Road Network Maintenance and Repair Considering Day-to-day Traffic Dynamics and Transient Congestion

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Declaration of Originality

I hereby declare that I have personally carried out the work described in this dissertation. In certain cases, my research has built upon working on several collaborative research papers with my supervisors that were presented at conference and submitted for journal publication. These are listed in the reference section and are all my own work. Any quotation from, or description of the work of others is acknowledged by reference to the sources.

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Yang Yu

Abstract

Road maintenance and repair (M&R) are essential for keeping the performance of traffic infrastructure at a satisfactory level, and extending their lifetime to the fullest extent possible. For road networks, effective M&R plans should not be constructed in a myopic or ad-hoc fashion regardless of the subsequent benefits and costs associated with those projects considered. A hallmark of road M&R studies is the use of user equilibrium (UE) models to predict network traffic for a given set of road conditions with or without M&R. However, UE approaches ignore the traffic disequilibrium states and transient congestion as a result of M&R derived disruptions to network traffic on a day-to-day (DTD) time scale, which could produce additional substantial travel costs. As shown in the numerical studies on a M&R plan of the Sioux Falls network, the additional maintenance derived travel cost is about $ 4 billion, which is far exceed the actual M&R construction cost of $ 0.2 billion. Therefore, it is necessary to recognise the substantial social costs induced by maintenance-derived disruptions in the form of transient congestion when planning M&R. This realistic and pressing issue is not properly addressed by the road M&R planning problems with traffic equilibrium constraints.

This thesis proposes a dual-time-scale road network M&R model aiming to simultaneously capture the long-term effects of M&R activities under traffic equilibria, and the maintenance-derived transient congestion using day-to-day (DTD) traffic evolutionary dynamics. The notion of 'day' is arbitrarily defined (e.g. weeks or months). The proposed M&R model consists of three sub-models: (1) a within-day dynamic network loading (DNL) model; (2) a day-to-day dynamic traffic assignment (DTD DTA) model; and (3) a day-to-day road quality model. The within-day traffic dynamics is captured by the Lighthill-Whitham-Richards (LWR) fluid dynamic network loading model. The day-to-day phase of the traffic dynamics specify travellers' route and departure time choices in a stochastic manner based on a sequential mixed multinomial or nested Logit model. Travel information sharing behaviour is further integrated into this macroscopic doubly dynamic (both within-day and day-to-day dynamic) traffic assignment (DDTA) model to account for the impact of incomplete information on travel experiences. A deterministic day-to-day road quality model based on an exponential form of traffic flow is employed to govern the road deterioration process, where a quarter-car index (QI) is applied. All these dynamics are incorporated in a holistic dual-time-scale M&R model, which captures realistic phenomena associated with short-term and long-term effects of M&R, including physical queuing and spillback, road capacity reduction, temporal-spatial shift of congestion due to on-going M&R activities, and the tendency to converge to an equilibrium after M&R actions.

Following the dual-time-scale road network M&R model, a bi-level road M&R optimisation model is proposed, where the aforementioned three sub-models are incorporated into the lower-level problem, while the upper-level is to minimise M&R expenditure and network travel costs while maintaining a satisfactory level of road quality. The M&R planning horizon is long yet finite (e.g. years or decades). A 'quality-usage' feedback mechanism is investigated in the proposed bi-level M&R model, namely, (1) the DTD road quality evolution as a result of DTD traffic loads and the M&R effectiveness; and (2) the evolution of DTD traffic in response to both DTD road deterioration and the improved road quality after M&R activities.

The effectiveness of developed M&R optimisation model is demonstrated through case studies on the Sioux Falls network. A metaheuristic Genetic Algorithm (GA) approach is employed to solve the M&R problems given its highly nonlinear, nonconvex and non-differentiable nature. Explicit travellers' choice behaviour dynamics and complex traffic phenomena such as network paradoxes arising from M&R activities are illustrated. Through a comparison with the results under the dynamic user equilibrium (DUE) method, the proposed DTD method achieves significant reduction in network travel cost of $ 25 million, approximately 20% of the total cost. This points to the benefit of using the DTD dynamics for capturing network's responses to M&R in a more realistic way. The M&R model proposed in this thesis could provide valuable managerial insights for road M&R planning agencies.

Acknowledgements

First and foremost, I would like to thank my supervisors Prof. Washington Yotto Ochieng and Dr. Ke Han for offering me the opportunity to conduct my research in transport modelling and optimisation at Imperial College London. In particular, I would like to thank Prof. Ochieng for his valuable insights from broader aspects in transport studies, his affirmation and encouragement on my research during some difficult times, and his continuous concerns for my mental health throughout my PhD. I would like to thank Dr. Han for his research direction, helpful advice on the more technical aspects of my research. I also thank Dr. Han for funding me to attend the TRB conference and for providing me with the computing resource in China during the special period. Without their inspirational guidance and excellent supervision, my goals would not have been achieved.

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List of Abbreviations

AIA	Asphalt Industry Alliance
ALARM	Annual Local Authority Road Maintenance
ASCE	American Society of Civil Engineers
ATIS	Advanced Traveller Information Systems
BLP	Bilevel Programming
BR	Bounded Rationality
CA	Cellular Automaton
CTM	Cell Transmission Model
DAE	Differential Algebraic Equation
DDTA	Doubly Dynamic Traffic Assignment
DfT	Department for Transport
DOT	Department of Transportation
DMRB	Design Manual for Roads and Bridges
DNL	Dynamic Network Loading
DPs	Deterministic Processes
DSO	Dynamic System Optimal
DTA	Dynamic Traffic Assignment
DTD	day-to-day
DUE	Dynamic User Equilibrium
DVI	Differential Variational Inequality
FFS	free-flow speed
FHWA	Federal Highway Administration
FIFO	first-in-first-out
GA	Genetic Algorithm
GIS	Geographic Information System
IDM	Intelligent Driver Model
IIA	Independent from Irrelevant Alternatives

IRI	International Roughness Index
IRRE	International Road Roughness Experiment
IS	Information Sharing
ITF	International Transport Forum
ITS	Intelligent Transport System
LP	Linear Programming
MC	Maintenance Cost
MDP	Markov Decision Process
MNL	Multinomial Logit
MP	Mathematical Programming
MPECs	Mathematical Programs with Equilibrium Constraints
M&R	Maintenance and Repair
MTC	Maintenance-derived Travel Cost
NLP	Nonlinear Programming
NP	Non-deterministic Polynomial-time
OD/O-D	origin-destination
OECD	Organization for Economic Co-operation and Development
PCU	Passenger Car Unit
PEMS	Portable Emission Measurement System
PIARC	The World Road Association
PS	Path Size
PSUE	Probit-based Stochastic User Equilibrium
RTFs	Road Traffic Forecasts
QI	Quarter-car Index
SDUE	Stochastic Dynamic User Equilibrium
SO	System Optimal
SPs	Stochastic Processes
SRDT	simultaneous-route-and-departure-time
TTC	Total Travel Cost
UE	User Equilibrium

UK	United Kingdom
US	United States of America
VI	Variational Inequality
VMT	Vehicle Mile Travelled
WALO	Weighted Average Learning Operator

1 Introduction

Road transport networks are a critical infrastructure particularly in urban areas, playing a pivotal role in economic and societal development. Road transport has grown rapidly since 1990s and is projected to continue to increase considerably in response an ever increasing demand for travel (DfT, 2018). Due to the consequent increase in traffic demand, road networks are increasingly afflicted with road condition deterioration. Under this circumstance, road maintenance and repair (M&R) is essential for ensuring an acceptable level of performance of road infrastructure as well as the overall efficiency of road transport networks. According to the Annual Local Authority Road Maintenance (ALARM) survey by the Asphalt Industry Alliance (AIA, 2019), the average overall maintenance budget for the UK's highway has increased by almost 20%, from £20.6 million in 2018 to £24.5 million in 2019. This level of investment will be difficult to maintain, necessitating road M&R activities to be carefully planned.

In addition to M&R expenditure, maintenance induced travel costs for the road network is significant and should be accounted for in road M&R planning. The complexity of road M&R planning is the investigation of the feedback mechanism between road quality and traffic usage. For road networks, M&R planning should not be conducted in a myopic without considering maintenance-derived disruptions in the form of transient congestion, as this could produce substantial social costs that outweigh the present value of post-project benefits arising from road M&R. This thesis addresses this gap by proposing an optimal road M&R planning model which for the first time, accounts for both within-day and day-to-day dynamics of network traffic flows as well as realistically capturing maintenance-induced transient congestion.

This chapter introduces the context for the research presented in this thesis. Section 1.1 gives the background knowledge and research motivations, leading to the aim and objectives of this thesis in Section 1.2. Section 1.3 presents the thesis structure. Finally, an overview of the overall methodology used in this thesis is presented in Section 1.4.

1.1 Background and Motivation

Road infrastructure, which aims to provide essential means for the movement of people and commodities through trips on road networks, is acknowledged as a part of the critical infrastructure of any nation. According to the World Road Association (PIARC, 2014), the average road length in OECD[1] countries is more than 500,000 km. Furthermore, 15%-20% of the city areas worldwide are covered by road infrastructure rising to about 40% in city centres. Within the global transport system, the Road transport network is important in terms of its social and economic benefits particularly in urban areas. Hence, the physical condition of road infrastructure is critical for city living (PIARC, 1994). The significance of roads networks requires the proper management of road infrastructure during its lifecycle to achieve efficient, safe, reliable and sustainable performance.

Road transport has played important roles in the development of social, economic, political as well as environmental aspects of the society. The demand for road traffic has continued to grow at a rapid rate world widely since 1990s. According to national road traffic survey by UK Department for Transport (DfT, 2018), the road traffic in Great Britain has increased by 29% from 1990 to 2018 and reaching at 328 billion vehicle miles in 2018. Figure 1.1 shows the forecasts for road traffic of all road classes in the regions of England and Wales for period 2015 to 2050. This survey covered seven scenarios of road traffic forecasts (RTFs) corresponding to different assumptions made about the key drivers of future road demand (scenarios S1-S7 , as shown in the descriptions in Figure 1.1).

[1] Organization for Economic Co-operation and Development

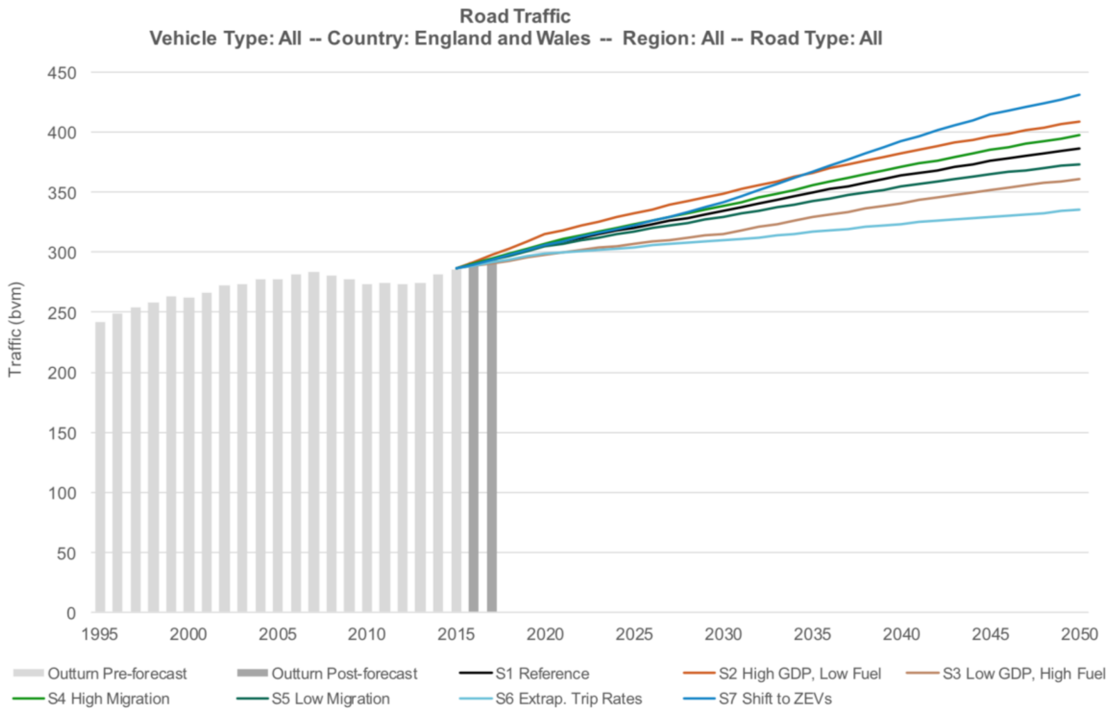


Figure 1.1 Road traffic forecasts for England and Wales *(DfT, 2018)*

Table 1.1 Congestion forecasts for England and Wales in 2050 *(DfT, 2018)*

	Bn Vehicle mile	Lost Seconds per Vehicle mile	Average Speed (mph)	% of Traffic in Congested Conditions
2015	286.2	16.4	33.7	7%
Scenario 1	386.9	23.1	31.9	11%
Scenario 2	408.9	25.3	31.3	13%
Scenario 3	361.3	20.8	32.5	9%
Scenario 4	397.6	24.1	31.6	12%
Scenario 5	373.7	21.5	32.4	10%
Scenario 6	335.2	17.3	34.2	8%
Scenario 7	430.8	27.7	30.8	16%

Derived from these RTFs, road traffic in England and Wales is forecast to increase across all scenarios, and the range of traffic growth is between 17%-51% for the period 2015-2050 with the road traffic increasing to 430 billion vehicle miles in 2050 (see Figure 1.1). As a result of increases in road traffic, the proportion of vehicles in congested conditions is forecast to be between 8%-16% in 2050, compared to 7% in 2015 (DfT, 2018), and the increase in congestion is broadly consistent across three different measurement methods, as shown in Table 1.1.

Road transport networks are facing with severe road deterioration due to the increasing of road traffic demand. According to the UK's Annual Local Authority Road Maintenance (ALARM) Survey by the Asphalt Industry Alliance (AIA, 2019), as shown in Figure 1.2, only 63% of roads in England and Wales are in good condition (GREEN), while 27% of roads are marked as in apparent deterioration (AMBER) and 10% of roads are in poor condition (RED) that need to be maintained in the next 12 months. In 2019 and 2020, there were about 24,000 and 22,600 miles of roads respectively that required maintenance (AIA, 2019). In the US road system, according to the American Society of Civil Engineers (ASCE, 2016), 32% of the US's roads are in poor condition, requiring some maintenance actions to improve the road condition. The physical condition of road infrastructure has obvious impacts on the quality of urban life, including safety, economy, health, and accessibility to commuting and leisure (Hanak et al., 2014). Hence, to adequately address road deterioration, road maintenance works be planned carefully and implemented properly as they are can be highly complex, and socially and economically sensitive.

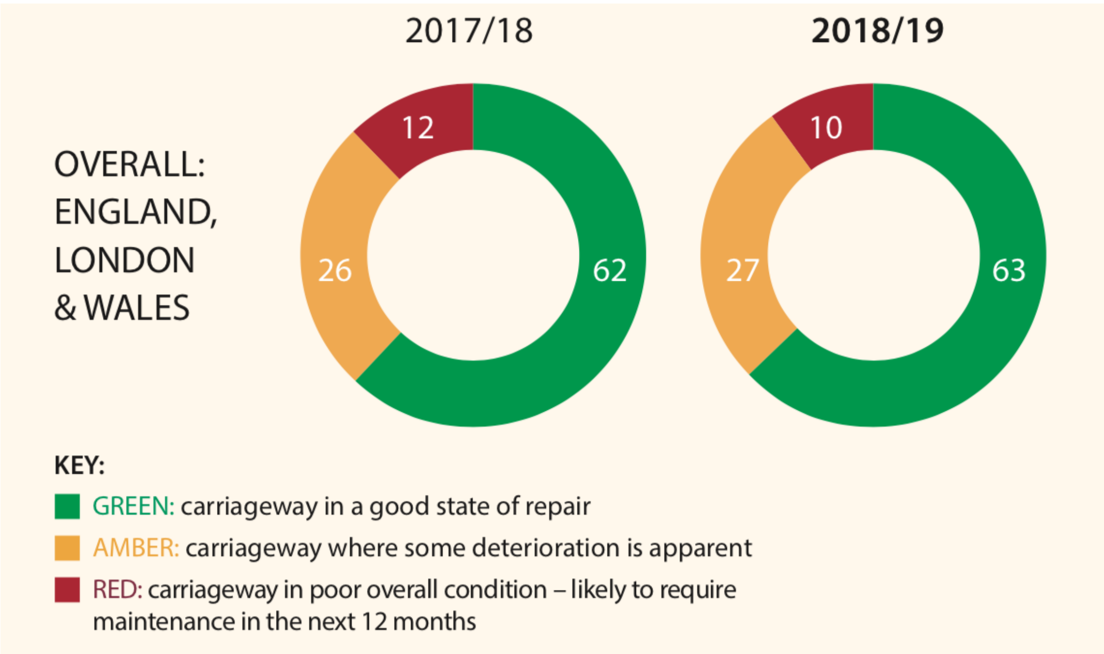


Figure 1.2 Road condition in England and Wales *(AIA, 2019)*

Transportation infrastructure maintenance and repair (M&R) can be broadly defined as a set of activities intended to restore or retain transportation facilities (such as pavement segments, railway segments and bridge spans) within a satisfactory level, which is essential for ensuring the performance of infrastructure system as well as the efficiency of traffic networks. As for road transport networks, M&R consists of various functional and structural treatments involving road surface dressing, resurfacing and partial or total reconstruction. In scheduling M&R actions over a road network, engineers and planers are faced with the challenges to determine when the M&R actions should be executed, which road segments to be maintained, and what type of M&R treatment to be used for each road segment. A broad introduction of road infrastructure M&R is given in Section 2.1. Effective M&R plans are critical for maintaining road serviceability, enhancing the performance of road networks, as well as extending the lifetime of road infrastructure to the most possible extent (Deshpande et al., 2010). Without adequate and proper road M&R, highways and rural roads could undergo undesirable deterioration, resulting in higher vehicle operating costs, increased road congestion and number of accidents, reduced reliability of transport services, as well as increased environmental problems (PIARC, 1994).

Because of very high costs, the current road infrastructure systems are facing maintenance budget shortfall issues. In the UK, the ALARM survey reported that total expenditure for carriageway maintenance in England and Wales was £2.2 billion in 2017, £2.04 billion in 2018 and £2.23 billion in 2019 (AIA, 2019). This survey also reported that the shortfall for road maintenance in 2019 was £657 million, and it estimated that overall, approximately £9.79 billion is required to bring the road networks to a satisfactory level. In the US, as shown in Figure 1.3, road maintenance expenditure has continued to increase. Data from the International Transport Forum (ITF) showed that $46.8 and $49.9 billion were spent in 2014 and 2015 respectively, for road maintenance in the US (ITF, 2019). The Federal Highway Administration (FHWA) estimates that the US should spend $231 billion annually in the next decade to keep existing roads in acceptable condition, far higher than the allocated budget (FHWA, 2019). It is clear that the consequence of such budgetary constraints must be addressed through streamlining and optimisation of M&R to ensure the attainment of acceptable service.

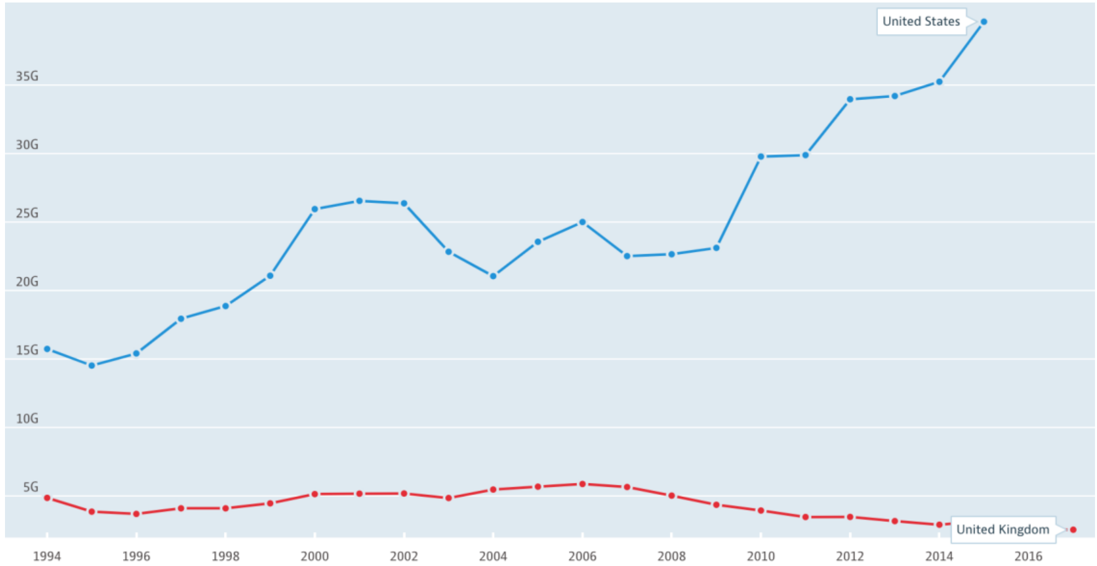


Figure 1.3 Road maintenance expenditure, measured in euros (ITF, 2019)

The complexity of road networks' M&R planning is partially revealed by the feedback mechanism between the dynamics of traffic usage and road quality (see details in Section 5.2). Accurate modelling of time-varying traffic flow among the road network with or without M&R is a critical factor to estimate road deterioration process as well as determine the optimal M&R plans. Dynamic traffic assignment (DTA) models aim to describe and predict time-varying traffic flows on networks consistent with established travel demand, travel behaviour, and traffic flow theory. A widely accepted classification of DTA models is influenced by Wardrop's principles (Wardrop, 1952), known as the dynamic extensions of system optimal (SO) and user equilibrium (UE). Peeta and Ziliaskopoulos (2001), Boyce et al. (2001), Szeto and Lo (2005, 2006), and Bliemer et al. (2017) provide a comprehensive review of these DTA models. Another perspective of differentiating DTA models concerns the time scales involved in traffic dynamics; namely within-day and day-to-day DTA models. Within-day models are typically associated with a single time horizon within a calendar day, such as morning peak hours, assuming that analyses carried out therein can be transferred to multiple days under the same, unperturbed network conditions (e.g. travel demand and network properties). Day-to-day (DTD) models, on the other hand, are concerned with the evolutionary nature of traffic on a sequence of days, which is influenced by the evolving network properties and travellers' adaptive learning and decision making. Here, the notion of 'day' is broadly interpreted to mean an epoch, be it a week, month or arbitrary period in which traffic undergoes a discernible change. A comprehensive literature review on within-day and day-to-day DTA models are presented in Section 2.3.

