport vehicle rate	Public transport energy intensity
Public transport land area per capita	1	2	1	1
Public transport utilisation rate	1/2	1	1/3	1/3
Green public transport vehicle rate	1	3	1	1
Public transport energy intensity	1	3	1	1
Prioritisation	27%	11%	31%	31%
CI	0.6%			
CR	0.67%			

Table C6

City score distribution matrix

Criteria	Local Weight (%)	Global Weight (%)
Basic public transport infrastructure level: 41%		
Public transport network ratio	35	14.3
Public transport coverage ratio	35	14.3
Harbour-type bus stop setting ratio	11	4.5
Public transportation priority lane setting ratio	19	7.9
Public transport service level: 19%		
Public transport on-time rate	34	6.5
Intersection blocking rate during peak hours	24	4.6
Passenger freight rate	28	5.3
Public transport driving accident rate	14	2.6
Economic benefit level: 11%		
Coverage rate	44	4.8
Bus ownership rate	39	4.3

Intact car rate	17	1.9
Sustainable development level: 29%		
Public transport land area per capita	27	7.8
Public transport utilisation rate	11	3.2
Green public transport vehicle rate	31	9
Public transport energy intensity	31	9

Appendix D

Table D1

Optimal solution for Bayswater

Decision Variable	Criteria	Actual Value	Optimal Value	Increase/Decrease Percentage
X_1	Public transport network ratio	17.64	50	183.34
X_2	Public transport coverage ratio	46.82	50	6.79
X_3	Green public transport vehicle rate	100	100	0
X_4	Public transport energy intensity	25.45	0	-
X_5	Public transport priority lane setting ratio	0	10	-
X_6	Public transport land area per capita	20.47	20.47	0
X_7	Public transport on-time rate	91.03	95	4.36
X_8	Passenger freight rate	1.75	1.75	0
X_9	Coverage rate	98.8	100	1.21
X_{10}	Peak hours intersection blocking rate	21	8	−61.9
X_{11}	Harbour-type bus stop setting ratio	19.04	25	31.3
X_{12}	Bus ownership rate	7	18	157.14
X_{13}	Public transport utilisation rate	0.8	0.8	0

X_{14}	Public transport driving accident rate	2.38	1.5	−36.97
X_{15}	Intact car rate	100	100	0

Table D2

Optimal solution for Cockburn

Decision Variable	Criteria	Actual Value	Optimal Value	Increase/Decrease Percentage
X_1	Public transport network ratio	19.21	50	160.28
X_2	Public transport coverage ratio	50.42	55	9.08
X_3	Green public transport vehicle rate	100	100	0
X_4	Public transport energy intensity	25.45	0	-
X_5	Public transport priority lane setting ratio	0.31	10	3125.8
X_6	Public transport land area per capita	26.23	26.23	0
X_7	Public transport on-time rate	91.03	95	4.36
X_8	Passenger freight rate	1.75	1.75	0
X_9	Coverage rate	98.8	100	1.21
X_{10}	Peak hours intersection blocking rate	8.1	8	−1.23
X_{11}	Harbour-type bus stop setting ratio	9.2	15	63.04
X_{12}	Bus ownership rate	7	18	157.14
X_{13}	Public transport utilisation rate	0.8	0.8	0

X_{14}	Public transport driving accident rate	2.38	1.5	−36.97
X_{15}	Intact car rate	100	100	0

Table D3

Optimal solution for Stonnington

Decision Variable	Criteria	Actual Value	Optimal Value	Increase/Decrease Percentage
X_1	Public transport network ratio	60.78	60.78	0
X_2	Public transport coverage ratio	83.72	83.72	0
X_3	Green public transport vehicle rate	100	100	0
X_4	Public transport energy intensity	83.59	30	−64.11
X_5	Public transport priority lane setting ratio	25.38	25.38	0
X_6	Public transport land area per capita	9.28	11	18.53
X_7	Public transport on-time rate	84.68	85	0.37
X_8	Passenger freight rate	2.33	2.33	0
X_9	Coverage rate	101.5	150	47.78
X_{10}	Peak hours intersection blocking rate	1.5	0	-
X_{11}	Harbour-type bus stop setting ratio	26.71	35	31.03
X_{12}	Bus ownership rate	7.36	18	144.56
X_{13}	Public transport	0.78	0.78	0

	utilisation rate			
X_{14}	Public transport driving accident rate	4.54	2.5	−44.93
X_{15}	Intact car rate	100	100	0