For road networks, M&R plans often constructed in an ad hoc or myopic fashion regardless of maintenance-derived disruptions in the form of transient congestion. For long-term M&R optimisation problems, the majority of the existing studies (Tsunokawa and Schofer, 1994; Guignier and Madanat, 1999; Smilowitz and Madanat, 2000; Li and Madanat, 2002; Durango & Madanat, 2002; Ouyang and Madanat, 2004; Ouyang and Madanat, 2006; Maji & Jha, 2007; Gao and Zhang, 2013) do not apply any form of traffic assignment modelling. Instead, they simply add user cost parameters into the objective function for M&R cost minimisation. Recent research on traffic assignment models for estimating user costs in long-term M&R planning all employ user equilibrium to predict network traffic for a given set of road conditions with or without M&R. Most of the studies apply static user equilibrium models (Uchida and Kagaya, 2006; Ouyang, 2007; Chu and Chen, 2012; Fontaine & Minner, 2017; Liu et al., 2020), and Ng et al. (2009) were among the first to introduce dynamic network traffic modelling to the M&R optimisation problems. A detailed literature review on the road M&R optimisation models is provided in Section 2.4.

Recognising from the above background, it is imperative that M&R plans for road networks should account for maintenance-derived disruptions, since these disruptions can result in substantial social costs in the form of transient congestion. In fact, transient congestion derived from myopic M&R policies can outweigh the present value of post-project benefits arising from road M&R projects. These critical issues are not accounted for in the current M&R planning methods with equilibrium traffic modelling. It is very promising to utilise day-to-day DTA models to describe and predict the traffic disequilibrium processes induced by M&R, understanding travellers' learning processes and adaptive behaviour, while remaining flexible in modelling network disruptions and incorporating various information provision and feedback mechanisms.

1.2 Aim and Objectives

The background section has identified the significance of infrastructure M&R planning and execution, as well as their social, economic and environmental externalities. It also motivates the explicit consideration of day-to-day traffic dynamics, transient congestion, and user responses pertaining to different M&R activities, network configurations and information dissemination paradigm. State of the art on road network M&R has not extended their modelling scope to subsume both within-day and day-to-day network dynamics, hence offering limited insights on the network-wide and long-term impact of M&R activities, as well as network paradoxes that could render naïve strategies globally detrimental.

The aim of this research is therefore, to develop a generic optimisation framework and systematic methodology for optimal long-term road network M&R planning considering day-to-day traffic dynamics and transient congestion. The proposed dual-time-scale M&R optimisation model is capable of simultaneously capturing the long-term effects of M&R activities under traffic equilibria, and the maintenance-derived transient congestion using day-to-day traffic evolutionary dynamics, which could be employed as decision-aids for infrastructure M&R planning. The objectives are formulated to achieve the aim of this research are to:

- Specify the objectives, constraints and requirements for long-term road network M&R planning considering day-to-day traffic dynamics;
- Construct a macroscopic dynamic network loading (DNL) model for predicting within-day traffic flow dynamics and capturing traffic phenomena (such as shockwaves, vehicle spillback) in the road network;
- Develop a day-to-day travel choice and traffic assignment model, together with the within-day DNL model, for modelling the day-to-day evolution of travellers' route and departure time choices and capturing the traffic flow evolutionary dynamics among road network under different network conditions (e.g. with and without M&R);

- Construct a realistic road deterioration model for capturing day-to-day road quality evolution based on the day-to-day traffic loading on the road;
- Model day-to-day road flow capacity reduction due to correspodning day-to-day road deterioration;
- Model the effect of M&R on road quality and flow capacity reduction and restoration during and after M&R;
- Propose a road M&R planning framework accounting for day-to-day traffic dynamics and transient congestion, which satisfies the objectives, constraints and requirements specified in the first objective of this thesis;
- Develop an optimal long-term road network M&R planning model considering day-to-day traffic dynamics, employing computational intelligence and metaheuristics to search for optimal M&R plans due to its intractability, as the M&R is a joint location-scheduling problem and can be studied as a Stackelberg game.

To maintain a manageable scope, the mathematical and numerical investigations of this thesis emphasise how the network M&R theory mentioned above may be specialized for the study of transport network M&R in congested urban environments where vehicular passenger trips dominate road networks. This thesis utilises large-scale road networks (e.g. the Sioux Falls Network) as its case studies to illustrate the proposed M&R optimisation problems and solutions. Traffic disequilibrium states, transient congestion, and complex phenomena such as network paradoxes and chaos arising from M&R activities are illustrated, which provides valuable managerial insights for road M&R planning and management for transport agencies.

1.3 Outline of the Thesis

This thesis is organized into eight chapters.

Chapter 1 presents the context and background to this thesis including the fundamentals of road transport, road infrastructure maintenance and repair (M&R) and road network traffic dynamics. The background identifies the motivations for the research leading to the aim and objectives of this thesis. This chapter concludes by presenting the overall research methodologies and outlining the thesis structure.

Chapter 2 provides a comprehensive literature review of the concepts and methodologies. It introduces the definition of road infrastructure M&R, road M&R classification and operations, and discusses the importance of performing road M&R. A detailed review of dynamic traffic assignment (DTA) is undertaken. Different route choice principles (e.g. user equilibrium and system optimal) for traffic assignment are introduced for within-day DTA, especially dynamic user equilibrium (DUE) models and the essential component of dynamic traffic loading (DNL). This is followed by a review of day-to-day (DTD) DTA models with different levels perfection and completeness of travel information. The essential need for road M&R planning accounting for DTD traffic dynamics and maintenance-derived transient congestion is highlighted based on a systematic review of the current literature on road M&R planning models. The techniques relevant to solving M&R optimisation problems are reviewed. These include mathematical programming, optimal control and metaheuristic methods.

Chapter 3 develops the underlying traffic models of the proposed M&R planning model. This chapter begins by a brief review of travel choice modelling, in which discrete choice models and random utility theory are discussed. Subsequently, a framework of macroscopic doubly dynamic traffic assignment (DDTA) with simultaneous-route-and-departure-time (SRDT) choices is developed, that is composed of: (1) a within-day traffic dynamic counterpart regarding the propagation of traffic flow and congestion on a road network within a conceptual day; and (2) a day-to-day traffic dynamic counterpart wherein travellers' route and departure time choices are updated day by day. As for the within-day time scale, the Lighthill-Whitham-Richards (LWR) based dynamic network loading (DNL) procedure is employed for describing the within-day traffic dynamics on large-scale traffic networks while capturing realistic traffic phenomena such as shock waves and vehicle spillback. As for the day-to-day time scale, two forms of DTD DTA models with imperfect and incomplete information are developed, to investigate realistic travel choice behaviours under network disruptions (e.g. road M&R) with different levels of availability of travel information. Two rigorous and analytical behavioural versions, with bounded rationality and information sharing behaviour respectively, are further considered and incorporated into the modelling of day-to-day SRDT choices, which forms six different DDTA models. This is crucial for analysing real-world networks with constant supply shortage due to recurrent or incidental disruptions such as M&R. This DDTA model allows a realistic representation of travellers' choice set as well as network traffic flow evolutionary dynamics in response to network conditions and changes (e.g. with and without M&R).

Chapter 4 conducts numerical case studies on the DDTA models developed in Chapter 3. A battery of sensitivity and scenario-based analyses are conducted on two large-scale networks, the Sioux Falls network and the Anaheim network. The case studies begin by examining the long-term behaviour of the proposed DDTA models by performing a sensitivity analysis on the model parameters. It then tests the network traffic under disruptions, where local capacity reduction and restoration are simulated. This is to illustrate the capability of explicitly modelling SRDT choices in DTD dynamics, and understand the interaction between travellers' decision making and traffic dynamics with different levels of information availability and user behaviour. The findings in this chapter will highlight the need for modelling network transient and disequilibrated states when planning road M&R actions, which are often overlooked in equilibrium-constrained network design and optimisation.

Chapter 5 presents the day-to-day road quality model and the modelling of M&R actions. This chapter firstly reviews road deterioration models and introduces the road roughness index used in this thesis. Subsequently, a framework of 'quality-usage' feedback mechanism is proposed, which partially reveals the complexity of M&R planning problems in this thesis. On one hand, this chapter proposes a realistic deterministic road quality model of capturing DTD road deterioration and the effectiveness of M&R, according to traffic loading among road networks that could be achieved by the DDTA model proposed in Chapter 3. On the other hand, this chapter also proposes a DTD road flow capacity model influenced by the DTD road quality as well as undergoing M&R actions, the outputs of which are input into the DDTA model and have impacts on DTD traffic loading among road networks. The applicability of these models is demonstrated by numerical examples on the Sioux Falls network, highlighting the necessity of modelling the quality-usage feedback mechanism in M&R planning.

Chapter 6 proposes a M&R planning framework and formulates the M&R performance models of network travel cost, M&R expenditure and salvage M&R cost. This together with the three sub-models (e.g. the DTD traffic dynamic model, DNL model, and DTD road quality model) proposed in Chapter 3 and Chapter 5, form the long-term road M&R planning model. This model is a dynamic Stackelberg game, where the planning agency makes M&R decisions by anticipating the reactions of the road network users who are competitors in a dynamic Nash game. The applicability of the proposed M&R planning model is then demonstrated by numerical case studies on the large-scale Sioux Falls network of both threshold-base M&R and periodic M&R approaches. In particular, the M&R planning solution under the proposed DDTA model is compared with the solution under the DUE model. This is to confirm the necessity of modelling DTD traffic dynamics in road M&R planning and capturing transient congestion derived by M&R activities, as it expected to generate significant travel costs that should not be ignored.

Chapter 7 develops a modelling framework for optimal road network M&R decision-making that could account for both within-day and day-to-day traffic dynamics as well as transient congestion. A M&R optimisation model for determining the optimal M&R threshold for threshold-based long-term network-level road M&R planning under the budget constraints is then proposed. This M&R model is formulated as a bi-level optimisation problem. Herein, the M&R activity selection takes place in the upper level while changes in the network traffic and road quality are computed in the lower level, and both levels communicate information to each other. This methodology is tested through the numerical studies on a large-scale network, and a computational intelligence and metaheuristics Genetic Algorithm (GA) method is employed in the search for optimal M&R plans due to its nonconvex and highly nonlinear problem setting. The resulting solutions, unlike those pursued in the existing literature, account for short-term as well as long-term benefits/impacts of the M&R activities in a realistic way.

Chapter 8 summarises the results and reviews the major contributions achieved by this thesis. A potential implementation of the proposed M&R planning framework is discussed. This chapter also identifies the uncertainty of the proposed models and provides directions for future research.

Figure 1.4 is a flow chart of the thesis structure capturing the chapter interdependencies. The chapters dedicated to model development are highlighted in red.

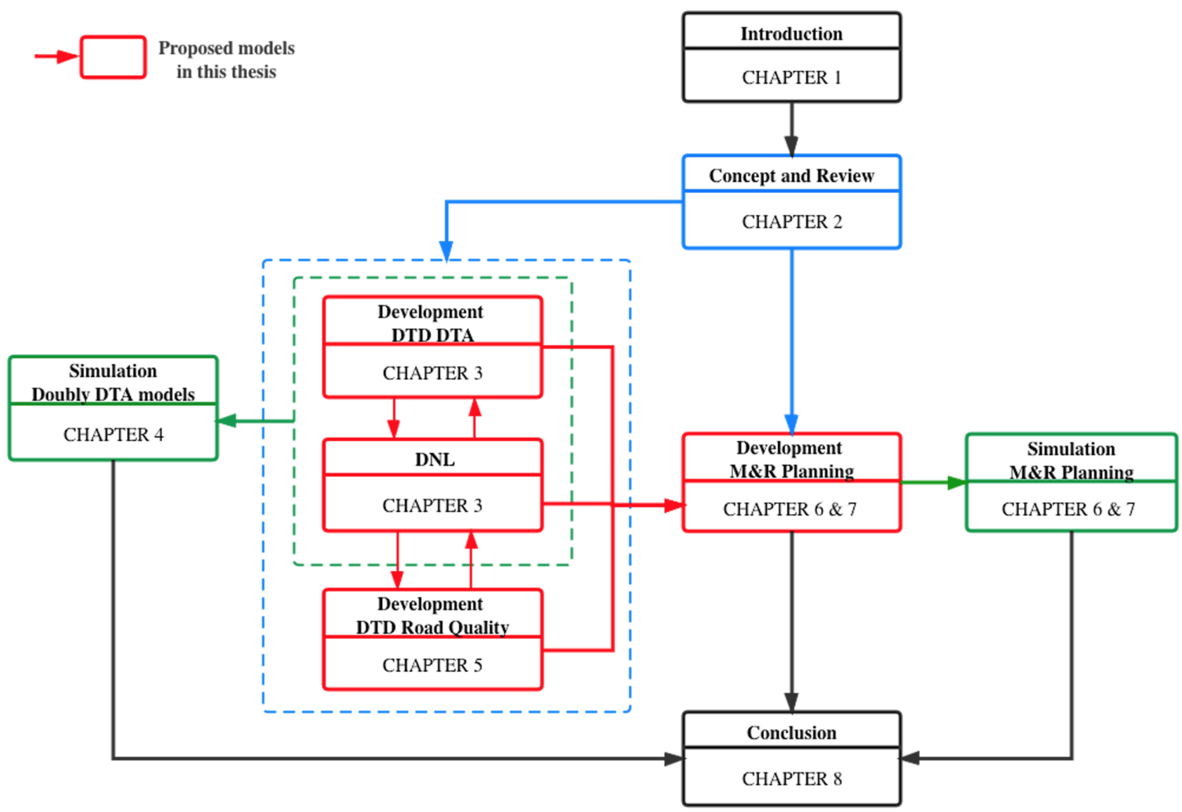


Figure 1.4 Flow chart of thesis structure and interdependencies between chapters

1.4 Overall Methodology

The overall research methodology is summarised here including the technical approaches employed for the purpose of achieving the aim and objectives of this thesis.

1.4.1 General Framework

The overall modelling framework of road network M&R planning consists of three major sub-models:

1) **The DTD traffic dynamic model**, for modelling the evolution of adapted travellers' route and departure time choices reacting to different road conditions day by day.

2) **The dynamic network loading (DNL) model**, which refers to the within-day traffic modelling of links and nodes dynamics, flow propagation phenomena and predicting travellers' experienced costs given the demand matrix and road conditions within a conceptual day.

3) **The DTD road quality evolution model**, which captures the adjustment of road quality due to traffic load, maintenance actions as well as natural deterioration.

The interdependencies between the above three sub-models as well as the enabling mechanisms are illustrated in the Figure 1.5 below.

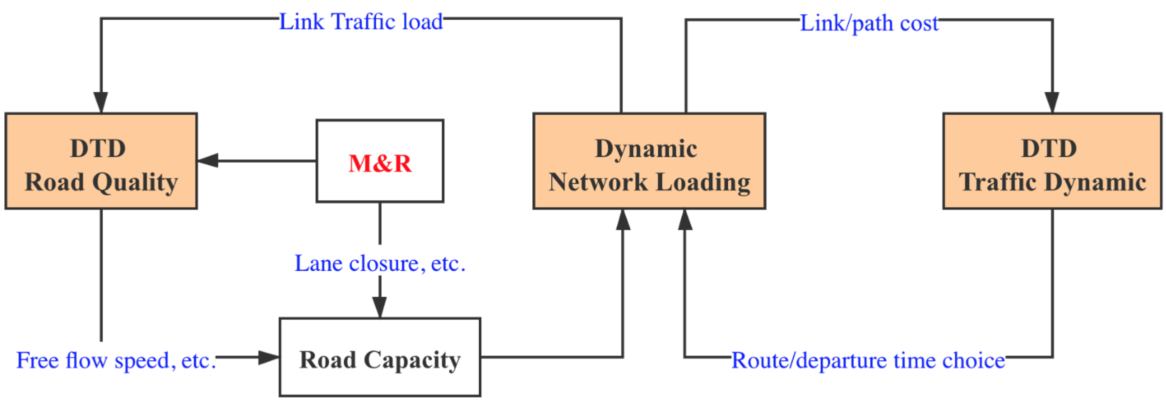


Figure 1.5 Overall modelling framework for this thesis

The proposed M&R optimisation model in this thesis is a bi-level problem. The upper level is to decide M&R plans (e.g. where, when, how) at a network level for the objective of minimising both M&R expenditures as well as user costs that subjects to constrains (e.g.

budget constraint or road quality-related constraints). The lower level problem is the combination of the three sub-models: the DTD road quality dynamics, the dynamic network loading, and the DTD traffic dynamics. This thesis develops the doubly dynamic traffic assignment (DDTA) models, including within-day DNL and day-to-day traffic dynamics, to describe time-varying traffic flows among networks under the conditions with and without M&R. According to the systematic review in Chapter 2 , this thesis is among the first in the literature to account for day-to-day traffic dynamics and transient congestion into long-term M&R planning theory. This methodology more realistically captures travellers' routing and departure time choice dynamics reacting to M&R actions, as well as estimate transient congestion induced by M&R disruptions to the road network. Such a decision support tool does not presently exist for road networks and makes this contribution quite unique.

1.4.2 The Conceptual Model

The conceptual mathematical formulations of the three sub-models (see Figure 1.5) are summarised as:

DTD Traffic Dynamic $$h^{\tau+1}(\cdot) = H\big(h^{\tau}(\cdot), C^{\tau}(\cdot)\big) \tag{1-1}$$

DNL $$\big(f^{\tau}, C^{\tau}(\cdot)\big) = \psi\big(Q^{\tau}, m^{\tau}, h^{\tau}(\cdot)\big) \tag{1-2}$$

DTD Road Quality $$Q^{\tau+1} = G(Q^{\tau}, f^{\tau}, m^{\tau}) \tag{1-3}$$

where, h is path flow, C is travel cost, f is link traffic load, Q is road quality, m is M&R action, $\tau = 1,2,3, \dots$ is the day-to-day time parameter, $C^{\tau}(\cdot)$ and $h^{\tau}(\cdot)$ are also functions of within-day time parameter t. All the quantities shown above are of appropriate dimensions and here use simplified notions for the conceptual illustration.

Equation (1-1) expresses flows dynamics on a day-to-day time scale, where travellers' route and departure time choices of a day is determined by the experienced travel costs in the previous days derived from the DNL model. This is utilised in Equation (1-2) together with the network conditions to determine the dynamic traffic loading of the day. Equation (1-3) defines the day-to-day road quality dynamics, showing that road quality of the day is determined by the traffic load and M&R activity of the previous day.

A subset of links in the road network are identified to be the subject of M&R. Based on the above three sub-models that serves as the underlying models of network dynamics, then the optimal M&R planning problem can be conceptually formulated as:

$$\min_{m^\tau} \sum_{\tau=1}^{N} [\omega \cdot TTC^\tau + F(m^\tau)] \tag{1-4}$$

where TTC^τ represents network total travel cost of the day τ, $F(m^\tau)$ is the financial cost of the M&R action m^τ, ω is the weighting parameter between two costs. Equations (1-1) - (1-3) are treated as constraints subject to the objective (1-4). In addition to these constraints, M&R budget constraint and quality-related constraints could be considered. The time horizon of the M&R planning problems in this thesis is long yet finite (e.g. years or decades), and the notion of ‘day’ in the model is an epoch that could be arbitrarily defined (e.g. weeks or months). Chapter 7 develop the M&R optimisation model and employs metaheuristic methods (e.g. Genetic Algorithm) to solve it on large-scale traffic networks, due to its highly nonlinear, nonconvex, and non-differentiable nature.

Table 1.2 summarises the fundamental methodologies and corresponding delivered outcomes of each chapter.

Table 1.2 Methodology and outcomes of analysis chapters

	CHAPTER	METHODOLOGY	OUTCOMES
1	Introduction	• Background to the problem	• Aim and objectives of the thesis
2	Road Maintenance and Repair and Traffic Dynamics	• Critical review of relevant literatures	• Gaps in the M&R and DTA literature • Research challenges
3	Day-to-day Dynamic Traffic Assignment Models	• Critical review of models • Development of mathematical models	• Submodel-1: DTD DTA model • Submodel-2: DNL model
4	Numerical Case Studies on the Doubly Dynamic Traffic Assignment Models	• Model programming and numerical analysis	• Significance and performance of the DDTA models
5	Day-to-day Road Quality Model and M&R Modelling	• Critical review of road quality models • Development of mathematical models • Model programming and numerical analysis	• Submodel-3: DTD road quality model • DTD flow capacity model • Significance of modelling quality-usage feedback mechanism
6	Road Network M&R Planning Considering Day-to-day Traffic Dynamics and Transient Congestion	• Development of mathematical models • Model programming and numerical analysis	• M&R performance models • Model Performance: quantitative and qualitative
7	Threshold-based Long-term Road M&R Optimisation Model	• Critical review on specific issues • Development of a	• Optimal M&R planning methodological framework

		mathematical model • Model programming and numerical analysis • Heuristic method	• A bi-level M&R optimisation model • Model Performance: quantitative and qualitative
8	Conclusion and Future Work	• Summary of the findings • Discussion of the further improvements	• Contributions • Framework implementation • Future research directions

2 Road Maintenance and Repair and Traffic Dynamics

This thesis investigates the need for a modelling framework for road network M&R planning, capable of accounting for both within-day and day-to-day traffic dynamics as well as transient congestion. For this, realistic traffic behaviour and dynamics are critical to understanding the short- and long-term impact of different M&R strategies. Therefore, this chapter provides background and literature review of the concepts and methodologies related to road M&R and traffic characteristics. Section 2.1 introduces road infrastructure M&R, its classification, operations, importance and current problems in M&R planning.

Section 2.2 reviews some well-known traffic flow models. Dynamic traffic assignment (DTA) is then discussed in Section 2.3. Different route choice principles (e.g. user equilibrium and system optimal) for traffic assignment are introduced for within-day DTA modelling, especially dynamic user equilibrium (DUE) models and the essential component of dynamic traffic loading (DNL). This is followed by a review of day-to-day DTA models with different levels of quality of travel information.

M&R planning and traffic modelling are brought together and reviewed in Section 2.4. The requirements of modelling day-to-day traffic disequilibrium and transient congestion in M&R planning are identified. Section 2.5 introduces the M&R optimisation problem, and reviews the relevant solution techniques for including mathematical programming, optimal control and metaheuristics.

2.1 Road Maintenance and Repair (M&R)

Road management agencies are increasingly paying more attention to road infrastructure maintenance and repair (M&R), before considering constructing new roads. Therefore, an effective method for optimizing M&R strategy is increasingly in demand. Road infrastructure M&R is defined as "activities to keep pavement, slopes, shoulders, drainage facilities and all other structures and property within the road margins as near as possible to their as-constructed or renewed condition" (PIARC, 1994). Effective M&R plans for road networks are essential for maintaining traffic facility serviceability, enhancing transportation network performance, and extending infrastructure lifetime to the most possible extent.

2.1.1 Road M&R and Significance

A road is designed to operate within a finite lifetime or lifecycle. This is because of condition deterioration due to many factors including environmental and traffic loading. Many countries face the problem of appropriately responding to the deterioration of road infrastructure through a lack of appropriate maintenance and repair strategies and plans. According to the UK's Annual Local Authority Road Maintenance (ALARM) Survey (AIA, 2019), 27% of UK are under apparent deterioration, with 10% in in poor condition. The survey estimated that approximately £9.79 billion is required to bring the road networks to a satisfactory level. The main goal of road M&R is to prevent road deterioration and maintain road quality within an acceptable level. The effects of road deterioration can be mitigated or even reversed by applying effective road M&R actions, with the potential to significantly reduce the current and future operational costs (Durango & Madanat, 2002). Figure 2.1 illustrates a typical pavement lifecycle and the corresponding road M&R action types for different pavement conditions.

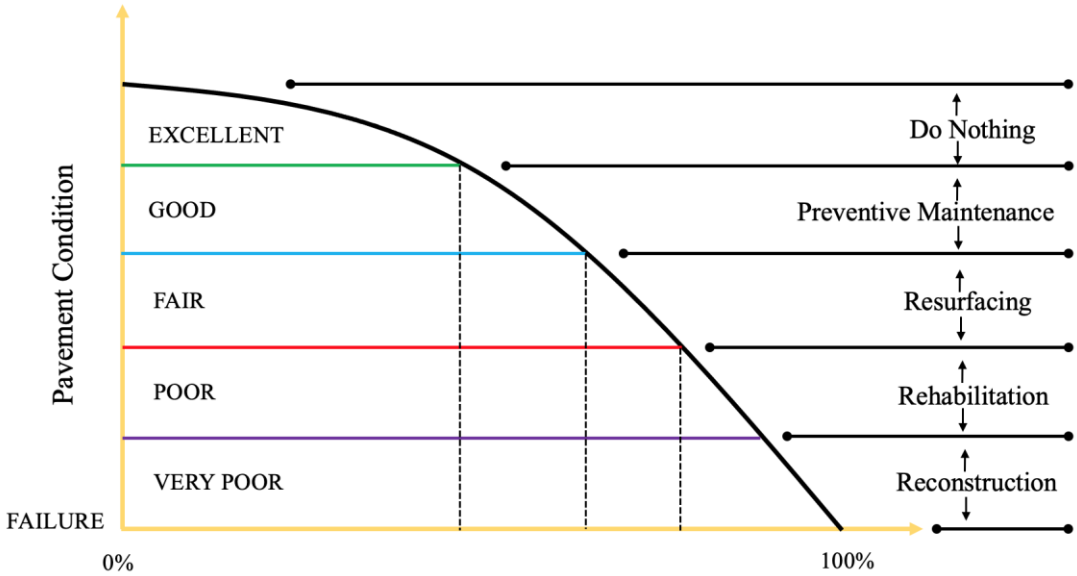


Figure 2.1 Pavement deterioration curve and M&R types regards to different condition levels

Recognition of the importance of road M&R is essential for decision-makers for making appropriate M&R plans for optimal and cost-effective outcomes. Effective and sustainable road M&R planning could stimulate economic and social benefits, while poor road M&R plans tends to obstruct social and economic development seriously (PIARC, 2014). The following lists the importance of road maintenance from different perspectives.

- **Social significance**. Roads are importance national and international property, consisting of millions of kilometers across the world. Road networks provide accessibility to social and community activities and the society would suffer enormous impacts due to poor road conditions. It is essential to come up with effective road M&R plans for road and network service quality.

- **Economic significance**. Road transport is significant for the national economy. The European Union (EU) estimates that, road transport accounts for 83% of surface passenger transport. Road M&R can ensure accessibility to business, agriculture and tourism industry, promoting economic growth. Furthermore, the impact of an effective road M&R on road quality can reduce vehicle operation costs such as fuel consumption and vehicle maintenance.

- **Safety significance**. It has been estimated that more than 1.1 million people are killed and 50 million are injured each year in road traffic crashes (World Highway, 2015). Among multiple reasons, road deterioration and sudden events (such as road collapse) are critical factors in the causality of road traffic crashes. Hence, M&R has a role to play in improving road safety.

- **Environmental significance**. Degradation of road quality could increase vehicle emissions, which seriously affects local and global air quality. The resulting poor driving condition induces further vehicular emissions and noise pollution. It is obvious that road M&R is environmentally important.

- **Urban road network maintenance**. Traffic congestion is a common phenomenon in urban road networks due to increasing vehicular population in urban areas. The congestion cost to the UK in 2019 was estimated at £6.9 billion (INRIX, 2019). Urban road network M&R is especially important, for both maintain road network in a good quality as well as improve road capacity to satisfy increasing traffic demand requirement. Poor road quality can obviously increase network travel delay, where road M&R is required to maintain road capacity so that reduce travel costs.

Therefore, effective road maintenance is especially important for economic, social, safety and environment sustainability. Appropriate road maintenance can significantly ameliorate significant associated costs due to poor road quality. Optimisation of M&R becomes even more critical in the context of shrinking budgets for road infrastructure.

In the consideration of expenditure, it is important to understand that implementing M&R induces impacts on road users, which result in direct and indirect social costs. Further, it is important that there is a feedback mechanism between road quality and traffic usage which partially reveals the complexity of road networks' M&R planning. Intuitively, road traffic load causes its deterioration, which in turn affects road capacity and subsequently traffic load. Since M&R activities are determined based on road deterioration levels, the prediction of time-varying traffic flow of road networks is a critical factor the formulation of M&R plans.

2.1.2 Road M&R Classification and M&R Operations for Pavement

Road M&R activities maintain the functional and structural performance of road facilities. Road maintenance can be classified into three categories: routine maintenance, periodic maintenance and urgent maintenance (Table 2.1).

- **Routine maintenance** involves regular M&R activities (such as patching and pothole repair and roadside verge clearing) conducted in small scale, aiming to maintain short-term road accessibility and safety, as well as to preserve roads from premature deterioration (PIARC, 1994).
- **Periodic maintenance** comprises large scale activities conducted on a road segment for a relatively long time, with the purpose of preserving the structural quality of the road. The actions taken are based on inspection performed at established intervals (e.g. monthly, seasonally, and yearly). The actions are usually categorised as preventive, resurfacing, overlay, and pavement reconstruction. Compared to routine maintenance, periodic maintenance activities tend to be more complicated and costly.
- **Urgent maintenance** refers to unforeseen M&R activities that need to be conducted immediately. Urgent maintenance includes M&R actions required to restore road condition following damage caused by natural disasters and road accidents.

Table 2.1 Road M&R classification and typical M&R activities

M&R category	M&R activity
Routine	Clearing of pavement
	Clearing of ditches and culverts
	Repair of traffic signs and road markings
	Shoulder grading
	Pothole patching and crack sealing
	Repair of cut and fill slopes

	Repair of sealants and expansion joints of bridges
Periodic	Regraveling
	Resealing/surface dressing
	Resurfacing/Overlay
Urgent	Removal of debris or obstacles from natural causes
	Repair of damage caused by traffic accidents

Road pavement M&R involves various operations for the purpose of maintaining the functional and structural performance of road pavements. In terms of frequency, deterioration level and impact on road quality, pavement M&R operations can be categorised into three main types: minor maintenance, surface treatments and major maintenance.

- **Minor maintenance** refers to preventive localised M&R operations. Minor maintenance is conducted a high frequency since it responds to even minor slight deteriorations such as:

  - *Pothole Patching,* an area of flawed materials on the pavement surface caused by freezing and thawing of water underneath the surface. Patching removes thawed materials from the surface layer and replacing them with new materials.

  - *Crack Sealing,* an action taken on a relatively good quality pavement with shallow cracks, through injecting bituminous materials into the cracks.

- **Surface treatments** is an M&R operation to improve pavement integrity and structural strength for the purpose of keeping road serviceability. It includes the following:

  - *Surface Dressing,* conducted when the bitumen surface of the pavement suffering signs of wear. Surface dressing is performed by spreading a thin bituminous seal on the finished pavement surface. This M&R operation could protect the pavement from water infiltrating into the pavement surface as well as improve the skid resistance.

- **Major maintenance**, which refers to M&R operations to improve pavement strength to a higher level compared with surface treatments or even restore the road condition. In comparison, major maintenance actions are often conducted with lower M&R frequency. They comprise:
    - *Resurfacing / Overlay,* performed by installing a new layer over the existing pavement. This M&R operation often conducted when the pavement is under a bad condition, which is able to improve the structural strength of the pavements and enhance road riding quality and serviceability.
    - *Reconstruction, an* activity to comprehensively rebuild the existing pavement, which is usually conducted when the pavement exceeds its service life.

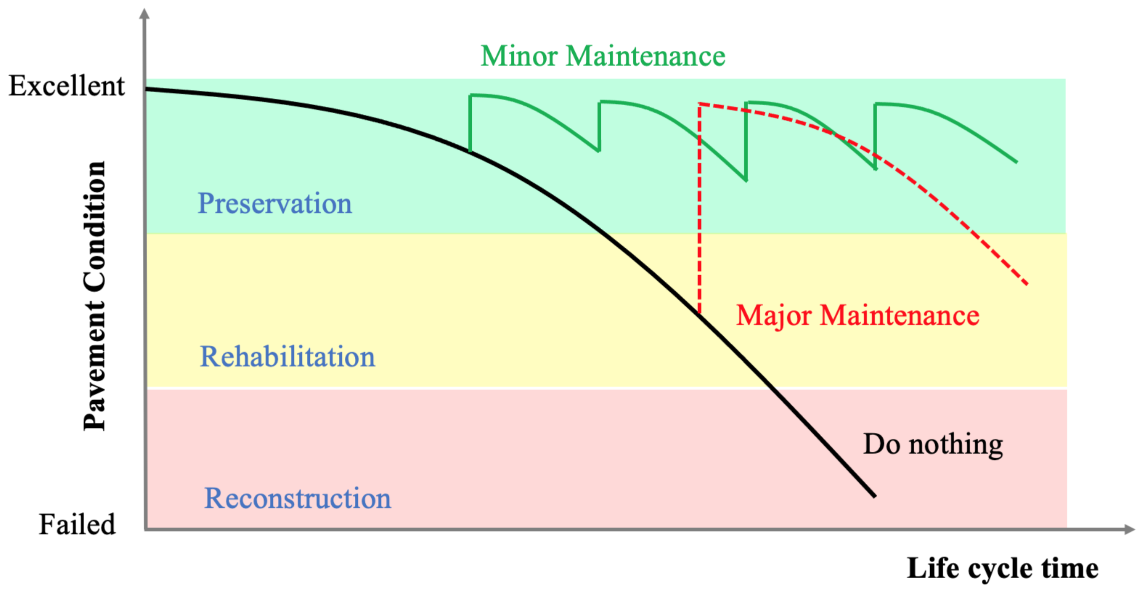


Figure 2.2 Pavement deterioration curve with minor or major maintenance

2.1.3 Road M&R Current Practices and Problems

Current road M&R planning in practice usually conduct in a myopic or ad-hoc fashion. In UK, the roads to be maintained is broadly decided in the following ways:

(1) Regular inspections from weekly to annually to examine how busy the traffic on roads and how important the roads from local and economic aspects.

(2) Annual mechanical detections of road conditions using specialist equipment.

Transport planning agencies then prioritise the road segments that need to be maintained based on the aforementioned inspections. The problems of the current M&R planning practices are that the road segments to be M&R are planned independently without considering the interdependency between roads in the network, and the impact of M&R activities to network traffic dynamics is not accounted for in M&R planning.

In fact, M&R derived disruption to the road network could induce changes in travellers' route or departure time choices, leading to a shift of network traffic flow pattern temporally and spatially. M&R induced impacts on road users could result in significant social costs far exceeding the M&R expenditure substantially (Wang et al, 2003). In this context, the benefits of a maintenance project can often be misinterpreted due to insufficient understanding of road users' costs during and after maintenance. Such considerations are intrinsically dynamic and cannot be adequately addressed via comparative statics. Moreover, since traffic disruptions produce alternative route and departure time choice behaviour, a single project analysed in isolation from other projects runs the risk of suboptimality and the Braess paradox. Therefore, intelligent road M&R planning approaches that consider traffic dynamics and M&R derived transient congestion at the network level is currently demanding.

2.2 Traffic Flow Modelling

Traffic flow models describe traffic flow dynamics and can be classified into three categories according to granularity: microscopic, mesoscopic and macroscopic models. The models are critical for developing dynamic traffic assignment models.

2.2.1 Macroscopic Traffic Flow Models

Macroscopic traffic flow models model traffic flow dynamics by accounting for the relationships between traffic flow (q), speed (v) and density (k). Traffic flow is analogous to fluid with continuum media. The well-known macroscopic models are the LWR model (Lighthill & Whitham, 1955; Richards, 1956) and its improved versions.

- **LWR-based models**

Two equations are crucial in developing macroscopic traffic flow models. One is the basic definition equation of traffic flow:

$$q = kv \tag{2-1}$$

which refers to traffic flow volume q equal to density k multiplied by speed v.

Another is based on the kinematic conservation equation:

$$\frac{\partial q}{\partial x} + \frac{\partial k}{\partial t} = S \tag{2-2}$$

which implies the number of leaving vehicles are equal to entering vehicles plus vehicles stored in traffic system. S equals to the inflow or outflow rate when the road has intermediate entrances or exits, otherwise S equals to zero.

The typical first-order macroscopic traffic flow model was proposed by Lighthill and Whitham (1955) and Richards (1956), namely LWR model. LWR model assumes an equilibrium speed-density relationship:

$$v(x,t) = v_e\left(k(x,t)\right) \tag{2-3}$$

According to observations, different forms of speed-density equations (Greenshields 1935, Greenberg 1959, etc.) have been introduced to describe the relationship of speed decreasing with increasing density. Because of the stationary relationship of speed-density, LWR model is able to modelling traffic flow shock waves, but unable to reflect stop-start waves and non-stationary traffic dynamics (Kuhne & Michalopoulos, 1998).

Payne (1971) and Whitham (1974) improved the model by considering inertia effects and proposed the higher-order PW model. Speed is no longer stationary but considering reaction time and anticipated location, which is more realistic to driving behaviours and flow nature.

PW model conquers the problems of stop-start waves and non-stationary traffic dynamics. Kuhne (1984) further added a viscosity term into the model to eliminate the sharp transformation when traffic flow moves from free flow to highly congested condition. Siebel and Mauser (2006) pointed out that higher-order models are able to describe traffic flow more realistic and accurate. However, with the increase of the order, parameters in the model will also increase, which is difficult to put into practical traffic engineering applications.

Macroscopic traffic flow models are applied to deal with aggregated traffic flow rather than individual vehicle in microscopic models, which appropriates to modelling traffic flow in large network.

2.2.2 Microscopic Traffic Flow Models

Microscopic traffic flow models focus on modelling individual behaviour of traffic flow elements (such as individual vehicle) and their interactions in detail. Typical types of microscopic models are car following models and cellular automaton (CA) model.

- **Car following models**

Car following models appeared from 1950s' as the first type of microscopic traffic flow models which describe traffic dynamics of one vehicle following another and interactions between them. The models assume that the acceleration or deceleration of a vehicle is depended on the vehicle in front. The basic function of car following model takes the form below.

$$Response(T+t) = Sensitivity \times Stimulus(t)$$

$$\ddot{x}_n(T+t) = \frac{a\left[\dot{x}_n(t+T)\right]^m}{\left[x_{n-1}(t)-x_n(t)\right]^l}\left[\dot{x}_{n-1}(t)-\dot{x}_n(t)\right] \qquad (2\text{-}4)$$

This equation means the driver's response (acceleration or deceleration) to the stimulus appears at time t after a time interval T. Sensitivity describes how strong the response would be due to the stimulus (e.g. the relative velocity between two vehicles). Various forms of car following models have been developed based on different sensitivity functions. The sensitivity is initially taken as constant coefficient and several modifications of the sensitivity function have been made, such as reciprocal of spacing (Gazis et al. 1959) and velocity multiplied by reciprocal of squared spacing (Edie 1961).

Car following model was initially introduced by Pipes in 1953. In this earliest model, the following vehicle keeps a safe distance from the leading vehicle. This safe distance is equal to a vehicle length when the relative velocity is zero, and it will increase a vehicle length when speed of following car increased by 10 mile/h. The sensitivity of this model is constant and the time leg equal to zero. Chandler et al. (1959) proposed the car following model according to response-stimulus relationship. This model is simplest which only considers the relative velocity between two vehicles (sensitivity is constant, $m = l = 0$) in modelling car following. It is unrealistic that the following vehicle will not respond when two vehicle speeds are the same, no matter how far the distance between them. Gazis et al. (1959) found that, in reality, the closer of the two vehicles, the higher the sensitivity should be. They proposed a new model which considered the spacing into sensitivity ($m = 0, l = 1$). Edie (1961) further improved the model to avoid unrealistic variation of the vehicle velocity and gave a model which $m = 1, l = 2$. Gazis et al. (1961) analysed of 18 groups of traffic flow data and gave that the scope of $m = 0 \sim 2, l = 1 \sim 2$ in the model are more realistic. Different value of 'm' and 'l' in the model were proposed in various further studies based on different traffic conditions (such as congested and non-congested, acceleration and deceleration), and different methods of measurement could generate different results. Newell (1961) introduced a new car following model in which the vehicle adjusts its speed to an optimised speed according to the headway between them. Bando et al. (1995) further corrected Newell's model and developed optimal velocity car following model. Treiber et al. (2000) proposed an Intelligent Driver Model (IDM) which additionally considered drivers' response behaviours to relative speed. Herman et al. (1959) present that car following models are useful to modelling detailed traffic operations and evaluate traffic stability, but more suitable for a small network due to its intensive computational requirements.

- **Cellular automaton models**

Cellular automaton (CA) models emerged from 1980s' as a new type of microscopic traffic flow model. In the CA models, a road section is divided into several cells and time also be split into discrete time steps. A cell can be empty or occupied by a vehicle. Each cell is given a certain value to represent the physical state of that point. Speed is defined as numbers of cell that the vehicle moving forward within a time interval. State of the system is updated in accordance with well-defined regulations.

Wolfram (1994) introduced the simplest one-dimensional CA model describing traffic dynamics on one traffic lane, called No.184 model. In this model, the traffic lane is divided into several equidistant grids which represent discrete cells, and the state of cell can only take the value 0 (empty) and 1 (occupied). Vehicle move a cell forward at the time step 't' when the cell in front is empty at the previous time step '$t-1$'. Nagel and Schreckenberg (1992) then proposed an important one-dimensional CA model called NS model. The state of the cell in this model could take the value of '$0-v_{\max}$' and the regulation further considered stochastic and acceleration. NS model could capture traffic congestion as well as stop-start wave. The regulations of system update of NS model in a time step is given below.

$$\text{Acceleration: } v_n(t) = Min\left[v_n(t-1)+1, v_{\max}\right] \tag{2-5}$$

$$\text{Breaking: } v_n(t) = Min\left[v_n(t), x_{n-1}(t)-x_n(t)-1\right] \tag{2-6}$$

$$\text{Stochastic: If } v_n(t) > 1 \text{ then } v_n(t) = v_n(t)-1 \tag{2-7}$$

$$\text{Move: } x_n(t+1) = x_n(t)+v_n(t) \tag{2-8}$$

where, $x_n(t)$ be the position of vehicle n at time t, $v_n(t)$ be the speed of vehicle n at time t, $v_{\max}$ be the desired speed of vehicle n.

Based on the NS model, a number of improved CA models have been developed. Fukui and Ishibashi (1996) proposed a new one-dimensional CA model which further modified the acceleration and stochastic regulations of the NS model. Biham, Middleton and Levine (1992) first developed the two-dimensional CA model called BML model, which is considered to be more realistic in modelling urban traffic network. This model divided road network into N*N grid network, in which each grid represents a cell. Each cell can take one of the three states (empty, move northward, move eastward). The regulation is that if the time step is odd, the cell which state is 'move eastward' will move according to No.184 model regulations; if the time step is even, the cell which state is 'move northward' will move according to No.184 model regulations. Some other more sophisticated two-dimensional CA models which considered non-uniform network or two-way traffic also have been developed based on BML model (Nagatani 1995).

2.2.3 Mesoscopic Traffic Flow Models

Mesoscopic traffic flow models are intermediate detailed level models that describe both individual vehicle (microscopic) and aggregate traffic flow (macroscopic) aspects. Typical mesoscopic models include the cell transmission model (CTM), gas-kinetic continuum models and time-headway distribution models.

- **Cell transmission model**

Cell transmission model (CTM) is a further improvement based on CA models. A typical CTM model is proposed by Daganzo in 1994. Daganzo (1994) proposed that if the relationship of flow and density satisfies:

$$q = \min\left\{kv, q_{\max}, w(k_{jam} - k)\right\} \tag{2-9}$$

where v is free-flow speed, $q_{\max}$ is capacity, k_{jam} is jam density and w is wave speed, the LWR model can be approximately discrete into the functions below.

$$n_j(t+1) = n_j(t) + \gamma_j(t) - \gamma_{j+1}(t) \tag{2-10}$$

$$\gamma_j(t) = \min\left\{ n_{j-1}(t), Y_j(t), \left(\frac{w}{v}\right) \times \left(N_j(t) - n_j(t)\right) \right\} \tag{2-11}$$

where, j represent cell, $n_j(t)$ is the number of vehicles in cell j at time t, $\gamma_j(t)$ is inflow rate of cell j at time t, $Y_j(t)$ is the maximum inflow capacity of cell j at time t, $N_j(t)$ is the maximum vehicle capacity of cell j at time t. This model can well modelling traffic flow shockwave, queue conformation and dissipation.

Prigogine and Herman (1971) initially proposed the first gas-kinetic mesoscopic traffic flow model, in which the state of a vehicle is described by the speed distribution temporal and spacial. There are two processes, first process is that drivers expect to reach desired speed according to different traffic conditions, and second process is the faster vehicles' reaction to slower vehicles. Paveri-Fontana (1975) improved the model by introducing desired speed as a variable rather than a parameter. Helbing (1997) developed a new gas-kinetic model considering multi-lane by adding additional terms (e.g. lane changing, vehicle entering and exiting rate). Hoogendoorn (1999) developed a generalized gas-kinetic mesoscopic traffic flow model for multi-lane as well as multiple user classes such as motor vehicle, bicycle and pedestrian. A number of studies have been carried out recently (Coscia et al., 2007; Delitala, 2003; Sopasakis, 2002; Lo Schiavo, 2002) and mesoscropic traffic flow model have been further improved.

Traffic flow models reviewed in this section are the fundation of traffic flow modelling in developing dynamic traffic assignment models reviewed in the next section.

2.3 Dynamic Traffic Assignment (DTA)

Dynamic traffic assignment (DTA) models aim to describe and predict time-varying traffic flows on networks consistent with established travel demand, travel behaviour, and traffic flow theory. This section provides a preliminary review on dynamic user equilibrium (DUE), within-day and day-to-day dynamic traffic assignment (DTD DTA) models.