Appendix E

Table E1

Bayswater model inputs

Variable	Risk level	Min	Mean value	Max	Shape
Public transport network ratio	Very low	47.5	50	55	Triangular
Public transport coverage ratio	Very low	47.5	50	55	Triangular
Harbour-type bus stop setting ratio	Very low	23.75	25	27.5	Triangular
Public transportation priority lane setting ratio	Very low	9.5	10	11	Triangular
Public transport on-time rate	Very low	90.25	95	100	Triangular
Intersection blocking rate during peak hours	Medium	6.8	8	10	Triangular
Passenger freight rate			1.75		

Public transport driving accident rate	High	1.125	1.5	2.25	Triangular
Coverage rate	Medium	85	100	125	Triangular
Bus ownership rate	Very low	17.1	18	19.8	Triangular
Intact car rate			100		
Public transport land area per capita			20.47		
Public transport utilisation rate	Medium	0.68	0.8	1	Triangular
Green public transport vehicle rate			100		
Public transport energy intensity	Very low	0	0	3	Triangular

Table E2

Cockburn model inputs

Variable	Risk level	Min	Mean value	Max	Shape
Public transport network ratio	Very low	47.5	50	55	Triangular
Public transport coverage ratio	Very low	47.5	55	55	Triangular
Harbour-type bus stop setting ratio	Very low	14.25	15	16.5	Triangular
Public transportation priority lane setting ratio	Very low	9.5	10	11	Triangular
Public transport on-time rate	Very low	90.25	95	100	Triangular
Intersection blocking rate during peak hours	Medium	6.8	8	10	Triangular
Passenger freight rate			1.75		

Public transport driving accident rate	High	1.125	1.5	2.25	Triangular
Coverage rate	Medium	85	100	125	Triangular
Bus ownership rate	Very low	17.1	18	19.8	Triangular
Intact car rate			100		
Public transport land area per capita			26.23		
Public transport utilisation rate	Medium	0.68	0.8	1	Triangular
Green public transport vehicle rate			100		
Public transport energy intensity	Very low	0	0	3	Triangular

Table E3

Stonnington model inputs

Variable	Risk level	Min	Mean value	Max	Shape
Public transport network ratio	Very low	57.74	60.78	66.86	Triangular
Public transport coverage ratio			83.72		
Harbour-type bus stop setting ratio	Very low	33.25	35	38.5	Triangular
Public transportation priority lane setting ratio	Very low	24.11	25.38	27.92	Triangular
Public transport on-time rate	Very low	80.75	85	93.5	Triangular
Intersection blocking rate during peak hours	Medium	0	0	0.5	Triangular
Passenger freight rate			2.33		

Public transport driving accident rate	High	1.87	2.5	3.75	Triangular
Coverage rate	Medium	127.5	150	187.5	Triangular
Bus ownership rate	Very low	17.1	18	19.8	Triangular
Intact car rate			100		
Public transport land area per capita	Medium	9.35	11	13.75	Triangular
Public transport utilisation rate	Medium	0.66	0.78	0.97	Triangular
Green public transport vehicle rate			100		
Public transport energy intensity	Very low	28.5	30	33	Triangular