2.3.1 Dynamic User Equilibrium and Dynamic Network Loading

Wardrop (1952) proposed two principles that are considered as theoretical foundations on traffic assignment, which classifies traffic assignment models as user equilibrium (UE) and system optimal (SO). UE is from the individual traveller's point of view, compared with SO which is from the network system point of view.

- ***User equilibrium (UE)*** is based on Wardrop's first principle (WP1). Travellers competing with each other for road capacity in a traffic network, which can be viewed as a Nash-like game. Each traveller seeks to minimise its own travel cost non-cooperatively by adjusting its route choice. A user equilibrium is envisaged that, for a given origin-destination (OD), "*the journey times in all routes actually used are equal and less than those which would be experienced by a single vehicle on any unused route*". No traveller could reduce his/her travel costs by shifting to alternative routes under UE states.

- ***System optimal (SO)*** is based on Wardrop's second principle (WP2) which states that "*each user behaves cooperatively in choosing his own route to ensure the most efficient use of the whole system*". A system optimal is envisaged where the total network travel costs induced by all travellers is minimised. Under SO, it is not necessary to be identical of the travel costs experienced by travellers between the same OD pair.

Dynamic traffic assignment (DTA) emerged from 1990s' that modelling time varying traffic flows on vehicular networks, is a dynamic extension of Wardrop's principles. This leads to the notations of ***dynamic user equilibrium (DUE)*** and ***dynamic system optimal (DSO)***. The DUE model provides that the experienced travel costs of travel choices (e.g. route and departure time choices) made by travellers between the same OD pair are identical. The DSO model seeks the minimisation of the total travel costs of the entire network subject to the constraints of network traffic flow dynamics and fixed travel demand.

Dynamic user equilibrium (DUE) models, which have been the predominant form of DTA research, are widely studied as network traffic models in transport planning applications. DUE can be viewed as the modelling of time varying traffic loading on networks as well as estimating travel choice (e.g. route and departure time choice) dynamics based on updated travel costs. DUE solution is a stable state when individual travel costs are minimised under the assumption that each traveller knows the traffic condition accurately, chooses correctly and behaves non-cooperatively. DUE are flow-based modelling of traffic from a macroscopic level, which is in contrast with the agent-based traffic models (e.g. Certin et al. 2003) from a microscopic point of view. The DUE models could well capture travel choice behaviours, especially route choice (Ran and Boyce 1996; Lo and Szeto, 2002; Bliemer and Bovy, 2003; Long et al., 2013) and departure time choice (Friesz et al, 1993; Szeto and Lo, 2004; Friesz et al, 2011; Friesz et al, 2013; Han et al., 2015). On the basis of the DUE principle, when equilibrium, the instant costs of used route and departure time choices are identical and less than unused routes for the same trip purpose.

Many efforts have been made to develop reasonable and accurate DUE models in the last two decades. Merchant and Nemhauser (1978) presented a fixed-demand, single-destination, single-mode dynamic system optimal model using mathematical programming approach, which greatly influence the analytical DUE models. Friesz et al. (1989) apply optimal control approach to DTA problem of single-destination cases for DUE objective, whose DUE model is a expand of static Beckmann model. Ran et al. (1993) also built an optimal control model with Beckmann-type objective function and its solution is a dynamic user equilibrium. Variational Inequality (VI) approach provides a unified mechanism for optimisation problems and a general formulation platform for several DTA problems, which is considered more general and analytical flexible in modelling DTA (Peeta & Ziliaskopoulos 2001). Friesz et al. (1993) applied variational inequality (VI) approach to study a DUE problem that combined departure time and route choice. Friesz et al. (2011) proposed a dual-time-scale DUE model with demand evolution which belongs to differential variational inequality (DVI) problems, and a fixed time algorithm is implemented to solve this model. A number of researches (Mahmassani & Peeta

1992; Ben-Akiva et al. 1997; Ziliaskopoulos & Waller 2000) have been conducted using traffic simulators in different granularity (macroscopic, mesoscopic, microscopic) to develop simulation-based DTA models in studying traffic flow propagation as well as optimal strategy decisions.

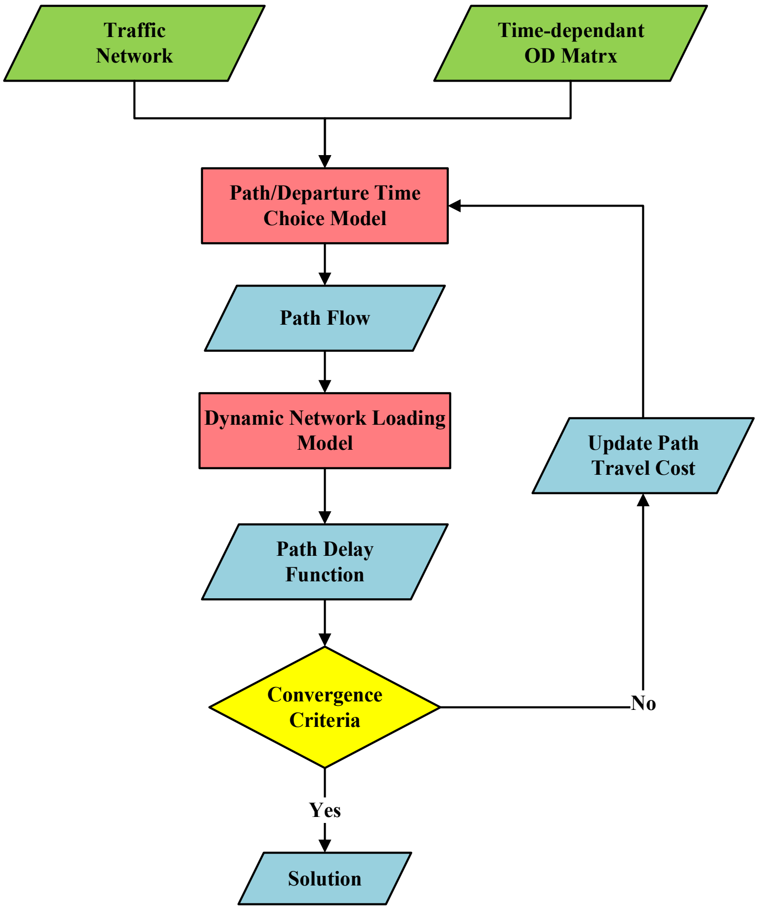


Figure 2.3 General Framework for DUE models

According to Peeta & Ziliaskopoulos (2001), dynamic user equilibrium (DUE) models are composed of five submodels:

1. a path delay operator;
2. flow dynamics;
3. flow propagation constraints;
4. a travel choice (e.g. route and/or departure time choice) model;
5. a demand evolution model.

DUE models have been studied as the solution of submodel 1-4, which focus on the dynamically traffic assignment on the within-day time scale. Submodel 1-3 represent the DNL procedure, which refers to the dissemination of traffic flows among network, including flow propagation within links as well as at junctions under the constraints of flow conservation, and predicts experienced link and path delay. The DNL model aims at modelling the flow dynamics temporally and spatially on a network given established departures of the traffic network. Submodel 4 mathematically express the DUE travel choice principle in a computable form, which is a Nash-like equilibrium. Submodel 5 represents the traffic demand updates on the day-to-day time scale. A general framework for the DUE models is given in Figure 2.3.

There are two essential components of DUE, which are (1) a ***dynamic network loading (DNL)*** procedure as the network performance model; and (2) a travel choice model based on equilibrium principle. Friesz et al. (2011) defined DNL as the problem of finding link activity under the condition of know traffic demand and path flows (departure rates). DNL can be viewed as the assignment of traffic flow on a network based on a delay function, which could capture the interactions between flow dynamics and travel delays. There are two major parts in modelling traffic flow dynamics: link (homogeneous road segments) dynamics and node (intersections and links' boundary) dynamics. Link delay that depends on link flow could construct path delay, delays on paths in turn will influence flows on links that the path travelled. There are a great number of studies on DNL models (Ran and Boyces. 1996; Lo and Szeto, 2002; Szeto and Lo, 2004; Yperman et al., 2005; Ukkusuri et al., 2012; Han et al., 2013; Han et al., 2019). Han et al. (2019) proposed a computational theory of a DNL model for simultaneous route-and-departure-time choice, which is based on the LWR fluid dynamic model and formulated as a system of differential algebraic equations. This model is suitable for the computation of large-scale networks, and will be used as the DNL model in this thesis for the within-day modelling of traffic dynamics.

2.3.2 Within-day Dynamic Traffic Assignment

Within-day models are typically associated with a single time horizon within a calendar day, such as morning peak hours, assuming that analyses carried out therein can be transferred to multiple days under the same, unperturbed network conditions (e.g. travel demand and network properties). The modelling of within-day dynamic traffic assignment (DTA) are currently classified into two methodological groups: analytical approaches and simulation-based approaches. The analytical approaches are further divided into mathematical programming, optimal control and variational inequality. The objectives of DTA models are major concentrate on dynamic user equilibrium (DUE) and dynamic system optimal (DSO).

Merchant and Nemhauser (1978) first attempted to study DTA problem using mathematical programming approach. The 'M-N' DTA model is limited to fixed-demand, single-destination, single-mode DSO cases. This model applied outflow rate function to describe traffic flow propagation and characteristic function to calculate travel cost. Carey (1992) gave that, for the mathematical programming approach, the satisfaction of first-in-first-out (FIFO) regulations, which is essential from a view of traffic flow realism when study multiple destinations or multiple traffic modes DTA, would introduce additional constraints, yield model non-convex, and significantly increase computational requirements. Traffic flow spilling-back on links is another problem which could infringe traffic realism of the mathematical programming DTA models.

DTA models based on optimal control theory are defined in a continuous time setting rather than discrete time setting in mathematical programming. Friesz et al. (1989) introduced optimal control approach into the DTA problem of single-destination cases for both DSO and DUE objectives. The DSO model is the discretization of 'M-N' model (Merchant and Nemhauser, 1978) and the DUE model is an expand of static Beckmann model. DTA models built through optimal control method also have limitations. Ran and Shimazakki (1989a) developed a SO DTA model for an urban traffic network with multiple OD, but the traffic congestion modelling is unrealistic and the FIFO requirement is not considered. Ran and Shimazakki (1989b) further presented an optimal control-based UE DTA model, however, no algorithms could efficiently solve this model due to its analytical difficulties.

Variational Inequality (VI) approach provides a unified mechanism for optimisation problems and a general formulation platform for several DTA problems, which is more analytical flexible in modelling DTA than other two approaches (Peeta & Ziliaskopoulos 2001). VI approach has increasingly been used in DTA studies in recent years because of its obvious advantages. While VI is more convenience than other analytical approaches in modelling DTA problems, there still exist several unsolved drawbacks. Friesz et al. (1993) applied VI approach to study DTA problems which combined departure time and route choice but faced difficulty in solving the problem. Wie et al. (1995) proposed that VI approach in modelling DTA equilibrium problems using exit flow functions could induce flow realism issues. Furthermore, VI approach is more computationally intensive, especially for path-based VI models (Ran & Boyce, 1996).

Simulation-based DTA models can achieve complex traffic flow dynamics repeatedly using a traffic simulator. A number of researches in DTA have been conducted using traffic simulators in different granularity (macroscopic, mesoscopic, microscopic) to develop simulation-based DTA models in studying traffic flow propagation as well as optimal strategy decisions. Mahmassani and Peeta (1992) first applied mesoscopic simulator DYNASMART to develop a DTA model considering Advanced Traveler Information Systems (ATIS) strategies for modelling single class of users only. Mahmassani et al. (1993) improved the model to accommodate multiple classes of users, which increased traffic realism of the model. Peeta and Mahmassani (1995) further proposed a rolling horizon DTA model to incorporate real-time network variations such as traffic congestions. Ben-Akiva et al. (1997) proposed DynaMIT as a dynamic traffic assignment system to estimate and predict in real-time traffic conditions, and generated UE route guidance in the DTA model. Ziliaskopoulos and Waller (2000) introduced GIS system to combine data and the simulation-based DTA model using mesoscopic simulator RouteSim. Peeta and Ziliaskopoulos (2001) proposed that simulation-based DTA models can satisfy the FIFO requirements and avoid the problem of traffic flow holding back, which is superior to modelling using analytical approaches.

The aforementioned studies show that simulation-based DTA models are able to model traffic conditions dynamically, such as traffic congestion and even detailed congestion build-up, queues, and dissipation. Furthermore, Simulation-based DTA models are able to capture complex traffic flow dynamics as well as interactions between vehicles, which are suitable for modelling issues such as multiple user classes, multiple control strategies, traffic information provision and driver response behaviours.

2.3.3 Day-to-day Dynamic Traffic Assignment (DTD DTA)

While dynamic system optimal and dynamic user equilibrium, which fall within the category of within-day models, are by far the most widely studied forms of DTA, there is a strong case for investigating day-to-day dynamic traffic models under disequilibrium conditions. Day-to-day (DTD) models are concerned with the evolutionary nature of traffic on a sequence of days, which is influenced by the evolving network properties and travellers' adaptive learning and decision making. Indeed, the equilibrium state may not exist in real-world traffic networks since it can be easily disturbed by varying travel demand (such as weather, special events, and departure time flexibility) and constant network perturbations (such as traffic incidents, M&R construction works, adaptive traffic controls), which could lead to travellers' route and departure time uncertainties and result in the daily fluctuations of network flow patterns. Instead of attempting to predict the unperturbed network equilibrium, day-to-day dynamic traffic assignment (DTD DTA) models aim to describe travellers' learning, adjustment, and decision-making behaviour on both within-day and day-to-day time scales. This modelling perspective is crucial for capturing network transient states as a result of abrupt network changes, or fluctuations near an equilibrium given complex interaction of information and decision making. DTD DTA models aim to describe and predict the traffic disequilibrium processes, understanding travellers' learning processes and adaptive behaviour, while remain flexible in modelling network disruptions and incorporating various information provision and feedback mechanisms.

Two classes of day-to-day traffic assignment models have been studied, namely Deterministic Processes (DPs) models and Stochastic Processes (SPs) models. DPs and SPs are based on different mathematical principles, where the DPs models arise from a non-linear dynamical system perspective, while the SPs models are typically based on random utility theory and Markov processes. Day-to-day traffic assignment models can be further categorized into the following:

(1) Deterministic processes based on deterministic choice models (Nagurney and Zhang, 1997; Friesz et al., 1994; Yang and Zhang, 2009; He et al., 2010; Smith and Mounce, 2011);

(2) Deterministic processes based on probabilistic/stochastic choice models (e.g. random utility theory) (Horowitz, 1984; Cantarella and Cascetta, 1995; Watling, 1999); and

(3) Stochastic processes based on probabilistic/stochastic choice models (Cascetta, 1989; Cantarella and Cascetta, 1995; Watling and Hazelton, 2003; Watling and Cantarella, 2013).

According to Cantarella and Watling (2016), stochastic models are more naturally associated with modelling the variability that is seen to occur in real-life systems, which are able to represent both dynamic transitions and steady-state fluctuations not seen in equilibrium models. A more detailed review of deterministic and stochastic DTD models could be found in Cantarella and Watling (2016) and Watling and Cantarella (2013, 2015). A significant number of studies are associated with DTD traffic network modelling (Guo and Liu, 2011; Cantarella and Watling, 2016; Wang et al., 2016; Xiao and Lo, 2016; Bifulo et al., 2016; Rambha and Boyles, 2016; Zhang et al., 2018; Guo and Szeto, 2018; Watling and Hazelton, 2018). The detailed review of these DTD models is given in Section 3.2.

The modelling of traveller's route and/or departure time choices in the DTA literature often assumes that the travellers have *perfect* and *complete* knowledge of the traffic system and behave in a totally *rational* manner. This means that travellers have access to the actual experienced costs associated with all travel choices and only choose those with minimum costs. Such an assumption has formed the basis of many deterministic DTD dynamics (Smith 1984; Nagurney and Zhang 1997; Friesz et al., 1994; He and Liu, 2012; Bie and Lo 2010; Guo et al. 2015), which have their limitations due to the lack of complete and accurate information on all the alternatives, and individual perception errors of the same situation.

Stochastic/probabilistic choice models are widely studied in DTD assignment to incorporate imperfect information as well as perception heterogeneity based on random utility theory (Cascetta, 1989; Watling, 1996; Hazelton and Walting, 2004; Watling and Cantarella, 2013; Parry and Hazelton, 2013). In contrast, incomplete information and bounded rationality (BR) are less studied and understood in stochastic modelling. Indeed, only a few recent studies aim to incorporate information sharing behaviour in day-to-day choice models (Iryo, 2016; Xiao and Lo, 2016; Wei et al., 2016; Shang et al., 2017; Zhang et al., 2018). However, most of these models investigate information sharing from an agent-based (i.e. microscopic) perspective, which are demonstrated on simple networks. Few have proposed generalizable and computationally efficient macroscopic modelling counterpart that is immediately suitable for simulating large-scale dynamic traffic networks. A detailed literature review on DTD DTA with information sharing modelling is given in Section 3.7.1.

Bounded rationality (BR) is an important generalization of choice modelling that allows sub-optimal alternatives to be chosen within an indifference band (Mahmassani and Chang, 1987). While a number of studies have incorporated BR into the DTD framework, they all focus on route choice (Guo and Liu, 2011; Di et al., 2015; Ye and Yang, 2017) or departure time choice (Guo et al., 2017) separately; none has considered doubly dynamic model with *simultaneous route-and-departure-time* (SRDT) choices. In addition, and more importantly, these DTD studies with BR all employ a deterministic approach assuming perfect and complete information, which is yet to be generalized in a stochastic context. A detailed literature review on BR in DTD DTA models is given in Section 3.6.1.

To summarise this section, both within-day and day-to-day dynamics, namely doubly dynamics, should be included in modelling traffic assignment to propose a more generalised framework of DTA in order to simulate traffic flows on road networks more realistically. The framework of doubly DTA model is shown in Figure 2.4. This thesis proposes a doubly-dynamic traffic assignment model for modelling network traffic under the conditions with or without M&R. A review on the doubly DTA models are given in Section 3.2.

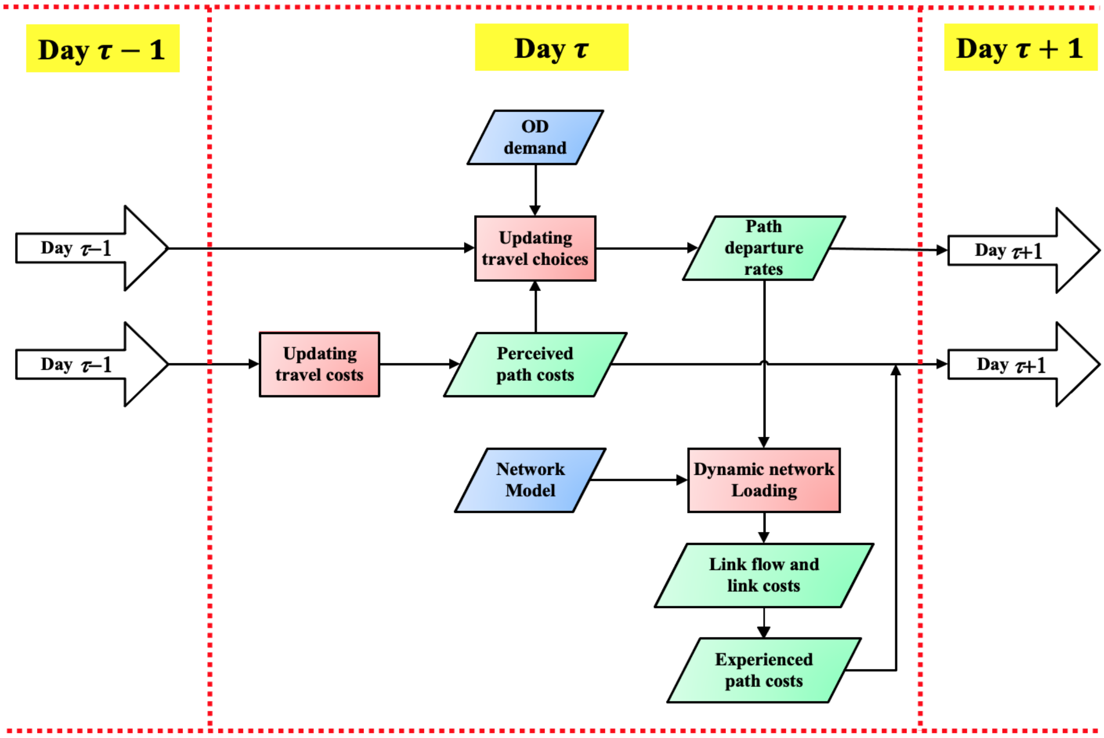


Figure 2.4 The framework of the doubly DTA model

2.4 Road M&R Planning Models Considering Traffic Dynamics

Road network maintenance and repair (M&R) is crucial for keeping an efficient and safe road transport system. In planning M&R activities over a transportation network, engineers and planers are faced with the challenges to determine when the maintenance actions should be executed, which road segments to be maintained, and what type of maintenance treatments to be used. At the network level, road M&R strategy is a set of M&R actions applied to road segments separately or simultaneously within the lifecycle time. An M&R action could have impacts on the pavement from two perspectives: an immediate improvement of road condition after M&R and an influence on the futural road deterioration process. M&R strategies are evaluated by estimating its associated costs and benefits regarding to the entire road network.

Road network M&R planning problems have been broadly classified as long-term and short-term M&R planning based on the time horizon. Short-term road M&R planning refers to a planning horizon of a few days to a few months, assuming that the road segments to be M&R is known in advance. The problem is usually to decide the M&R plan by minimising travel costs under the M&R budget constraint. As for long-term road M&R, the planning horizons often lasting for several years, and the problems are to schedule the M&R actions temporally and spatially among the road network for the purpose of maintaining the road segments above certain service levels. Long-term road M&R problems account for more aspects for decision-making, such as travel cost, M&R expenditure, budget constraint as well as road deterioration process. The M&R planning problems considered in this thesis are finite-horizon long-term M&R problems.

Benefits of a maintenance project are often misinterpreted due to insufficient understanding of road users' costs during and after maintenance. M&R derived disruption to the road network could induce changes in travelers' route or departure time choices, leading to a shift of network traffic flow pattern temporally and spatially. Explicit models to capture network users' response to M&R activities is essential to estimate the benefits and costs of M&R planning accurately. As mentioned in Chapter 1 , for long-term M&R planning problems that consider travel costs into the objective, majority of the studies introduce user cost parameters without apply any form of traffic assignment among road networks (Tsunokawa and Schofer, 1994; Li and Madanat, 2002; Ouyang and Madanat, 2004; Ouyang and Madanat, 2006; Gao and Zhang, 2013). Most of the recent research that apply traffic assignment models for estimating user costs in long-term M&R planning applied static user equilibrium models. Uchida and Kagaya (2006) among the first that consider route choices in long-term M&R planning, where a static probit-based stochastic user equilibrium (PSUE) model is served as traffic flow modelling. Their research accounts for two periods: repair (during-maintenance) and in-service (post-maintenance) and the user cost is considered as travel time and driving cost. Ouyang (2007) proposes a dynamic program for highway road maintenance at a network level and infinite time horizon. The model minimises maintenance expenditures and user costs simultaneously, under deterministic user equilibrium constraints. Chu and Chen (2012) presents a bi-level program, in which a threshold-based network-level maintenance optimisation is the upper level problem, and a static user equilibrium model is served as the lower level problem. Since static equilibrium models could underestimate user cost especially in congested traffic networks, more realistic dynamic traffic models are needed to address this drawback and describe traffic flow more accurately. Ng et al. (2009) first employ dynamic traffic assignment (DTA) to long-term road network M&R modelling. This paper formulates a bi-level problem, in which the upper level is to minimise both user and maintenance costs, and the lower level using network-level cell transmission model (CTM) to capture dynamic user equilibrium.

However, the aforementioned models are unable to capture travellers' learning and adjustment behaviours, and the variation day by day, since only the equilibrium state is necessary. Within-day dynamic models cannot explain the evolutions in traffic flow pattern derived by random events and traffic controls, inducing the transient states disequilibrium which evolutes toward equilibrium (Friesz et al., 1994). For road network M&R planning, recognition of maintenance-derived disruptions is especially essential, since these disruptions can produce substantial social and economic costs in the form of transient congestion. The present value of post-maintenance benefits can be offset or even overpowered by the social costs associated with short-term maintenance-derived transient congestion. Therefore, the capability to modelling the variation of travel behaviours and traffic system over days is of vital important for transportation planning applications.

This thesis, among the first in the literature, introduces day-to-day dynamic traffic assignment (DTD DTA) modelling of network traffic into long-term road M&R planning, which is able to capture traffic disequilibrium states and transient congestion induced by M&R disruptions to the road network. Since UE models tend to underestimate travel costs by ignoring M&R derived transient congestion, the doubly dynamic traffic assignment models proposed in this thesis could address this weakness to more realistically capture traffic dynamics.

2.5 Mathematical Optimisation and Computational Intelligence

An optimisation problem refers to the maximization or minimisation of a real function for a certain problem by selecting input values systematically from a defined domain under constraints and compute the value of the function. Figure 2.5 shows the key characteristics and process of mathematical optimisation. In transport, optimisation problems have been widely studied for the minimisation of travel cost, travel time or traffic delay, with the aim of achieving optimal traffic efficiency and minimising traffic congestion of transportation networks.

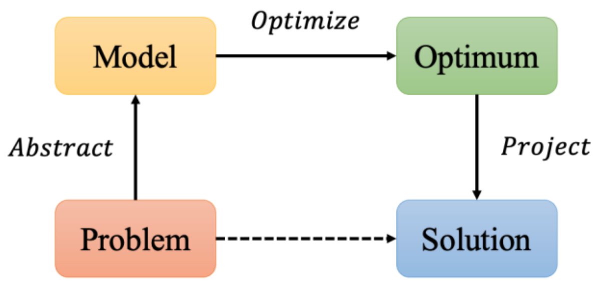


Figure 2.5 Mathematical optimisation

2.5.1 Mathematical Programming and Applications in M&R

A great number of optimisation problems can be represented and solved by Mathematical Programming (MP) techniques. Mathematical programming, originated in the 1940s, is the use of mathematical models, especially optimisation models, to assist in planning or scheduling problems. The essential components of a mathematical programming problem are:

- the candidate solutions are described by the values of the **decision variables**
- the quality of alternative solutions is measured by the **objective function**
- the relationships between decision variables are expressed by **constraints**

A mathematical programming or optimisation problem can be represented as: given an objective function $f : A \to R$ (from set A to real numbers) and variables in search space A satisfy some equalities or inequalities constraints. The aim is to find an optimal solution x^* from A such that $f(x^*) \le f(x)$ (minimisation) or $f(x^*) \ge f(x)$ (maximization) for all x in A.

In general, a MP problem is to find an optimal value of the objective function given a predefined domain. Optimisation problems are usually stated in terms of *minimisation*, and its general form can be represented as below.

$$\begin{aligned} &\text{minimise } f(x) \\ &s.t. \quad g_i(x) = 0 \text{ , } for \ i = 1, 2, ..., m \\ &\qquad\ \ h_j(x) \le 0, for \ j = m+1, m+2, ..., l \end{aligned} \tag{2-12}$$

$f(x)$ is the objective function; the variable x are decision variables; $g(x)$ and $h(x)$ are equality and inequality constraints. Minimising the value of f is equivalent to maximising the value of –*f*, which can convert any maximisation problem to a minimisation problem.

Road M&R optimisation problems are generally formed as MP models. Gaolabi et al. (1982) use a linear programming for statewide pavement management. Ouyang and Madanat (2004) and Lee and Madanat (2014) apply calculus of variation in solving optimal M&R planning problems in an analytical way. A number of M&R studies solve the road maintenance optimisation problems using dynamic programming approach (Madanat & Ben-Akiva, 1994; Durango-Cohen, 2007; Bai et al., 2015). Ouyang (2007) apply an approximate dynamic programming approach to solve the optimal pavement resurfacing planning for highway networks. Some of the M&R optimisation MP models applied Lagrange multiplier method for searching solutions (Sathaye & Madanat, 2012; Hajibabai et al., 2014; Lee & Madanat, 2017).

2.5.2 Optimal Control and Applications in M&R

Optimal control originates from calculus of variations, which is a mathematical optimisation approach for deriving control strategies. It is the process to determine a control law over a period of time for a dynamic system such that the performance of the system is optimised. A control problem includes a cost function that consists of state and control variables. An optimal control is a solution of the path of control variables that minimise the cost function. There are a variety of optimal control problems depending on different problem formulations and time domain (discrete, continuous). The formulation of an optimal control problem consists of the following components:

- a mathematical model for the controlled system (the state equation)
- specification of the boundary conditions on state variables
- specification of the constraints to be satisfied by control variables
- a cost function (the performance index)

Thus, the optimal control problem can be described as the problem of finding an optimal control law within control constraints as well as state boundary conditions, to achieve the optimisation of the performance index of the system. The general method of optimal control is to minimise the objective function:

$$J = \Phi\left[x(t_0), t_0, x(t_f), t_f\right] + \int_{t_0}^{t_f} L\left[x(t), u(t), t\right] dt \qquad (2\text{-}13)$$

subject to:

state equation $$\dot{x}(t) = F\left[x(t), u(t), t\right] \qquad (2\text{-}14)$$

state boundary conditions $$\phi\left[x(t_0), t_0, x(t_f), t_f\right] = 0 \qquad (2\text{-}15)$$

control constraints $$u(t) \in U \qquad (2\text{-}16)$$

where, $x(t)$ is state variable and $u(t)$ is control variable, t is time, t_0 and t_f are initial and terminal time respectively. Φ is the so-called end point cost and L is called Lagrangian. The optimal control problem can be derived from the Pontryagin's minimum principle (a necessary condition) or be solved by the Hamilton–Jacobi–Bellman equation (a sufficient condition).

Friesz and Fernandez (1979) prosed an optimal transport maintenance model with demand responsiveness, solved by an optimal control approach. Tsunokawa and Schofer (1994) introduced an optimal control approach with trend curve approximation for highway pavement maintenance planning. Rashid and Tsunokawa (2012) apply the trend curve optimal control approach for optimizing pavement maintenance of various treatments.

2.5.3 Mathematical Programs with Equilibrium Constraints and Applications in M&R

A bi-level optimisation problem is a mathematical program where a part of the variables is constrained and determined by an optimal solution of a second optimisation program. The general definition of a bilevel programming (BLP) problem can be formulated as below.

$$\begin{aligned} &\min_{x\in X, y} F(x,y) \\ &s.t. G(x,y) \le 0 \\ &\min_{y} f(x,y) \\ &s.t. g(x,y) \le 0 \end{aligned} \tag{2-17}$$

where, the problem is composed of two classes, one is called the upper-level variable x, and another is called the lower-level variable y. Functions F and f are the objective functions of upper and lower level problems respectively. G and g are the constraints for upper-level and lower-level respectively.

Mathematical programs with equilibrium constraints (MPECs) are considered as bi-level programs where the lower-level problem is in a variational inequality form. Variational inequalities are mathematical programs which are capable of modelling equilibrium phenomena such as dynamic user equilibrium (DUE) in transportation field. The general formulation of MPECs is:

$$
\begin{aligned}
&\min_{x,y} F(x,y) \\
&s.t. (x,y) \in Z \\
&y \in S(x)
\end{aligned}
\tag{2-18}
$$

where $S(x)$ is the solution set of the variational inequality problem:

$$
y \in S(x) \Leftrightarrow y \in C(x) and (v-y)^T \psi(x,y) \geq 0, for \forall v \in C(x) \tag{2-19}
$$

C is a closed convex set. The upper-level and lower-level variables in bi-level problems refer to x and y here in the MPEC program.

Studies on road M&R optimisation models considering user equilibrium traffic models are usually formed as MPECs. Uchida & Kagaya (2006) proposed a pavements life-cycle-cost minimisation problem, constrained by static probit-based stochastic user equilibrium, and is solved by parametric approximation approach. Ouyang (2007) presented a framework for optimal pavement resurfacing plan, in which the discounted life-cycle costs is minimised subject to static deterministic user equilibrium. This optimisation problem is solved by a parametric function approximation method together with policy iteration. Ng et al. (2009) introduced a mixed-integer bi-level program that minimise the long-term M&R expenditure and travel costs, constrained to a dynamic user equilibrium problem. Liu et al. (2020) proposed a bi-level eco-based pavement lifecycle maintenance scheduling optimisation program that constraints to static user equilibrated network.

2.5.4 Metaheuristic Methods and Applications in M&R

M&R optimisation problems considering traffic dynamics are highly nonlinear and typical NP-hard problems. A nonlinear programming (NLP) is the optimisation problem where the objective function and/or the constraints satisfied by the feasible region containing nonlinear expressions. NLP problems differ from the linear programming (LP) problems, where the LP models could reach a global optimal solution that is greater than or as good as all other feasible solutions. However, NLP models could not confirm of the convergence to a global optimum. NLPs may have a number of local optimal solutions, that is, a solution that is greater than or is as good as any other solutions within a neighbourhood region.

Various solution algorithms have been applied in the studies of road M&R optimisation problems, which can be broadly classified into two categories: exact algorithms and approximation algorithms. Friesz and Fernandez (1979) first applied continuous state optimal control method in modelling a maintenance scheduling optimisation problem and they applied Pontryagin maximum principle to solve this problem. Ouyang and Madanat (2004) develop a mixed-integer nonlinear mathematical program to formulate a M&R optimisation problem and use both exact branch-and-bound algorithm and approximation greedy heuristic approach to solve this formulation. Ouyang (2007) presents a multidimensional dynamic program for maintenance planning and use policy iteration accompanied by a parametric function approximation approach to solve the model. Exact algorithms are designed in a way that it could guarantee an optimal solution in a finite amount of time. Regards to NP-hard problems even more sophisticated optimisation problems such as the bi-level M&R problem of this thesis, the computation time may increase exponentially according to the dimensions of the problem, which makes exact algorithm infeasible in solving large-scale network M&R problems.

Metaheuristic methods (such as genetic algorithm, simulated annealing, particle swam optimisation, tabu search algorithm), which belongs to approximation algorithms, have been widely used in solving NLP and NP-hard problems. Although metaheuristic algorithms could not guarantee the global optima, they usually could find good quality solutions in a reasonable amount of computation time. Maji and Jha (2007) propose a non-linear non-convex mathematical programming formulation for the M&R optimisation problem and solved it by genetic algorithm. Ng et al. (2009) formulate a bi-level problem, in which the upper level is to minimise both user and maintenance costs, and the lower level using network-level cell transmission model (CTM) to capture dynamic user equilibrium. This MPEC problem is solved by genetic algorithm. Chu and Chen (2012) also presents a bi-level program, in which a threshold-based network-level maintenance optimisation is the upper level problem, and the lower level problem is a static user equilibrium model. A modified tabu search algorithm is used to solve this bi-level program. Lee and Madanat (2015) proposed a joint pavement rehabilitation and reconstruction optimisation model and solved by genetic algorithm.

2.6 Summary

This chapter has reviewed the literature on the concepts and methodologies relevant to this thesis, including road maintenance and repair (M&R), traffic flow models, dynamic traffic assignment, M&R planning models and optimisation approaches. It firstly reviewed the definitions and interpretations of road infrastructure M&R and its social, economic as well as environmental significance. The classification of road M&R as routine, periodic and urgent M&R is introduced, and the typical operations regarding minor and major road M&R are given.

Since M&R activities are determined based on road deterioration levels, the prediction of time-varying traffic flow among the road network is a critical factor contributing to road deterioration therefore determine M&R plans. Next, the widely used traffic flow models (e.g. the LWR model, the CTM model) are introduced, followed by a detailed literature review on dynamic traffic assignment (DTA) based on traffic flow modeling. DTA models aim to describe and predict time-varying traffic flows on networks consistent with established travel demand, travel behaviour, and traffic flow theory. Two principles for traffic assignment are introduced, that is user equilibrium (UE) and system optimal (SO); and the relevant literature on within-day DTA models based on the principles are reviewed. In addition, this chapter provides a detailed literature review on day-to-day (DTD) DTA models that describe and predict the traffic disequilibrium processes and understand travellers' learning processes and adaptive behaviour.

This chapter then conducts a review of the studies on long-term road M&R planning that considered traffic assignment modelling and found that the literature all applied static or dynamic user equilibrium models. This confirms the shortage of the existing road M&R models of underestimation of network travel costs, since the equilibrium state can be easily disturbed by M&R construction works, which could lead to the daily fluctuations of network flow patterns and cause disruptions to the road network. For road M&R planning, recognition of maintenance-derived disruptions is especially essential, since these disruptions can produce substantial social and economic costs in the form of transient congestion. To address the gap, this thesis will propose the doubly dynamic (both within-day and day-to-day) traffic assignment models (Chapter 3) in capturing traffic evolutionary dynamics and transient congestion under the conditions with and without M&R in long-term road M&R planning. Following this, an introduction of the optimisation approaches, such as mathematical programming, optimal control as well as metaheuristic methods are given in support of the M&R optimisation problems. This chapter provides a theoretical foundation for the following chapters.

3 Doubly Dynamic Traffic Assignment Models

The previous chapter introduced infrastructure M&R and identified the necessity in capturing disruption-induced traffic disequilibrium states and transient congestion in M&R planning for road networks. Subsequently, via a review of state-of-the-art literature on day-to-day dynamic traffic assignment (DTD DTA) models as well as traffic models in M&R planning problems, it derived the motivation for proposing a doubly dynamic (e.g. both within-day and day-to-day) traffic assignment (DDTA) model for the purpose of allowing M&R disruptions to be realistically modelled for richly detailed time-varying flow scenarios both in long-term equilibrium and short-term disequilibrium states of the road network.

This chapter[*] presents a doubly dynamic traffic assignment (DDTA) model with simultaneous route-and-departure-time (SRDT) choices while incorporating incomplete and imperfect information as well as bounded rationality. Two day-to-day SRDT choice models are proposed in this chapter to incorporate imperfect travel information: One based on multinomial Logit (MNL) model and the other on sequential, mixed multinomial/nested Logit model. These two variants, serving as base models, are further extended with two features: bounded rationality (BR) and information sharing. BR is considered by incorporating the indifference band into the random utility component of the MNL model, forming a BR-based DTD stochastic model. A macroscopic model of travel information

[*] Part of the contents in this chapter has been published in *Transportation Research Part C* (Yu et al., 2020).

sharing is integrated into the DTD dynamics to account for the impact of incomplete information on travellers' SRDT choices. These DTD choice models are combined with within-day dynamics following the Lighthill-Whitham-Richards (LWR) fluid dynamic network loading model.

The proposed DDTD models allow a realistic representation of travellers' choice set as well as network traffic flow evolutionary dynamics in response to network conditions (e.g. with and without M&R), which are superior in accurately capturing traffic disequilibrium and transient congestion derived by M&R activities to the road networks. This chapter contributes to the aim of this thesis by developing doubly DTA models that will serve as traffic modelling in the road network M&R planning and optimisation models proposed in Chapter 6 and 7 for a more realistic capturing of network traffic dynamics during the M&R planning horizon.

This chapter is organized as follows. Section 3.1 provides a brief background of travel choice modelling, in which discrete choice models and random utility theory are introduced. Section 3.2 provides a literature review on doubly dynamic traffic assignment (DDTA) models and the motivation of the proposed DDTA model in this chapter. The DDTA model framework is presented in Section 3.3, following by the notations and essential background pre-defined before modelling in Section 3.4. Section 3.5 proposes two DTD SRDT choice models with imperfect information, which serves as based models and are further extended to incorporate random utility and information sharing in Section 3.6 and Section 3.7 correspondingly. The within-day dynamic network loading model is described in Section 3.8 and Appendix I.

3.1 Travel Choice Modelling

Traffic distribution in a network is a result of travellers' choice decisions among a set of alternatives. A number of factors can influence travellers' choice behaviour, such as personal factors (e.g. gender, age, driving experiences, etc.), road and traffic conditions, traffic controls as well as pre-trip and en-route travel information. Network conditions as well as traffic demand changes day to day may affect travellers' route and departure time choices because of different travel costs perceived on their preferred choices. DTD DTA models are able to capturer this daily uncertainty of travel choices and predict the evolutionary assignment of traffic flow among road networks.

The heterogenous travellers' choice behaviour dedicated to decision-making is a complex system that need to be simplified using travel choice models based on the specific set of assumptions. Several empirical mathematical models (e.g. Probit model, Logit model) or models in other fields (e.g. BP neural network model) and their enhanced versions can be applied to study travel choice behaviours. Discrete choice models, that describe choice behaviour of individual travellers, have been widely applied for analysing travel behaviour and predicting travel decisions. According to Ben-Akiva and Bierlaire (2003), discrete choice models can be formed based on a set of assumptions about the:

- **decision-maker** --- to define the entity of decision-making and its characteristics;
- **alternatives** --- to determine the choice set considered by the decision-maker;
- **attributes** --- to measure the costs and benefits of each alternative to the decision-maker;
- **decision rules** --- to describe the decision process for choosing an alternative by the decision-maker.

This thesis considers travellers' route and departure time choices for the prediction of day-to-day traffic flow assignment under the road condition with and without M&R. The often-considered assumptions for forming the route or departure time choice models are summarized in Table 3.1, in which the assumptions considered in the proposed DTD DTA models are highlighted in purple. In addition, assumptions on bounded rationality and information sharing behaviour in decision-making of travel choices are also considered in this thesis to form different DTD DTA models. This section first introduces the background knowledge of the random utility models in forming the proposed DTD DTA models.

Table 3.1 Assumptions for route and departure time choice modelling

Travel Choices	Decision-maker Characteristics	Alternatives	Attributes	Decision Rules
Route choice	▪ Value of time ▪ Trip purpose (e.g. commute, leisure) ▪ Information availability (e.g. pre-trip, en-route information)	Considered route set	▪ Travel time ▪ Traffic condition (e.g. congestion) ▪ Route length ▪ Road condition ▪ Other travel costs (e.g. tolls, car operating costs)	▪ Shortest path ▪ Multinomial Logit ▪ Probit ▪ C-logit ▪ Path Size Logit
Departure time choice	▪ above mentioned ▪ Desired arrival time ▪ Arrival penalty	Discretized departure time intervals	▪ above mentioned ▪ Early or late delay	▪ Multinomial Logit ▪ Probit ▪ Nested Logit ▪ Cross-Nested Logit

3.1.1 Random Utility Theory

Different assumptions made on decision-maker, alternatives, attributes as well as decision rules in travel behaviour applications contribute to different family of travel choice models. A value named *utility* is commonly used to describe the attribute of each alternative in discrete choice models, which could serve as an evaluation criterion in the choice decisions. It firstly appears in the choice model based on the decision rules of neoclassical economic theory assuming that the alternative with highest utility is selected. However, the complexity of traveller's choice behaviour requires that a choice model should explicitly capture some degree of *uncertainty*. Choice models based on *random utility theory* are capable to capture the uncertainty in utilities represented by random variables, which are the most applied discrete choice model in transport studies (Ben-Akiva & Bierlaire, 2003).

In random utility models, the utility of individual i associated with alternative k is represented by

$$u_k^i = v_k^i + \varepsilon_k^i \tag{3-1}$$

where, v_k^i is the deterministic part of the utility and ε_k^i is the random part that captures the uncertainty. Different assumptions made on the deterministic term v_k^i and the error term ε_k^i could produce various types of choice models.

The deterministic term can be represented as a function of attributes of both the decision-maker and the alternative, which is given by

$$v_k^i = v_k^i(x_k^i) \tag{3-2}$$

where, x_k^i is a vector of attributes that considered for individual i and alternative k. The attribute should be a measurable quantity or a deterministic function that identified for specific applications. Equation (3-2) is normally assumed to be a linear function (Ben-Akiva & Bierlaire, 2003), for example, if n attributes are supposed,

$$v_k^i(x_k^i) = \alpha_1 x_k^i(1) + \alpha_2 x_k^i(2) + \alpha_3 x_k^i(3) + \cdots + \alpha_n x_k^i(n) = \sum_{j=1}^{n} \alpha_j x_k^i(j) \tag{3-3}$$

where $\alpha_1 \dots \alpha_n$ are parameters related to different attributes that need to be estimated. For specific transport application, assumptions on attributes of alternatives and on characteristics of travellers (see Table 3.1) could form specific deterministic part of the utility.

In terms of the error term, the distribution could be assumed as different functional forms, which could generate different categories of choice models such as acknowledged Probit and Logit models. The error term of the Probit model follows normal distribution while the Logit model is based on Gumbel distribution. Probit models suffer from the complexity and there is no analytical form of the probability function, which limits the practical usage of this kind of choice models (Bierlaire,1998). Logit models with its tractability have been the most widely used random utility model category in transport applications (Ben-Akiva & Bierlaire, 2003).

3.1.2 Multinomial Logit Model

The Multinomial Logit (MNL) model is the generalization of the binary Logit model to account for more than two alternatives. The error terms of MNL models are assumed to be independent and identically Gumbel distributed (Gumbel, 1958). The probability density function of Gumbel distribution is given by Equation (3-4) and the cumulative distribution function is given by Equation (3-5).

$$f(x) = \gamma e^{-(z+e^{-z})} \tag{3-4}$$

$$F(x) = e^{-e^{-z}} \tag{3-5}$$

where, $z = \theta(x - \mu)$, and $\theta > 0$ is the scale parameter and μ is the location parameter. The examples of Gumbel distribution are illustrated in Figure 3.1 with different selections of scale and location parameters.