Appendix F

Table F1

Bayswater summary statistics for total

Name Description Cell Function	Public transport network ratio Input B1 RiskTriang(47.5,50,55)	Public transport coverage ratio Input B2 RiskTriang(47.5,50,55)	Harbor type bus stop setting Input B3 RiskTriang(23.5,25,27.5)	Public transportation priority lane setting ratio Input B4 RiskTriang(9.5,10,11)	Public transport on-time rate Input B5 RiskTriang(90.25,95,100)	Intersection blocking rate during peak hours Input B6 RiskTriang(6.8,8,10)	Public transport driving accident rate Input B7 RiskTriang(1.125,1.5,2.25)	Coverage rate Input B8 RiskTriang(85,100,125)	Bus ownership rate Input B9 RiskTriang(17.1,18,19.8)	Public transport utilization rate Input B10 RiskTriang(0.68,0.8,1)	Public transport energy intensity Input B11 RiskTriang(0,0,3)
General											
Graph											
Category/Range											
Statistics											
Minimum	47.5757	47.5516	23.5241	9.5079	90.3107	6.8278	1.12967	85.080	17.1050	0.68167	0.000118
Maximum	54.9388	54.9282	27.4268	10.9851	99.8424	9.9718	2.23112	124.504	19.7931	0.99674	2.9533
Mean	50.8021	50.8456	25.3239	10.1697	95.0670	8.2672	1.62607	103.226	18.3004	0.82731	1.0026
Mode	50.1569	50.8709	25.1896	10.0466	94.6966	8.2478	1.50116	98.045	17.9596	0.81102	0.0508
Median	50.6512	50.7187	25.2660	10.1350	95.0402	8.2244	1.60420	102.528	18.2412	0.82232	0.8829
Std. Deviation	1.5548	1.5457	0.8188	0.3157	1.9984	0.6616	0.23502	8.263	0.5635	0.06503	0.7119
Variance	2.417	2.389	0.6704	0.09965	3.994	0.4377	0.05524	68.27	0.3175	0.004230	0.5068
Skewness	0.3341	0.2743	0.2301	0.3283	0.0242	0.2046	0.2734	0.2315	0.2923	0.2373	0.5755
Kurtosis	2.4351	2.4044	2.4103	2.4127	2.3567	2.3644	2.3716	2.4142	2.3664	2.4230	2.4070
Errors	0	0	0	0	0	0	0	0	0	0	0
Percentiles											
1%	47.9423	47.8973	23.7617	9.5849	90.8506	6.9989	1.18211	87.248	17.2467	0.70310	0.0160
3%	48.1859	48.1615	23.8797	9.6368	91.2999	7.0984	1.21676	88.599	17.3502	0.71384	0.0389
5%	48.4592	48.4739	24.0458	9.6884	91.7767	7.2209	1.26511	90.256	17.4491	0.72765	0.0694
10%	48.8639	48.9007	24.2686	9.7764	92.3835	7.4063	1.32963	92.678	17.5913	0.74373	0.1488
20%	49.3899	49.4525	24.5842	9.8893	93.2820	7.6744	1.41561	95.884	17.7949	0.76918	0.3182
25%	49.6484	49.6836	24.7076	9.9343	93.6105	7.7776	1.44542	97.148	17.8787	0.77872	0.4051
30%	49.8488	49.8851	24.8322	9.9764	93.8986	7.8663	1.47927	98.335	17.9534	0.78834	0.4959
35%	50.0314	50.0801	24.9431	10.0128	94.2359	7.9576	1.50881	99.338	18.0208	0.79696	0.5847
40%	50.2108	50.2916	25.0554	10.0493	94.5160	8.0470	1.54068	100.347	18.0893	0.80540	0.6768
45%	50.4319	50.4856	25.1615	10.0921	94.7778	8.1328	1.57329	101.406	18.1637	0.81324	0.7787
50%	50.6512	50.7187	25.2660	10.1350	95.0402	8.2244	1.60420	102.528	18.2412	0.82232	0.8829
55%	50.8657	50.9273	25.3788	10.1778	95.3043	8.3087	1.63717	103.779	18.3266	0.83136	0.9869
60%	51.0791	51.1805	25.4955	10.2232	95.5614	8.4048	1.67112	104.954	18.3989	0.84100	1.0974
65%	51.3197	51.4069	25.6226	10.2753	95.8875	8.5046	1.70788	106.238	18.4950	0.85092	1.2179
70%	51.5816	51.6424	25.7606	10.3302	96.1834	8.6281	1.75044	107.614	18.5947	0.86190	1.3509
75%	51.9094	51.9210	25.9067	10.3941	96.5048	8.7509	1.79612	109.069	18.6995	0.87317	1.4920
80%	52.2371	52.2177	26.0600	10.4586	96.8769	8.8751	1.83853	110.589	18.8310	0.88616	1.6728
90%	53.0088	53.0883	26.4690	10.6244	97.7727	9.1921	1.96308	114.884	19.1074	0.91765	2.0782
95%	53.6098	53.5539	26.7580	10.7406	98.4241	9.4304	2.04516	117.842	19.3046	0.94247	2.3507
98%	54.0690	53.9744	26.9873	10.8227	98.8618	9.5951	2.10559	120.088	19.4384	0.95932	2.5364
99%	54.4025	54.3121	27.1947	10.8925	99.2561	9.7271	2.14651	121.810	19.5711	0.97468	2.6878

Table F2

Cockburn summary statistics for total

Name Description Cell Function	Public transport network ratio Input B1 RiskTriang(47.5,50,55)	Public transport coverage ratio Input B2 RiskTriang(52.25,55,60.5)	Harbor type bus stop setting Input B3 RiskTriang(14.25,15,16.5)	Public transportation priority lane setting ratio Input B4 RiskTriang(9.5,10,11)	Public transport on-time rate Input B5 RiskTriang(90.25,95,100)	Intersection blocking rate during peak hours Input B6 RiskTriang(6.8,8,10)	Public transport driving accident rate Input B7 RiskTriang(1.125,1.5,2.25)	Coverage rate Input B8 RiskTriang(85,100,125)	Bus ownership rate Input B9 RiskTriang(17.1,18,19.8)	Public transport utilization rate Input B10 RiskTriang(0.68,0.8,1)	Public transport energy intensity Input B11 RiskTriang(0,0,3)
General											
Graph											
Category/Range											
Statistics											
Minimum	47.5757	52.3067	14.2628	9.5079	90.3107	6.8278	1.12967	85.080	17.1050	0.68167	0.000118
Maximum	54.9388	60.4210	16.4575	10.9851	99.8424	9.9718	2.23112	124.504	19.7931	0.99674	2.9533
Mean	50.8021	55.9301	15.2446	10.1697	95.0670	8.2672	1.62607	103.226	18.3004	0.82731	1.0026
Mode	50.1569	55.9580	15.1578	10.0466	94.6966	8.2478	1.50116	98.045	17.9596	0.81102	0.0508
Median	50.6512	55.7906	15.2022	10.1350	95.0402	8.2244	1.60420	102.528	18.2412	0.82232	0.8829
Std. Deviation	1.5548	1.7003	0.4640	0.3157	1.9984	0.6616	0.23502	8.263	0.5635	0.06503	0.7119
Variance	2.417	2.891	0.2153	0.09965	3.994	0.4377	0.05524	68.27	0.3175	0.004230	0.5068
Skewness	0.3341	0.2743	0.3000	0.3283	0.0242	0.2046	0.2734	0.2315	0.2923	0.2373	0.5755
Kurtosis	2.4351	2.4044	2.4137	2.4127	2.3567	2.3644	2.3716	2.4142	2.3664	2.4230	2.4070
Errors	0	0	0	0	0	0	0	0	0	0	0
Percentiles											
1%	47.9423	52.6870	14.3888	9.5849	90.8506	6.9989	1.18211	87.248	17.2467	0.70310	0.0160
3%	48.1859	52.9776	14.4514	9.6368	91.2999	7.0984	1.21676	88.599	17.3502	0.71384	0.0389
5%	48.4592	53.3212	14.5394	9.6884	91.7767	7.2209	1.26511	90.256	17.4491	0.72765	0.0694
10%	48.8639	53.7908	14.6576	9.7764	92.3835	7.4063	1.32963	92.678	17.5913	0.74373	0.1488
20%	49.3899	54.3977	14.8250	9.8893	93.2820	7.6744	1.41561	95.884	17.7949	0.76918	0.3182
25%	49.6484	54.6520	14.8904	9.9343	93.6105	7.7776	1.44542	97.148	17.8787	0.77872	0.4051
30%	49.8488	54.8737	14.9565	9.9764	93.8986	7.8663	1.47927	98.335	17.9534	0.78834	0.4959
35%	50.0314	55.0881	15.0156	10.0128	94.2359	7.9576	1.50881	99.338	18.0208	0.79696	0.5847
40%	50.2108	55.3207	15.0798	10.0493	94.5160	8.0470	1.54068	100.347	18.0893	0.80540	0.6768
45%	50.4319	55.5341	15.1414	10.0921	94.7778	8.1328	1.57329	101.406	18.1637	0.81324	0.7787
50%	50.6512	55.7906	15.2022	10.1350	95.0402	8.2244	1.60420	102.528	18.2412	0.82232	0.8829
55%	50.8657	56.0201	15.2677	10.1778	95.3043	8.3087	1.63717	103.779	18.3266	0.83136	0.9869
60%	51.0791	56.2985	15.3355	10.2232	95.5614	8.4048	1.67112	104.954	18.3989	0.84100	1.0974
65%	51.3197	56.5476	15.4093	10.2753	95.8875	8.5046	1.70788	106.238	18.4950	0.85092	1.2179
70%	51.5816	56.8067	15.4895	10.3302	96.1834	8.6281	1.75044	107.614	18.5947	0.86190	1.3509
75%	51.9094	57.1131	15.5744	10.3941	96.5048	8.7509	1.79612	109.069	18.6995	0.87317	1.4920
80%	52.2371	57.4395	15.6634	10.4586	96.8769	8.8751	1.83853	110.589	18.8310	0.88616	1.6728
90%	53.0088	58.3971	15.9010	10.6244	97.7727	9.1921	1.96308	114.884	19.1074	0.91765	2.0782
95%	53.6098	58.9093	16.0690	10.7406	98.4241	9.4304	2.04516	117.842	19.3046	0.94247	2.3507
98%	54.0690	59.3718	16.2022	10.8227	98.8618	9.5951	2.10559	120.088	19.4384	0.95932	2.5364
99%	54.4025	59.7433	16.3227	10.8925	99.2561	9.7271	2.14651	121.810	19.5711	0.97468	2.6878