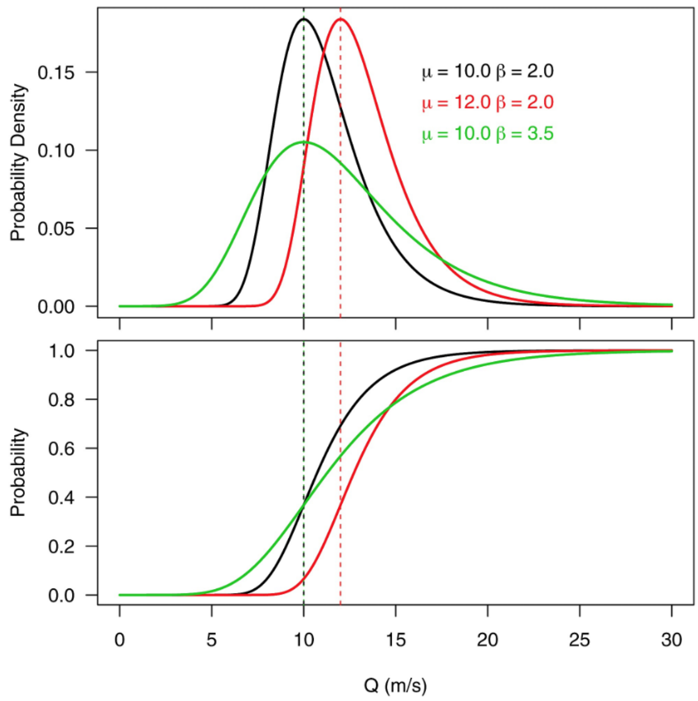


Figure 3.1 Gumbel distribution, $\beta = {}^{1}/_{\theta}$ (Tolentino et al. 2016)

Based on this assumption with the location parameter μ takes 0, the MNL choice probability of a given individual i choosing alternative k in the choice set $\mathcal{S}$ then can be represented by the formulation shown in Equation (3-6). The detailed derivation of the MNL model can be find in Ben-Akiva and Lerman (1985).

$$P^i_{k|\mathcal{S}} = \frac{e^{\theta v^i_k}}{\sum_{j\in\mathcal{S}} e^{\theta v^i_j}} \tag{3-6}$$

MNL models suffer from an important property of *Independent from Irrelevant Alternatives (IIA)*, that is, the alternatives in the choice set are independent and the probability of choosing each alternative is not influenced by the utilities of other alternatives in the choice set (Bierlaire,1998). Although MNL models are most widely used for travel choice modelling in the literature, this IIA assumption is a limitation of MNL models in the cases of route choice modelling due to the overlapping of routes in reality. Therefore, various adaptations of the MNL model (e.g. Nested Logit model, C-logit model, Cross-Nested Logit model, Hybrid Logit model) are proposed to capture the correlations between alternatives.

3.1.3 Path-Size-Based Nested Logit Model for Route Choice Modelling

The Nested Logit model that firstly proposed by Ben-Akiva (1974) is an extension of the MNL model to partially correct the IIA assumption. The choice set $\mathcal{S}$ is divided into several nests $\mathcal{S}_n$ satisfy the condition that

$$\mathcal{S} = \bigcup_n \mathcal{S}_n \qquad, and \qquad \mathcal{S}_n \cap \mathcal{S}_m = \emptyset, \qquad \forall n \neq m \tag{3-7}$$

The correlations of alternatives within each nest can be accounted for in the Nested Logit model. For the choice in the nest $\mathcal{S}_n$, the deterministic part of the utility in Equation (3-1) is corrected by including a correlation index $V^i_{\mathcal{S}_n}$ in order to reflect the correlation among alternative k and other alternatives within the nest $\mathcal{S}_n$, formed

$$u_k^i = v_k^i + V_{\mathcal{S}_n}^i + \varepsilon_k^i \tag{3-8}$$

Different models about the correlation index can be formulated for specific choice problems. In the Nested Logit model, the probability for individual i choosing alternative k within the choice set $\mathcal{S}$ can be formulated as a conditional probability form in Equation (3-9). The details about Nested Logit model can be find in Ben-Akiva and Bierlaire (2003).

$$P_{k|\mathcal{S}}^i = P_{k|\mathcal{S}_n}^i \cdot \ P_{\mathcal{S}_n|\mathcal{S}}^i \tag{3-9}$$

As for the route choice problems, the correlation index in the Nested Logit model could be formulated as a Path Size (PS) attribute to estimate the path overlapping, which forms the PS-based Nested Logit Model. The original PS attribute formulation is firstly proposed by Ben-Akiva and Bierlaire (1999), which assumes that the PS of a path is proportional to the size of its links. Thus, the PS for path k of individual i is given by

$$PS_k^i = \sum_{a \in k} \frac{L_a}{L_k} \cdot \frac{1}{\sum_{j \in \mathcal{S}_i} \delta_{aj}} \tag{3-10}$$

where, L_a is the length of link a and L_k is the length of path k. $\mathcal{S}_i$ is the path choice set considered by individual i. δ_{aj} is the incidence variable between links and paths.

The correlation part in the utility function shown in Equation (3-8) can be substitute by this PS contribute and form the new utility function:

$$u_k^i = \boldsymbol{v_k^i} + \boldsymbol{\eta} \ \ \mathbf{ln}\, \boldsymbol{PS_k^i} + \varepsilon_k^i \tag{3-11}$$

where, η is the scale parameter for the PS attribute. The MNL probability model in Equation(3-6), of which the deterministic term of utility v_k^i can be substitute by the bold part in Equation (3-11) and form the PS-based Nested Logit probability model. Bierlaire and Frejinger (2005) have provided the detailed derivation of the PS-based nested Logit model.

3.2 Doubly Dynamic Traffic Assignment (DDTA)

DTD models are capable of capturing the transient states disequilibrium and its evolution toward equilibrium induced by construction works, random events and traffic controls, which traditional equilibrium models cannot adequately describe. Watling and Hazelton (2003) state that DTD models are flexible to accommodate a wide range of behaviour rules, level of aggregation, and traffic model types. Significant effort has been dedicated to developing behaviourally sound (and sometimes sophisticated) DTD choice models with relevant considerations of information availability and user heterogeneity. However, few studies employ realistic within-day traffic dynamics or network examples beyond small-size problems (e.g. a bottleneck).

Horowitz (1984) first propose a discrete time DTD deterministic models for a two-link network based on the system-optimal principle. Friesz et al. (1994) apply a projective algorithm for the approximation of continuous-time deterministic DTD traffic evolution process. Nagurney and Zhang (1997) also form a projected dynamical system and applied Euler's method to solve it. He et al. (2010) study the continuous-time deterministic approach and the DTD traffic evolution process towards dynamic user equilibrium. On the other hand, stochastic DTD models are suited for modelling traffic variability observed in real-world networks, and are able to represent both transient states and steady-state fluctuations. Cantarella and Watling (2016) present a general stochastic DTD process considering travellers' habits in route choice behaviour. Xiao and Lo (2016) consider a microscopic, stochastic process model with departure time choice evolution incorporating information sharing via social media. Wang et al. (2016) propose approximate models for DTD traffic evolution using sensitivity analysis of the (static) network loading process. Rambha and Boyles (2016) propose a stochastic day-to-day dynamic route choice model and then present an average cost Markov decision process to minimise the total network travel time by dynamic pricing. Bifulco et al. (2016) develop a DTD DTA model to capture the effects of advanced traveller information system to departure time choices under recurrent network conditions. Guo and Szeto (2018) propose a DTD dynamic system to model the decision-making processes of travellers and transportation authority as well as their interactions under both private and public transport system. Watling and Hazelton (2018) propose asymptotic approximations to study the transient process in DTD traffic dynamics by relying solely on the knowledge of the equilibrium state without the need for simulation.

The aforementioned DTD literature focuses on the learning and decision making of travellers, with simplified, static within-day traffic models. Within-day dynamics, on the supply side of the traffic system, are just as important since they inform and influence travellers' decisions on an iterative basis. Cascetta and Cantarella (1991) employ a traffic queuing model to describe link and network delays. Friesz et al. (1994) and Balijepalli et al. (2007) employ the affine link delay function to propagate link flows and delays. Iryo (2016), Guo et al. (2017) and Liu et al. (2017) focus on a single bottleneck following Vickrey's queuing model. Only a few studies consider both within-day and day-to-day traffic dynamics; i.e. doubly-dynamic traffic assignment (Cantarella and Astarita 1999; Balijepalli and Watling, 2007; Friesz et al, 2011; Szeto and Jiang, 2011). These doubly-dynamic DTA models are applied to small traffic networks and only the route choice behaviour is considered. Large-scale implementation of such doubly dynamic models, while capturing important and realistic travel choice behaviours and congestion phenomena, remains a key step towards their applications.

This chapter proposes dual-timescale (both within-day and day-to-day) models of dynamic traffic assignment (DTA) with travel demand as well as network properties evolution, which will serve as network traffic modelling for the M&R planning problems. This is among the first in the literature, a doubly-dynamic DTA model with simultaneous route and departure time choices.

3.3 DDTA Modelling Framework

The proposed DDTD modelling framework is comprised of DTD learning and travel choice models, and a within-day dynamic network loading (DNL) model. As illustrated in Figure 3.2, the DTD model consists of two parts: formulation of perceived travel costs and SRDT choice model. The former presents two different models, one of which involves the information sharing behaviour; the latter has three versions, one of which is the proposed BR-based choice model. As the travel cost perception and SRDT choice models are sequential, in total six different DTD models will be proposed in this chapter.

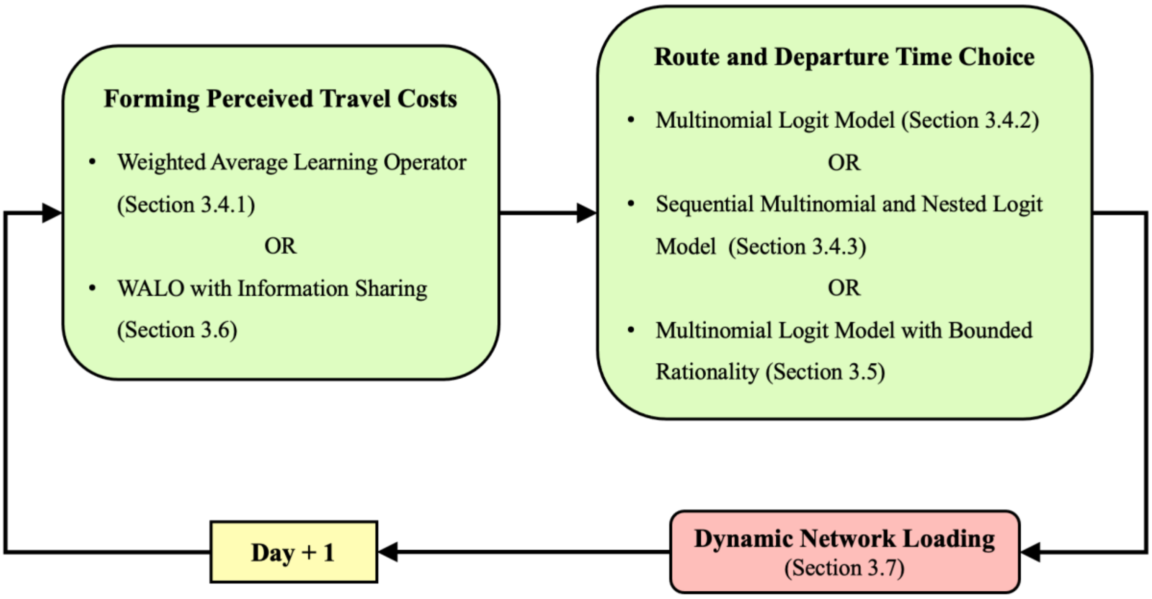


Figure 3.2 Structure and logic flow of the proposed DDTA models

3.4 Notation and Essential Background

This thesis employs a route-based assignment approach, as opposed to link-based models (e.g., Ran and Boyce, 1996; He et al., 2010; Long et al., 2018), which means that the route set for each O-D pair is pre-defined. The proposed DTD DTA models use a route set generation scheme following Friesz et al. (1992, 1993). Specifically, the Frank-Wolfe algorithm is applied to generate a priori route sets, by making the network increasingly congested through uniformly scaling up the O-D demand matrix, and saving route information produced by the F-W algorithm. This method is intrinsically similar to the well-known technique of column generation as they only calculate routes as they are used. Route sets generated in this way encapsulate essential network information such as O-D demand table, network topology and interactions of O-D flows through congestion; they are arguably more reasonable than others such as those produced by k-shortest-path algorithms, which only consider free-flow link travel times with no consideration of the distribution of O-D demands or their interactions on the network.

This section begins by listing the key notations employed in this chapter.

Parameters/variables

t: Departure time window

s: Within-day time parameter[2]

τ: Day-to-day time parameter

r: Route taken by travelers

w: Origin-destination (O-D) pair

d^w: Demand between O-D pair w

$f_{(r,t)}(\tau)$: Departure volume along $r \in R$ at departure window t on day τ

$\bar{C}_{(r,t)}(\tau)$: Perceived cost for route $r \in R$ and departure time t on day τ

$C_{(r,t)}(\tau)$: Experienced (actual) cost for route $r \in R$ and departure time t on day τ

Sets

T: Set of within-day departure windows

R: Set of all routes in the network

[2] Here, the parameter t represents departure time window (e.g. 8:00-8:30), while s is on a smaller time scale (e.g. 15 seconds) which is used to represent traffic dynamics in the dynamic network loading procedure discussed in Section 3.8.

W: Set of all O-D pairs in the network

R^w: Set of routes between O-D pair w

3.5 SRDT DTD DTA Model with Imperfect Information

This thesis invokes the notion of perceived travel cost to account for travel experiences that have been accumulated over the course of the daily congestion game. Throughout the rest of the thesis, travellers make choices on route r and departure time t.

3.5.1 Formulation of Perceived Travel Cost

To this end, this section applies the weighted average learning operator (Cascetta 1989; Ouyang, 2007) for calculating the perceived travel cost, denoted $\bar{C}_{(r,t)}(\tau)$ for route r and departure window t:

$$\bar{C}_{(r,t)}(\tau) = \frac{1}{s(\lambda)}\Big(C_{(r,t)}(\tau-1) + \lambda C_{(r,t)}(\tau-2) + \lambda^2 C_{(r,t)}(\tau-3) + \cdots + \lambda^{M-1} C_{(r,t)}(\tau - M)\Big) \qquad \forall r \in R^w, t \in T \tag{3-12}$$

where the parameter $\lambda \in (0,1)$ and its powers represent the weights of past days' experienced costs; earlier trips are envisaged to have less influence on the present travel choices, and therefore carry less weight in Equation (3-12). M is the number past days that influences present day's decision. $1/s(\lambda)$ is a normalization factor where $s(\lambda) = \sum_{i=1}^{M} \lambda^{i-1}$. Equation (3-12) specifies the dynamics for the perceived cost associated with the choice pair (r,t).

In the following two sections, two different choice models are presented based on such perceived costs.

3.5.2 Multinomial Logit Choice Model (Base Model I)

In the first choice model, each alternative is treated as a route-and-departure-time pair

$(r,t) \in R^w \times T$, and the perceived costs defined in Equation (3-12) as the disutility of this alternative. Following the random utility theory, this section defines the expected travel cost as the sum of the perceived cost and a random observation error term:

$$\hat{C}_{(r,t)}(\tau) = \bar{C}_{(r,t)}(\tau) + \epsilon^w_{(r,t)} \qquad \forall r \in R^w, t \in T \tag{3-13}$$

In case the opposite of the error terms, $-\epsilon^w_{(r,t)}$, are independent and identically Gumbel distributed, the probability of choosing (r,t) is given by the multinomial Logit model:

$$\begin{aligned} P^w_{(r,t)}(\tau) &= \Pr\left\{\bar{C}_{(r,t)}(\tau) + \epsilon^w_{(r,t)} \leq \bar{C}_{(r',t')}(\tau) + \epsilon^w_{(r\prime,t\prime)} \qquad \forall (r',t') \neq (r,t)\right\} \\ &= \frac{\exp\left(-\theta \bar{C}_{(r,t)}(\tau)\right)}{\sum_{(r',t')} \exp\left(-\theta \bar{C}_{(r',t')}(\tau)\right)} \qquad \forall r \in R^w, t \in T \end{aligned} \tag{3-14}$$

where $\theta > 0$ is the scale parameter of the Gumbel distribution. Given such probabilities, the departure volumes can be calculated as

$$f_{(r,t)}(\tau) = d^w \cdot P^w_{(r,t)}(\tau) \qquad \forall r \in R^w, t \in T \tag{3-15}$$

The model (3-12), (3-14) and (3-15) is called Base Model I in this thesis.

By assuming that the departure time choice and route choice are independent, Base Model I, conforms to the conventional notion of SRDT choices in dynamic traffic assignment (Friesz et al., 1993), where travelers' collective choices are represented by the macroscopic quantity of route departure rates $h_r(t)$, where r and t denote route and departure time, respectively. The fact that $h_r(t)$ can be any square-integrable function (or a bounded vector in a discrete-time setting) as long as the demand conservation constraint is satisfied suggests that the departure time and route choices are independent. For this reason, Model Base I could be treated as a natural extension of the SRDT notion widely studied in the literature (e.g. Friesz et al. 1993; Szeto and Lo, 2004; Han et al., 2015), when a stochastic choice model based on the random utility theory is employed.

3.5.3 Sequential Choice Model with Multinomial and Nested Logit Models (Base Model II)

Despite the strong ties to other notions of SRDT choices in the literature, Base Model I has some limitations. For example, in reality travellers may consider departure time and route choices sequentially, rather than independently. Furthermore, the multinomial Logit model suffers from the IIA (Independence from Irrelevant Alternatives) assumption as mentioned in Section 3.1.2, which leads to unrealistically decorrelated perception errors when alternatives have substantial overlap (e.g. routes that share a number of links).

To address these limitations, the second choice model presented in this section assume that travellers make decisions about departure time and route sequentially based on Nested Logit Model introduced in Section 3.1.3. That is, the probability of choosing the pair (r,t) is given by

$$\begin{aligned} P_{(r,t)}^{w}(\tau) &= \Pr\{\text{choose departure window } t\} \\ &\quad \cdot \Pr\{\text{choose route } r \mid \text{departure window } t\} \\ &= P_{t}^{w}(\tau) \cdot P_{(r|t)}^{w}(\tau) \qquad r \in R^{w}, t \in T \end{aligned} \tag{3-16}$$

In particular, a traveller makes a departure-time choice based on the following perceived cost associated with the departure time $t \in T$:

$$\bar{C}_{t}^{w}(\tau) \doteq \frac{1}{|R^{w}|} \sum_{r \in R^{w}} \bar{C}_{(r,t)}(\tau) \qquad \forall\ t \in T \tag{3-17}$$

Equation (3-17) means that the perceived cost of departure time window t is the arithmetic mean over all the perceived route costs with the same departure window. The departure-time choice is described by the following multinomial Logit model:

$$P_t^w(\tau) = \frac{\exp(-\theta_1 \bar{C}_t^w(\tau))}{\sum_{t'} \exp\left(-\theta_1 \bar{C}_{t'}^w(\tau)\right)} \qquad \forall\ t \in T, w \in W \tag{3-18}$$

where $\theta_1 > 0$ is the scale parameter.

As a variation of Equation (3-17), this section also considers the case where routes with lower disutilities are given higher weights within a departure window. In other words, traveller's give more considerations to the better routes when making decisions on their departure times. Specifically, the following form may be considered:

$$\bar{C}_t^w(\tau) \doteq \sum_{r \in R^w} \omega_{(r,t)} \bar{C}_{(r,t)}(\tau), \qquad \omega_{(r,t)} = \frac{1/\bar{C}_{(r,t)}(\tau)}{\sum_{r' \in R^w} 1/\bar{C}_{(r',t)}(\tau)} \qquad \forall\ t \in T \tag{3-19}$$

which reduces $\bar{C}_t^w(\tau)$ to the harmonic mean of $\{\bar{C}_{r,t}(\tau), r \in R^w\}$:

$$\bar{C}_t^w(\tau) \doteq \frac{|R^w|}{\sum_{r \in R^w} 1/\bar{C}_{(r,t)}(\tau)}, \qquad \forall\ t \in T \tag{3-20}$$

This variant will be tested later in Section 4.4 in comparison with (3-17).

Once the departure window t is chosen, the probability of choosing route $r \in R^w$ is expressed by the nested Logit model instead of the multinomial Logit model to correct the IIA assumption and account for the correlations in the perception errors for different route alternatives (Bierlaire and Frejinger, 2005). For this purpose, the Path Size formulation (Ben-Akiva and Bierlaire, 2003) is employed as follows. This thesis defines the Path Size as an attribute of each route $r \in R^w$:

$$\mathrm{PS}_r = \sum_{a \in r} \frac{L_a}{L_r} \cdot \frac{1}{\sum_{r' \in R^w} \delta_{ar'}} \tag{3-21}$$

where the route r is expressed as a set of arcs a that it traverses; the lengths of the arc and the route are denoted L_a and L_r, respectively. Moreover, $\delta_{ar} = 1$ if $a \in r$ and 0 otherwise.

The static attribute PS_r reflects the level of overlap (number of shared links) between two routes, and the corrected route choice probability reads

$$P^w_{(r|t)}(\tau) = \frac{\exp\left(-\theta\left(\bar{C}_{(r,t)}(\tau) + \eta \ln \mathrm{PS}_r\right)\right)}{\sum_{r'} \exp\left(-\theta\left(\bar{C}_{(r',t')}(\tau) + \eta \ln \mathrm{PS}_{r'}\right)\right)} \qquad r \in R^w \tag{3-22}$$

where $\eta > 0$ is the weight for the Path Size attribute. The detailed derivation of the PS-based nested Logit model can be found in Ben-Akiva and Bierlaire (2003) and Bierlaire and Frejinger (2005). Finally, the departure volumes are given by

$$f_{(r,t)}(\tau) = d^w \cdot P^w_t(\tau) \cdot P^w_{(r|t)}(\tau) \qquad \forall r \in R^w, w \in W, t \in T \tag{3-23}$$

The model (3-12) and (3-17)-(3-23) is called Base Model II in this thesis.

3.5.4 Steady States of Base Model I and II

This section analyses the steady states of the proposed two DTD models, and show that they correspond to relevant notions of stochastic dynamic user equilibrium (SDUE) with SRDT choices. It begins by defining such equilibria for the choice behaviour elaborated in Section 3.5.2 (SRDT-SDUE-I) and Section 3.5.3 (SRDT-SDUE-II).