Table F3

Stonnington summary statistics

Name Description Cell Function	Public transport network ratio Input B1 RiskTriang(57.74,60.78,66.86)	Harbor type bus stop setting Input B2 RiskTriang(33.25,35,38.5)	Public transportation priority lane setting ratio Input B3 RiskTriang(24.11,25.38,27.92)	Public transport on-time rate Input B4 RiskTriang(80.75,85,93.5)	Intersection blocking rate during peak hours Input B5 RiskTriang(0,0,0.5)	Public transport driving accident rate Input B6 RiskTriang(1.87,2.5,3.75)	Coverage rate Input B7 RiskTriang(127.5,150,187.5)	Bus ownership rate Input B8 RiskTriang(17.1,18,19.8)	Public transport land area per capita Input B9 RiskTriang(9.35,11,13.75)	Public transport utilization rate Input B10 RiskTriang(0.66,0.78,0.97)	Public transport energy intensity Input B11 RiskTriang(28.5,30,33)
General											
Graph											
Category/Range											
Statistics											
Minimum	57.8320	33.2861	24.1317	80.817	1.986E-05	1.8854	127.764	17.1051	9.3587	0.66164	28.5231
Maximum	66.7856	38.4497	27.8480	93.373	0.48871	3.7329	186.525	19.7654	13.7392	0.96688	32.9428
Mean	61.7554	35.5919	25.7943	86.443	0.16588	2.7071	155.053	18.2928	11.3671	0.80397	30.5024
Mode	60.9708	35.6096	25.6471	85.396	0.00106	2.6882	148.779	17.9302	10.9501	0.78871	30.0137
Median	61.5718	35.5031	25.7224	86.148	0.14482	2.6740	154.151	18.2334	11.2904	0.79954	30.4072
Std. Deviation	1.8906	1.0820	0.7857	2.683	0.11815	0.3915	12.441	0.5618	0.9112	0.06288	0.9423
Variance	3.574	1.171	0.6173	7.200	0.01396	0.1532	154.8	0.3157	0.8302	0.003953	0.8879
Skewness	0.3341	0.2743	0.3000	0.3283	0.5565	0.2710	0.2035	0.3025	0.2231	0.2161	0.3131
Kurtosis	2.4351	2.4044	2.4137	2.4127	2.3397	2.3616	2.3771	2.4146	2.3697	2.4226	2.4011
Errors	0	0	0	0	0	0	0	0	0	0	0
Percentiles											
1%	58.2778	33.5281	24.3450	81.471	0.00195	1.9805	130.731	17.2430	9.6035	0.68273	28.7683
3%	58.5741	33.7130	24.4510	81.913	0.00599	2.0357	132.690	17.3290	9.7824	0.69331	28.9170
5%	58.9064	33.9317	24.6001	82.352	0.01274	2.1037	135.426	17.4345	9.9533	0.70690	29.0555
10%	59.3986	34.2305	24.8002	83.100	0.02521	2.2067	139.076	17.5887	10.1992	0.72272	29.3080
20%	60.0381	34.6167	25.0836	84.059	0.05237	2.3556	143.939	17.7927	10.5512	0.74777	29.6645
25%	60.3525	34.7785	25.1945	84.441	0.06522	2.4130	145.626	17.8731	10.6959	0.75717	29.8038
30%	60.5962	34.9196	25.3064	84.800	0.07794	2.4622	147.540	17.9486	10.8251	0.76664	29.9308
35%	60.8182	35.0561	25.4064	85.108	0.09474	2.5131	149.203	18.0126	10.9410	0.77512	30.0418
40%	61.0363	35.2041	25.5152	85.419	0.11044	2.5666	150.871	18.0813	11.0507	0.78331	30.1546
45%	61.3052	35.3399	25.6195	85.783	0.12673	2.6185	152.555	18.1552	11.1681	0.79084	30.2794
50%	61.5718	35.5031	25.7224	86.148	0.14482	2.6740	154.151	18.2334	11.2904	0.79954	30.4072
55%	61.8327	35.6491	25.8333	86.511	0.16374	2.7251	155.854	18.3206	11.4251	0.80822	30.5345
60%	62.0922	35.8263	25.9481	86.898	0.18214	2.7834	157.607	18.4025	11.5393	0.81747	30.6699
65%	62.3847	35.9849	26.0731	87.340	0.20550	2.8438	159.505	18.4920	11.6908	0.82698	30.8174
70%	62.7032	36.1497	26.2089	87.807	0.22669	2.9187	161.703	18.5880	11.8482	0.83752	30.9803
75%	63.1019	36.3447	26.3526	88.350	0.24970	2.9931	164.062	18.6894	12.0135	0.84833	31.1531
80%	63.5003	36.5524	26.5034	88.898	0.27635	3.0683	166.252	18.7954	12.2210	0.86079	31.3745
90%	64.4387	37.1618	26.9058	90.308	0.34050	3.2604	172.684	19.0948	12.6572	0.89100	31.8711
95%	65.1695	37.4877	27.1901	91.295	0.38715	3.4049	176.922	19.3010	12.9683	0.91481	32.2047
98%	65.7279	37.7821	27.4157	91.993	0.41849	3.5046	180.043	19.4575	13.1795	0.93097	32.4322
99%	66.1334	38.0184	27.6197	92.586	0.44673	3.5847	182.156	19.5776	13.3888	0.94571	32.6177

Appendix G

Table G1

Bayswater MCS model results

Criteria	Most likely value
Public transport network ratio	50.83
Public transport coverage ratio	50.83
Harbour-type bus stop setting ratio	25.33
Public transportation priority lane setting ratio	10.16
Public transport on-time rate	95.08
Intersection blocking rate during peak hours	8.26
Public transport driving accident rate	1.62
Coverage rate	103.33
Bus ownership rate	18.3
Public transport utilisation rate	0.83
Public transport energy intensity	1

Table G2

Cockburn MCS model results

Criteria	Most likely value
Public transport network ratio	50.83
Public transport coverage ratio	55.91
Harbour-type bus stop setting ratio	25.33
Public transportation priority lane setting ratio	10.16
Public transport on-time rate	95.08
Intersection blocking rate during peak hours	8.26
Public transport driving accident rate	1.62
Coverage rate	103.33
Bus ownership rate	18.3
Public transport utilisation rate	0.83
Public transport energy intensity	1

Table G3

Stonnington MCS model results

Criteria	Most likely value
Public transport network ratio	61.79
Harbour-type bus stop setting ratio	35.58
Public transportation priority lane setting ratio	25.8
Public transport on-time rate	86.41
Intersection blocking rate during peak hours	0.16
Public transport driving accident rate	2.7
Coverage rate	155
Bus ownership rate	18.3
Public transport land area per capita	11.36
Public transport utilisation rate	0.8
Public transport energy intensity	30.5