Definition (SRDT-SDUE-I). *A path departure rate vector* $\left(f^*_{(r,t)}: r \in R^w, t \in T\right)$ *corresponds to a SRDT-SDUE-I solution if it satisfies the following:*

$$f^*_{(r,t)} = d^w \cdot \frac{\exp\left(-\theta C^*_{(r,t)}\right)}{\sum_{(r',t')} \exp\left(-\theta C^*_{(r',t')}\right)}, \qquad \forall r \in R^w, w \in W, t \in T \tag{3-24}$$

where $C^*_{(r,t)}$ *is the travel cost associated with route* r *and departure time* t*, which is given by the DNL sub-model.*

Definition (SRDT-SDUE-II). *A path departure rate vector* $\left(f^*_{(r,t)}: r \in R^w, t \in T\right)$ *corresponds to a SRDT-SDUE-II solution if it satisfies the following:*

$$f^*_{(r,t)} = d^w \cdot \frac{\exp(-\theta_1 \bar{C}_t^{w,*})}{\sum_{t'} \exp\left(-\theta_1 \bar{C}_{t'}^{w,*}\right)} \cdot \frac{\exp\left(-\theta\left(C^*_{(r,t)} + \eta \ln \mathrm{PS}_r\right)\right)}{\sum_{r'} \exp\left(-\theta\left(C^*_{(r',t')} + \eta \ln \mathrm{PS}_{r'}\right)\right)} \qquad (3\text{-}25)$$

$$\forall r \in R^w, w \in W, t \in T$$

where $\bar{C}_t^{w,*} = \frac{1}{|R^w|} \sum_{r \in R^w} C^*_{(r,t)}$, $C^*_{(r,t)}$ *is the travel cost associated with route* r *and departure time* t,PS_r *is given in Eqn.*(3-21).

Proposition (steady states of Base Models I). *If the DTD process detailed in Base Models I converges, then the steady state is a SRDT-SDUE-I solution. In other words, if*

$$f_{(r,t)}(\tau) = f_{(r,t)}(\tau - 1) = f_{(r,t)}(\tau - 2) = \cdots = f_{(r,t)}(\tau - M), \quad \forall r \in R^w, w \in W, t \in T \qquad (3\text{-}26)$$

then there must hold

$$f_{(r,t)}(\tau) = d^w \cdot \frac{\exp\left(-\theta C_{(r,t)}(\tau)\right)}{\sum_{(r',t')} \exp\left(-\theta C_{(r',t')}(\tau)\right)}, \qquad \forall r \in R^w, w \in W, t \in T \qquad (3\text{-}27)$$

Proof. Given (3-26), it must have that $C_{(r,t)}(\tau) = C_{(r,t)}(\tau - 1) = \cdots = C_{(r,t)}(\tau - M), \forall r \in R^w, t \in T$. Therefore, Eqn. (3-12) yields $\bar{C}_{(r,t)}(\tau) = C_{(r,t)}(\tau - 1) = \cdots = C_{(r,t)}(\tau - M)$. By definition (3-15), it have:

$$f_{(r,t)}(\tau) = d^w \cdot \frac{\exp\left(-\theta \bar{C}_{(r,t)}(\tau)\right)}{\sum_{(r',t')} \exp\left(-\theta \bar{C}_{(r',t')}(\tau)\right)} = d^w \cdot \frac{\exp\left(-\theta C_{(r,t)}(\tau)\right)}{\sum_{(r',t')} \exp\left(-\theta C_{(r',t')}(\tau)\right)}$$

Following the same proof, it readily deduce:

Proposition (steady states of Base Models II). *If the DTD process detailed in Base Models II converges, then the steady state is a SRDT-SDUE-II solution.*

An important theoretical issue is the convergence of Base Models I & II to their respective equilibrium. However, this is a very difficult problem due to the lack of analytical and provable regularity conditions of the network delay operator. In particular, the uniqueness of the aforementioned SDUEs and the convergence of the proposed DTD models are dependent on the generalized monotonicity of the delay operator (Szeto and Lo, 2004; Friesz et al., 2011; Han et al., 2019), which, in the case of large-scale and arbitrary traffic networks, are difficult to prove. In fact, they are unlikely to hold. Furthermore, the convergence is also dependent on model parameters such as θ in the Logit model, as well as the initial traffic state. While these theoretical problems cannot be solved in this thesis, the numerical results do present insightful findings on the behaviours of the DTD processes. As clarified at the beginning of this chapter, this work is intended for modelling scenarios where a disequilibrium model is required (such as adaptive network traffic control or management, transient congestion), where a flexible tool for large-scale network modelling and simulation is missing.

3.6 DTD DTA Model with Bounded Rationality

Building on the Base Model I presented in Section 3.5.2, this section further considers the scenario where some travellers may prefer to maintain their previous choices if the expected benefits of switching to alternatives is insignificant. This choice behaviour has been well documented as bounded rationality (BR) in many existing studies (see Section 3.6.1), but none has investigated BR in a doubly dynamic context while incorporating imperfect and incomplete information.

Remark. *BR is combined with Base Model I instead of Base Model II for the following reasons. (1) It is mathematically complicated to incorporate the notion of BR in Base Model II, given its sequential choice structure. This could be a future study. (2) The combination of Base Model I + BR offers better generality and transferability to other types of DTD models, such as DTD models with static traffic flow.*

3.6.1 Review on Bounded Rationality in Traffic Assignment Models

Conventional user equilibrium type models are based on the behavioural assumption that travellers make rational choices by aiming to minimise their experienced costs. In reality, however, travellers do not always follow the least costly alternative, a phenomenon coined "bounded rationality" (BR) (Simon, 1957; Mahmassani and Chang, 1987). This is corroborated by empirical studies and experiments (Avineri and Prashker, 2004; Zhu and Levinson, 2012). A growing literature on BR in traffic modelling has linked this behavioural mechanism to traffic equilibrium analysis. Since the work of Mahmassani and Chang (1987), BR-based user equilibrium models have been studied as simulation-based DTA (Mahmassani and Jayakrishnan, 1991; Hu and Mahmassani, 1997; Mahmassani and Liu, 1999; Mahmassani et al., 2005) and static traffic assignment (Han and Timmermans, 2006; Gifford and Checherita, 2007; Lou et al., 2010; Guo and Liu, 2013; Watling et al., 2018).

BR has also received increased attention in analytical dynamic traffic assignment. Ridwan (2004) applies fuzzy system theory to study BR in dynamic traffic modelling. Szeto and Lo (2006) propose a dynamic user equilibrium model with boundedly rational route choice behaviour, and apply a heuristic route-swapping algorithm to solve the BR-DUE problem. Ge and Zhou (2012) develop a boundedly rational route choice DUE model with indifference band determined endogenously; but no solution method is provided. Han et al. (2015) propose a BR-DUE model that simultaneously captures route and departure time choices. Solution existence and characterization, as well as three different computational methods are proposed by the authors.

A few studies have adapted the BR notion to DTD models. Guo and Liu (2011) is among the first to propose boundedly rational DTD models with a static, route choice within-day component. The convergence towards a BR user equilibrium and its stability property are later comprehensively analysed by Di et al. (2015) and Ye and Yang (2017). Guo et al., (2017) investigate a different type of BR-based DTD models with departure time choice at a single bottleneck. Most of existing BR-based DTD models have a static within-day component, and the doubly dynamic ones only focus on departure time choice at a single bottleneck. There does not exist any BR extension of the doubly dynamic DTD models with SRDT choices. Furthermore, all these BR-based DTD dynamics are restricted to deterministic choice models, relying primarily on projective or route-swapping type dynamics (Nagurney and Zhang, 1997; Smith, 1984) assuming complete and perfect travel information.

This chapter proposes the first boundedly rational doubly dynamic DTA model with SRDT choices. The BR is incorporated in the random utility component of the choice model, which allows travellers' random perception errors to interact with the indifference band in the formulation of the DTD model.

3.6.2 DTD DTA Model with Bounded Rationality

For modelling purposes, the BR is often represented as an indifference band (Mahmassani and Chang, 1987; Han et al., 2015), denoted $\delta \geq 0$, which measures the acceptable difference between the expected cost of a reference choice, and the minimum expected cost among all alternatives. In other words, a traveller will not switch to alternatives on the next day if such a difference is smaller than δ. To quote the taxonomy of Xu et al. (2017), the type of BR choice considered here is status quo-dependent in the sense that travellers' choices are in reference to their choice on the previous day (the status quo) instead of the best (most cost-effective) alternative.

Fix a given choice pair $(r, t) \in R^w \times T$. At an atomic (microscopic) level, the BR choice principle can be described as follows: a traveler with a choice of (r, t) on day $\tau - 1$ does not alter his/her route and departure time choices on day τ provided that the expected costs satisfy

$$\hat{C}_{(r,t)}(\tau) - \hat{C}_{(r',t')}(\tau) \leq \delta \qquad \forall (r', t') \neq (r, t) \tag{3-28}$$

means that no alternative can offer a gain larger than δ. Therefore, on a macroscopic level, the probability of not changing the travel choice on day τ (that is, keep choosing (r, t)), denoted $\phi^w_{(r,t)}(\tau)$, is:

$$\begin{aligned}\phi_{(r,t)}^{w}(\tau) &= \Pr\left\{\hat{C}_{(r,t)}(\tau) - \hat{C}_{(r',t')}(\tau) \le \delta \qquad \forall (r',t') \neq (r,t)\right\} \\ &= \Pr\left\{\bar{C}_{(r,t)}(\tau) - \delta + \epsilon_{(r,t)}^{w} \le \bar{C}_{(r',t')}(\tau) + \epsilon_{(r,t)}^{w} \qquad \forall (r',t') \neq (r,t)\right\} \\ &= \frac{\exp\left(-\theta\left(\bar{C}_{(r,t)}(\tau) - \delta\right)\right)}{\exp\left(-\theta\left(\bar{C}_{(r,t)}(\tau) - \delta\right)\right) + \sum_{(r',t')\neq(r,t)} \exp\left(-\theta \bar{C}_{(r',t')}(\tau)\right)}\end{aligned} \tag{3-29}$$

Here, the last equality is established by viewing $\bar{C}_{(r,t)}(\tau) - \delta$ as the disutility associated with the choice (r,t). Equation (3-29) is seen as an extension of the binary logit model with indifference (Krishnan, 1977).

On the other hand, a traveller with a choice of (r,t) on day $\tau - 1$ choses $(r_1,t_1) \neq (r,t)$ on day τ if and only if

$$\begin{aligned}&\hat{C}_{(r_1,t_1)}(\tau) < \hat{C}_{(r,t)}(\tau) - \delta \quad \text{and} \\ &\hat{C}_{(r_1,t_1)}(\tau) < \hat{C}_{(r',t')}(\tau) \qquad \forall (r',t') \neq (r,t) \text{ or } (r_1,t_1)\end{aligned} \tag{3-30}$$

Based on (3-30) and calculation (3-29), it is not difficult to conclude that the choice modelling, among travellers who chose (r,t) on day $\tau - 1$, amounts to a multinomial Logit model where the disutility of (r,t) is revised to be $\bar{C}_{(r,t)}(\tau) - \delta$, and the systematic disutilities of other alternatives remain unchanged. Note that each choice pair (r,t) is associated with such a multinomial Logit model. Therefore, the departure volume for the choice (r,t) on day τ can be calculated as

$$\begin{aligned}&f_{(r,t)}(\tau+1) \\ &= \phi_{(r,t)}^{w}(\tau) \cdot f_{(r,t)}(\tau) \\ &+ \sum_{(r',t')\neq(r,t)} \frac{\exp\left(-\theta \ \bar{C}_{(r,t)}(\tau)\right)}{\exp\left(-\theta\left(\bar{C}_{(r',t')}(\tau) - \delta\right)\right) + \sum_{(r_1,t_1)\neq(r',t')} \exp\left(-\theta \bar{C}_{(r_1,t_1)}(\tau)\right)} \cdot f_{(r',t')}(\tau)\end{aligned} \tag{3-31}$$

where the first term on the right-hand side represents the amount of travellers who stick with their previous choice (r, t) due to BR, and the second summation term represents travelers who switch to (r, t) from their previous choices. Figure 3.3 is used to illustrate (3-31), where three alternatives, A, B and C are considered. Within each alternative there are two types of flows: sticking with previous choice, which is denoted by the curved arrows and represented as the first term of (3-31), and switching to other alternatives, which is denoted by the straight arrows and represented as the second term of (3-31).

In the derivation of the BR DTD DTA model, the key idea lies in the incorporation of the indifference band δ into the random utility model, namely (3-28), (3-29) and (3-30). The same modelling framework can be applied to other types of DTD models, such as route choice DTD models with static traffic flow model.

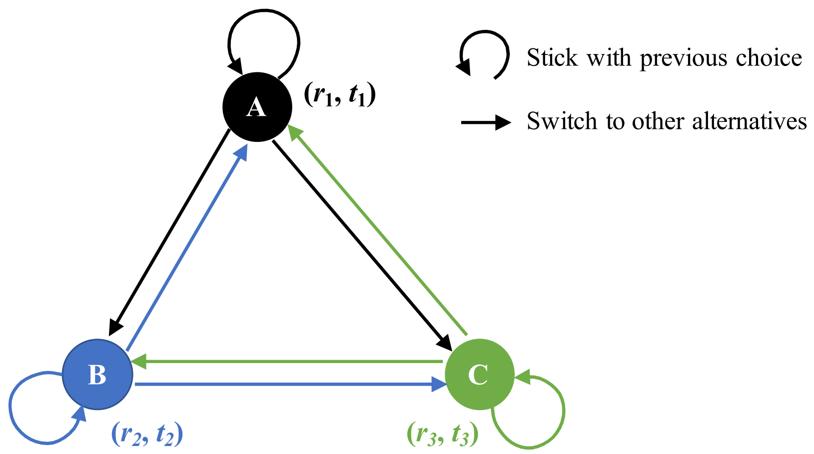


Figure 3.3 Illustration of the DTD model with bounded rationality

3.7 DTD DTA Model with Information Sharing Behaviour

In this section, information sharing is factored into travellers' route and departure time decisions. According to the literature review in Section 3.7.1, there lacks a computationally efficient macroscopic modelling counterpart of information sharing that could suitable for simulating large-scale dynamic traffic networks. The proposed model in this section will bridge this gap.

3.7.1 Review on Information Sharing Behaviour in DTD Models

Travelers make route and departure time choices based on their perceived travel costs, which directly rely on the levels of availability, relevance, and reliability of travel information they receive. Traditional traffic assignment models tend to assume that travellers have complete information of all other alternatives (Cascetta and Cantarella, 1993; Cantarella and Cascetta, 1995; Watling and Hazelton, 2003; Watling and Cantarella, 2013; Cantarella and Watling, 2016), which is an ideal situation compared to a real-world traffic system. On the other hand, the emergence of advanced traveller information system (ATIS) as well as social media platforms offer travellers opportunity to perceive parts of the traffic network beyond what they experience on a daily basis, thereby affecting their daily travel choices to a considerable degree. Properly representing the mechanisms of information dissemination and collection thus becomes a crucial part of traffic assignment modelling.

While information incompleteness can be partially taken into account using the notion of perception error of travel costs in a stochastic assignment framework, it is still a meaningful and important undertaking to explicitly model different levels of information availability and sharing behaviour. Iryo (2016) develops a deterministic DTD model that explicitly incorporates individual information collection behaviour in their daily adjustment. This is done at a microscopic (agent-based) level. Under some restrictive assumptions (e.g. a single user group, among others), the agent-based dynamic is aggregated to derive the macroscopic counterpart as an ordinary differential equation. Xiao and Lo (2016) propose a general framework for DTD commuters' departure time choice, which investigated the influence of friends' information sharing by social media. The day-to-day learning process is modelled with a Bayesian learning theory. Wei et al., (2016) propose a microscopic route choice behaviour based on information shared from other travellers, before converting it to a macroscopic traffic flow model, which resembles Smith's proportional route-swapping mechanism (Smith, 1984). Zhang et al. (2018) study the effects of travel information collected from friends on commuters' DTD route choice adjustment based on the cumulative prospect theory. All these DTD models approach information sharing from an agent-based (i.e. microscopic) perspective, which offers valuable insights at individual and system levels. However, there is a lack of generalizable and computationally efficient macroscopic modelling counterpart that is immediately suitable for simulating large-scale dynamic traffic networks. This chapter aims to address this issue by proposing an intuitive mathematical model to incorporate information sharing behaviour while retaining a computationally tractable form for large-scale simulations.

3.7.2 DTD DTA Model with Information Sharing Behaviour

In order to factor information sharing into travellers' route and departure time decisions, the notion of information reliability is invoked, which depends on the number of travellers using each alternative.

Fix a choice pair $(r,t) \in R^w \times T$. The information sharing behavior can be described as follows. Travelers choosing (r,t) on day $\tau - 1$ share their experienced travel cost $C_{(r,t)}(\tau - 1)$ within a group, which is defined here as the set of travellers between the same O-D pair w.[3] Such information will be utilized, with a weight $g^w_{(r,t)}(\tau - 1)$, by the rest of the group to inform their own perceived costs. Here assume that the weight

$$g^w_{(r,t)}(\tau - 1) = G\left(\frac{f_{(r,t)}(\tau - 1)}{d^w}\right), \qquad \forall (r,t) \in R^w \times T \tag{3-32}$$

where $G(\cdot)$ is an increasing function that satisfies $G(0) = 0, G(1) = 1$; it is a function of the traveller proportion who use (r,t) on day $\tau - 1$. Given such weights, the perceived travel cost on day τ is given by

$$\bar{C}_{(r,t)}(\tau) = \frac{1}{s(\lambda, g)} \sum_{n=\tau-M}^{\tau-1} g^w_{(r,t)}(n) \cdot \lambda^{\tau-n-1} \cdot C_{(r,t)}(n) \qquad \forall (r,t) \in R^w \times T \tag{3-33}$$

---

[3] In fact, the group can be arbitrarily defined without affecting the model formulation. Here treat travellers between each O-D pair as a group for simplicity.

which is adapted from (3-12) by adding the multiplicative weights. Here, the normalization factor

$$s(\lambda, g) = \sum_{n=\tau-M}^{\tau-1} g_{(r,t)}^{w}(n) \cdot \lambda^{\tau-n-1} \tag{3-34}$$

Intuitively, model (3-33) indicates that the cost of certain pair (r, t) perceived by the group is accumulated from the past experienced costs; and the more travelers use (r, t) on certain day, the more significantly their collective experience affects the overall perception of (r, t). This is a reasonable assumption as the reliability of travel information depends on the volume of travellers who report it. Moreover, the functional form of G is likely to be non-linear and may be piece-wise defined.

One choice for the weighting function is $G(x) = x^n$ where $x \in [0,1]$, $n > 0$ (other choices of such a function will be tested later in Section 4.4. Here, the argument x represents the percentage of travelers within a group (O-D pair) who chose (r, t) on a given past day. The stipulation that $G(x)$ is monotonically increasing reflects the reasonable assumption that more travellers choosing (r, t) leads to higher reliability of their reported information, which receives larger weight in forming individuals' perceptions towards (r, t). When $n = 1$, the weights are proportional to the corresponding percentages. For $n > 1$, the travelers are prone to information reported by larger crowds, and tend to ignore experienced costs reported by smaller crowds. And such a tendency will be intensified as n becomes larger. For $0 < n < 1$, the tendency is reversed in the sense that even a small crowd could influence the perception to a degree not significantly lower than what a much larger crowd can achieve. See Figure 3.4. In the case where $n = 0$, Equation (3-33) reduces to the case with complete travel information (3-12). Therefore, the parameter n can be treated as a simplified representation of the strength of communication among travellers. Different values of n correspond to different behavioral situations, and are worthy of further investigation beyond this thesis. More numerical insights regarding n will be provided in Section 4.4; in particular, n has an impact on the daily oscillation of network traffic and travellers' perceptions, and such impact is case dependent.

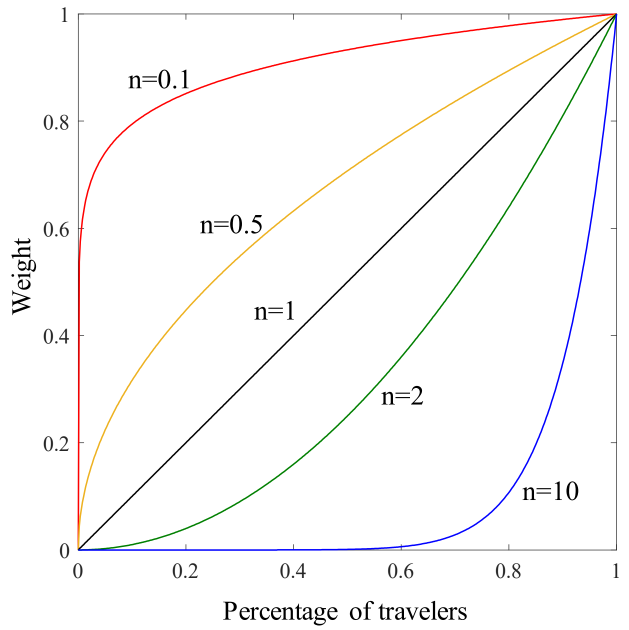


Figure 3.4 Function $G(x) = x^n$ that expresses the weight (reliability) of experienced information as a function of percentage of travellers that chose (r, t).

The proposed macroscopic information sharing behaviour is articulated at the travel cost perception level. This may be immediately applied in conjunction with the travel choice models discussed in Sections 3.5 and 3.6 and; see Figure 3.2.

3.8 Dynamic Network Loading for Within-day Modelling

Section 3.5, 3.6, 3.7 present a learning and decision-making framework for daily adjustment of travel choices in terms of route and departure time. In other words, it illustrates how the experienced travel costs on day $\tau - 1$, together with the perceived costs accumulated from past experience, can jointly affect travelers' decisions on the next day τ, that is, the day-to-day dynamics. The within-day dynamics, on the other hand, determines the physical states of the traffic network and experienced travel costs on day τ, which allows the process to continue towards the next day (see Figure 3.2). The within-day component of the proposed doubly-dynamic model is, in effect, a dynamic network loading (DNL) model (Friesz et al., 1993). The DNL procedure aims at describing and predicting the dynamic evolution of traffic flows and congestion on a road network consistent with traffic flow theory and established route and departure time choices of travellers.

3.8.1 Dynamic Network Loading (DNL)

Dynamic network loading (DNL) can be viewed as a problem capturing the relationship between traffic flow dynamics and travel delays, via modelling link (homogeneous road segments) flow dynamics, node (intersections and links' boundary) flow dynamics, flow propagation, link delay and path delay. Link delays which depends on the link flows could construct path delays, delays on paths in turn can influence flows on links that the path travelled. As for the model of flows on links, Lighthill and Witham (1955) and Richards (1956) proposed the well-know LWR kinematic waves model based on the fundamental diagram in which flow is a function of density such as in Greenshields (1935). Daganzo (1994, 1995) presented a cell transmission model (CTM) for a single origin destination then extended the model to a network level. Further second order models where introduce inertia into the model has been proposed such as in Payne (1971). For flow passing nodes, for example Daganzo (1995) and Lebacque (1996) proposed the first order node flow models.

The DNL model aims at describing and predicting the dynamic evolution of traffic flows and congestion on a road network consistent with traffic flow theory and established route and departure time choices of travellers. This is done by achieving the general components of DNL models as follows (Han et al., 2019). The DNL procedure is usually performed under the first-in-first-out (FIFO) principle (Szeto and Lo, 2006).

- some form of link and/or path dynamics;
- an analytical relationship between flow/speed/density and link traversal time
- flow propagation constraints;
- a model of junction dynamics and delays;
- a model of path traversal time; and
- appropriate initial conditions.

As mentioned in the introduction, the majority of DTD models focus on developing behaviourally sound travel choice models while simplifying the within-day component by either resorting to static flow representation, or employing relatively simple dynamic traffic flow models in small networks. For the within-day dynamics, this thesis employs a *dynamic network loading* (DNL) procedure based on the Lighthill-Whitham-Richards (LWR) fluid dynamic model (Lighthill and Whitham, 1955; Richards 1956). This macroscopic perspective of dynamic traffic flow is chosen here not only for its widely recognized capabilities of capturing realistic dynamic traffic network phenomena including shock wave, physical queues, and vehicle spillback, but also for its consistency with the macroscopic travel choice and information sharing models inherent in the day-to-day component. The LWR type kinematic wave model has been widely applied to DTA problems (Han el al., 2015; Garavello et al., 2016; Bliemer et al., 2017), sometimes in its discrete or variational forms such as the cell transmission model (Daganzo, 1994;1995), link transmission model (Yperman et al., 2005), and double-queue model (Osorio et al., 2011). Nie and Zhang (2005), Garavello et al. (2016) and Han et al. (2016) provided a review of relevant literature and computational examples. Individual travellers' route and departure time choices will be represented in a macroscopic way as path departure rates, and the within-day traffic dynamics amount to the DNL procedure, which predicts the corresponding travel costs including travel time and arrival penalties (Friesz et al., 1993).

3.8.2 DNL Model Notations

In view of the models proposed in Section 3.5, 3.6, 3.7, the main purpose of DNL is to numerically evaluate the experienced cost $C_{(r,t)}$ for all $r \in R^w$, $w \in W$, $t \in T$ with given departure profile $f_{(r,t)}$, $r \in R^w$, $w \in W$, $t \in T$. This thesis employs the variational formulation of the Lighthill-Whitham-Richards (LWR) model known as the Lax-Hopf formula (Han et al., 2016), and the DNL model formulated as a system of differential algebraic equations.

Let $s = 1, 2, 3, \ldots$ be the discrete time steps with step size ds. A network is represented as a directed graph consisting of links and nodes. The following additional notations are introduced to facilitate the presentation. Since only discuss within-day dynamics here, the day label τ is dropped throughout the section.

S:	Set of origins in the network
R:	Set of routes employed by all travelers
R^o:	Set of routes originating from $o \in S$
I^J:	Set of incoming links of a junction J
O^J:	Set of outgoing links of a junction J
A^J:	Flow distribution matrix of junction J
$f_r(s)$:	Route departure rate along $r \in R^w$ at time s
$f(s)$:	Set of route departure rates $f(s) = (f_r(s): \quad r \in R)$ at time s
$\mathrm{TT}_r(s)$:	Travel time along route r with departure time s
$C_r(s)$:	Travel cost along route r with departure time s
$f_i^{\mathrm{in}}(s)$:	Inflow of link i
$f_i^{\mathrm{out}}(s)$:	Outflow of link i
$N_i^{\mathrm{up}}(s)$:	Link i's cumulative entering count
$N_i^{\mathrm{dn}}(s)$:	Link i's cumulative exiting count
$D_i(s)$:	Demand of link i
$S_i(s)$:	Supply of link i
$\mu_i^r(s)$:	Percentage of flow at the entrance of link i associated with route r
$q_o(s)$:	Point queue at the origin node $o \in S$
$\xi_i(s)$:	Entry time of link i corresponding to exit time s
$\zeta_i(s)$:	Exit time of link i corresponding to entry time s

dt:	Duration of a single departure window
ds:	Time step size for the dynamic network loading
$L_i, C_i, v_i, u_i, \rho_i^{\text{jam}}$	Length, capacity, forward wave speed, backward wave speed, and jam density of link i (assuming triangular fundamental diagram)

3.8.3 Computation of Path Travel Costs

The input of the DNL problem is the set of route departure rates $f(s) = (f_r(s)\colon \quad r \in R)$. Through computations involving link dynamics, junction dynamics, link delay and path delay, the DNL calculates path travel times (path delays) as $\mathrm{TT}_r(s)$ for route $r \in R$ and departure time s. The modeling of departure time choice requires the specification of generalized travel cost with arrival penalties:

$$C_r(s) = \alpha \cdot \mathrm{TT}_r(s) + \beta \cdot \mathrm{EP}_r(s) + \gamma \cdot \mathrm{LP}_r(s) \tag{3-35}$$

where the early arrival penalty $\mathrm{EP}_{(r,t)}$ and late arrival penalty $\mathrm{LP}_{(r,t)}$ are part of the travel cost and are relative to a target arrival time TA. α, β, γ are positive parameters to balance the weights of travel time, and early and late penalties. It is reasonably set $\beta < \alpha < \gamma$ to reflect the different values of time (Small, 1982).

The important difference between route departure rate $f_r(s)$ and departure volume $f_{(r,t)}$ should be noted. The former is associated with the DNL model and the latter is invoked in the DTD choice model in Section 3.5, 3.6 and 3.7. Moreover, $f_r(s)$ represents flow (unit: vehicle/unit time) defined for every time step s, while $f_{(r,t)}$ represents traffic volume (unit: vehicle) in a given departure window $t \in T$.

In the LWR-based dynamic network loading, the time step size ds should satisfy the Courant-Friedrichs-Lewy numerical stability condition (LeVeque, 1992), which means that it should be no longer than the free-flow time on any link in the network. This thesis deliberately makes the duration of the departure window dt (e.g. 15 min) significantly larger than the time step size ds (e.g. 15 s) to reduce departure time uncertainties. To reconcile both time scales, the following procedure is proposed to convert the departure volumes $f_{(r,t)}$ to the route departure rates $f_r(s)$ and then to the experienced costs $C_{(r,t)}$.

1. Given the departure volumes $f_{(r,t)}$ for all $(r,t) \in R^w \times T$, the average departure rate is computed as $f_{(r,t)}/dt$ and set

$$f_r(s) = \frac{f_{(r,t)}}{dt} \qquad \text{for all } s \text{ within the departure window } t \tag{3-36}$$

2. Perform the DNL procedure (see the Section 3.8.4 for details) with $f_r(s), r \in R$ given by (3-36), and obtain the path travel costs $C_r(s)$ $\forall r \in R$.

3. Average the costs $C_r(s)$ over the departure window to obtain the costs $C_{(r,t)}$:

$$C_{(r,t)} = \frac{ds}{dt} \cdot \sum_{s \in t} C_r(s) \qquad \forall\ r \in R^w, t \in T \tag{3-37}$$

3.8.4 Dynamic Network Loading Procedure

In deriving the DNL model, this thesis employs the variational formulation of the Lighthill-Whitham-Richards (LWR) model known as the Lax-Hopf formula (Han et al., 2016), which enables us to formulate the DNL model as a system of differential algebraic equations (DAEs) and solve the DNL problem with computational efficiency. This section only outlines the main steps of the DNL and presents its discretized DAE version here without going through the detailed derivation. A supplement of the DNL model is given in Appendix I and also see Han et al. (2019) for further derivation and details.

Recalling the notations from Section 3.8.2, the DNL procedure in discrete time is presented as follows.

$$D_o(s+1) = \begin{cases} M & \text{if } q_o(s) > 0 \\ \sum_{r \in R^o} f_r(s) & \text{if } q_o(s) = 0 \end{cases} \qquad o \in S \tag{3-38}$$

$$D_i(s+1) = \begin{cases} f_i^{\text{in}}(s - L_i/v_i) & \text{if} \quad N_i^{\text{up}}(s - L_i/v_i) \leq N_i^{\text{dn}}(s) \\ C_i & \text{if} \quad N_i^{\text{up}}(s - L_i/v_i) > N_i^{\text{dn}}(s) \end{cases} \tag{3-39}$$

$$S_j(s+1) = \begin{cases} f_j^{\text{out}}\left(s - L_j/u_j\right) & \text{if} \quad N_j^{\text{up}}(s) \geq N_j^{\text{dn}}\left(s - L_j/u_j\right) + \rho_j^{\text{jam}} L_j \\ C_j & \text{if} \quad N_j^{\text{up}}(s) < N_j^{\text{dn}}\left(s - L_j/u_j\right) + \rho_j^{\text{jam}} L_j \end{cases} \tag{3-40}$$

$$N_i^{\text{dn}}(s) = N_i^{\text{up}}(\xi_i(s)), \quad N_i^{\text{up}}(s) = N_i^{\text{dn}}(\zeta_i(s)) \tag{3-41}$$

$$\mu_j^r(s) = \frac{f_i^{\text{out}}(s)\mu_i^r\left(\xi_i(s)\right)}{f_j^{\text{in}}(s)} \qquad \forall r \ \text{ s.t.} \quad \{i,j\} \subset r \tag{3-42}$$

$$A^J(s) = \{\alpha_{ij}(s)\}, \qquad \alpha_{ij}(s) = \sum_{r \ni i,j} \mu_i^r(\xi_i(s)) \tag{3-43}$$

$$\left([f_i^{\text{out}}(s)]_{i=1}^m \ , \left[f_j^{\text{in}}(s)\right]_{j=1}^n\right) = \Theta\left([D_i(s)]_{i=1}^m \ , \left[S_j(s)\right]_{j=1}^n \ ; A^J(s)\right) \tag{3-44}$$

$$q_o(s+1) = q_o(s) + ds \sum_{r \in R^o} f_r(s) - \min\{D_o(s), S_j(s)\} \tag{3-45}$$

$$N_i^{\text{up}}(s+1) = N_i^{\text{up}}(s) + ds \cdot f_i^{\text{in}}(s), \quad N_i^{\text{dn}}(s+1) = N_i^{\text{dn}}(s) + ds \cdot f_i^{\text{out}}(s) \tag{3-46}$$

$$\text{TT}_r(s) = \zeta_o \circ \zeta_1 \circ \ldots \circ \zeta_K(s), \quad \forall r = \{o, 1, \ldots, K\} \tag{3-47}$$

Equation (3-38) defines the demand at the origin o, to be utilized later in (3-45) to determine the queuing dynamics at the origins following a Vickrey type model. (3-39) and (3-40) respectively express the link demand and supply using the variational formulation (Han et al., 2016). They are also key to capture vehicle spillback and inter-link congestion propagation. (3-41) is known as the flow propagation constraint (Friesz et al., 2011), which defines the link entrance and exit time functions. (3-42) and (3-43) together determine the link distribution matrix at the junction based on the first-in-first-out principle. Such a matrix serves as an input of the junction dynamic model (3-44), where the inflows and outflows of incident links are jointly determined by their respective demands and supplies, via the Riemann Solver (Garavello et al., 2016). (3-46) updates the link cumulative entering/exiting counts by definition. Finally, (3-47) defines the path travel time based on individual link travel times using the composition $\circ$ of functions, namely $y_1 \circ y_2(s) \doteq y_2(y_1(s))$.

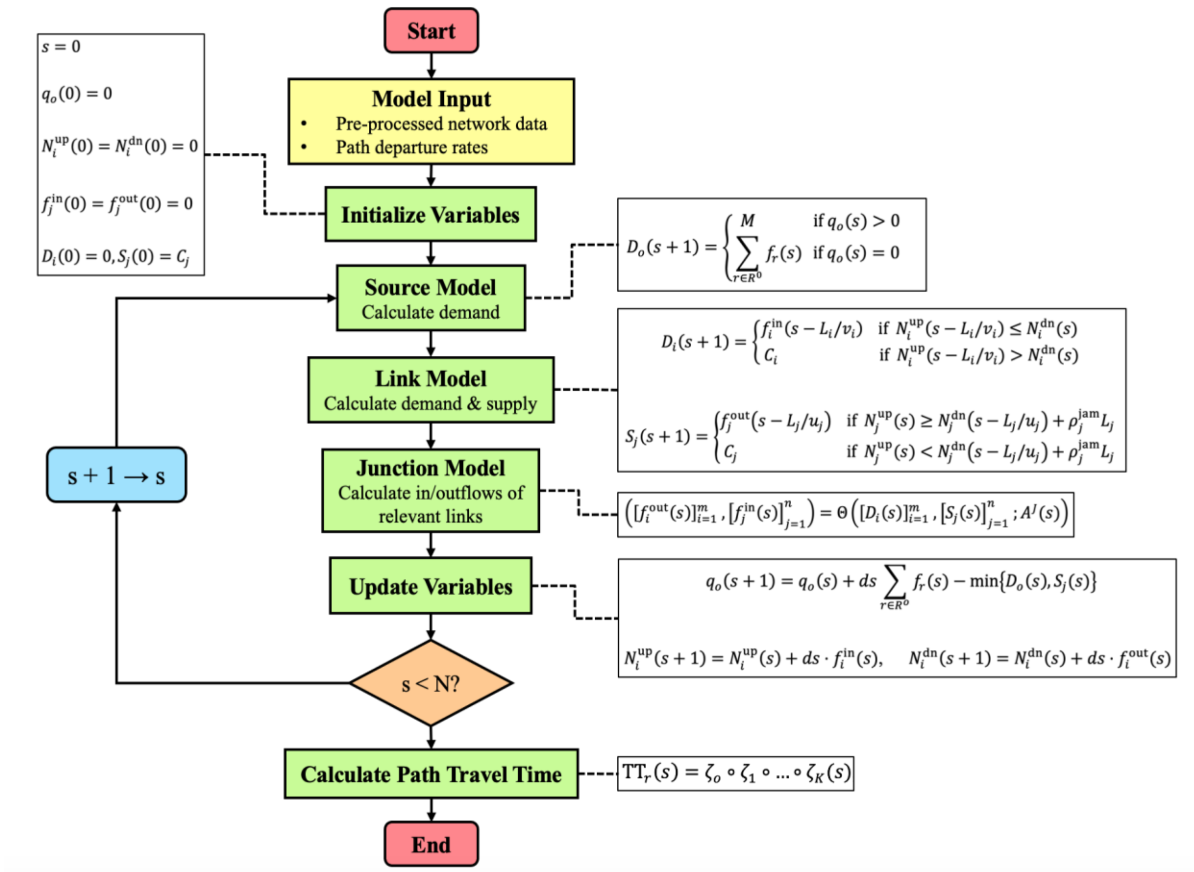


Figure 3.5 The DNL process and the discretised DAE system

Figure 3.5 illustrates the logic flow of the DNL model in this thesis and the corresponding discretized DAE system (as shown in Equation (3-38)-(3-47)) for each step of the model. Figure 3.6 shows a testing of the performance of DNL model on the Sioux Falls network, in which the color shades represent the relative inflow (flow/capacity) on each link. It can be seen that the DNL model is able to capture dynamic evolution of traffic flows and congestion on a large-scale network, and output the experienced travel time for each path and each departure time step (see Figure 3.7 for an example path).

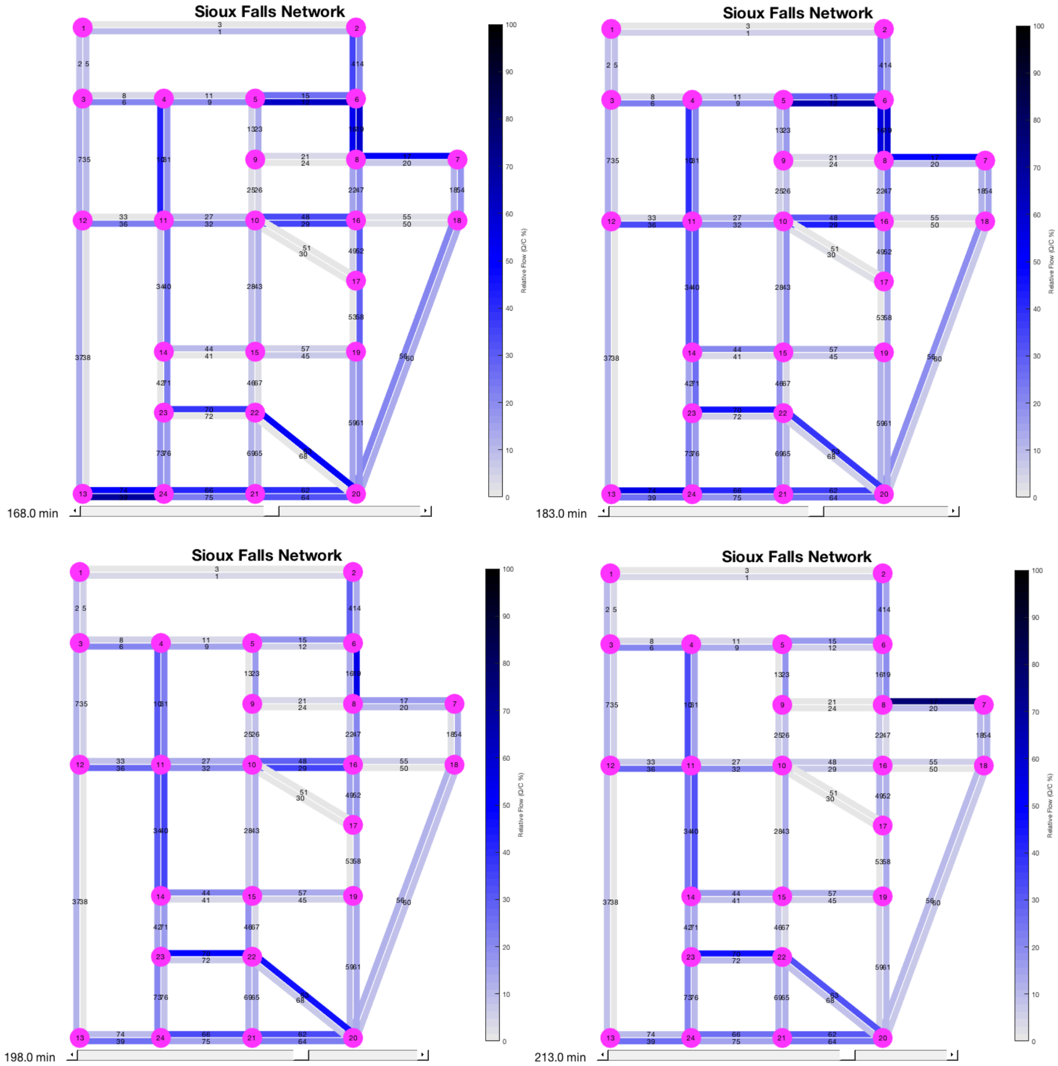


Figure 3.6 Flow dynamics on the Sioux Falls network

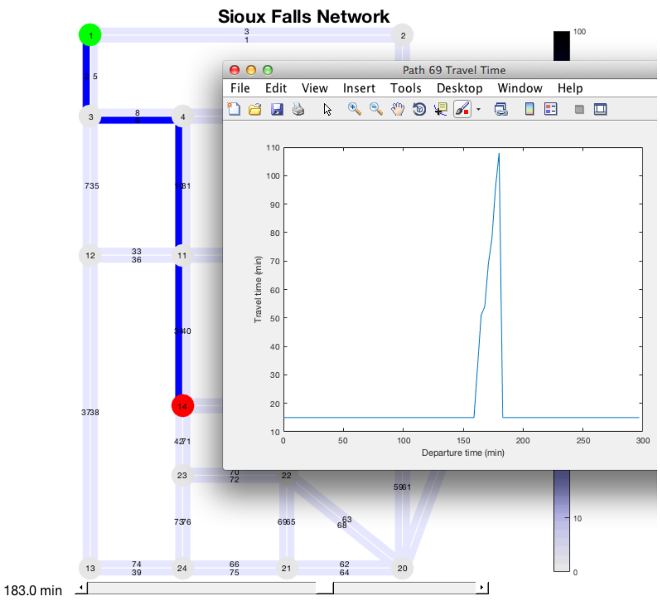


Figure 3.7 Travel time along path 69 in the Sioux Falls network

3.9 Summary

This chapter presents doubly dynamic traffic assignment (DDTA) models with realistic user behaviour pertaining to imperfect and incomplete information as well as bounded rationality. In particular, this chapter propose two stochastic DTD models where travellers choose departure time and routes based on their adaptive learning and decision making. The first model is based on a multinomial Logit model where each route-and-departure-time pair is treated as an independent alternative. The second model is derived by viewing the departure time and route as sequential choices, which are respectively captured by multinomial Logit and nested Logit models. The nested Logit model for route choices also corrects the IIA assumption.

Building on these models, this chapter further incorporate bounded rationality (BR) and information sharing mechanism into the macroscopic choice modelling framework. The BR assumes that travellers are reluctant to change their previous day's choice unless a gain larger than a threshold (indifference band) is expected. The random utility theory with indifference band is invoked and extend adapt it to the DTD SRDT choice update. On the other hand, travel information availability and reliability are incorporated into the choice model. This is done by assuming that the weight of information on certain alternative reported by a crowd depends on the number (or percentage) of travellers who chose that alternative. A simple yet insightful functional form is provided to parameterize the strength of information sharing.

The within-day dynamics follow the LWR-based dynamic network loading (DNL), which explicitly captures physical queuing and network-wide propagation of congestion. The DNL model is formulated as a system of difference algebraic equations in discrete time.

In particular, the following contributions are highlighted.

(1) **Doubly dynamic traffic assignment model with SRDT choices (SRDT-DDTA).** This chapter propose a macroscopic DTD model with simultaneous-route-and-departure-time (SRDT) choices, where the within-day dynamics follow the Lighthill-Whitham-Richards

(LWR) fluid dynamic network loading model. According to the literature review in Section 3.2, this is the first doubly dynamic model with SRDT choices. The proposed model allows a realistic representation of travellers' choice set in response to network conditions and changes.

(2) **Realistic traffic dynamics and transferability.** The LWR-based DNL procedure is employed for describing the within-day traffic dynamics that are suitable for large-scale traffic networks while capturing realistic traffic phenomena such as shock waves and vehicle spillback. This is crucial for analysing real-world networks with constant supply shortage due to recurrent or incidental disruptions.

(3) **Model extension with bounded rationality.** The SRDT-DDTA model is extended with bounded rationality, by incorporating the indifference band in the random perception errors in the DTD model. This leads to the first BR-based DDTA model with SRDT choices.

(4) **Model extension with macroscopic information sharing mechanism.** The SRDT-DDTA model is further extended with a model of travel information sharing to account for the effect of incomplete information on travellers' SRDT choices. This is done at the macroscopic level for computational efficiency, and consistent with the SRDT choices and fluid-based dynamic network loading. This is suitable for large-scale simulations with generalizable insights not easily accessible from agent-based simulations.

The proposed DDTA models in this chapter allow a realistic representation of travellers' choice set as well as network traffic flow evolutionary dynamics in response to network conditions (e.g. with and without M&R), which are capable to accurately capturing traffic disequilibrium and transient congestion derived by M&R activities to the road networks. Numerical studies on the proposed DDTA models are presented in the next chapter to demonstrate the models' performance.

4 Numerical Studies on the Doubly Dynamic Traffic Assignment Models

Chapter 3 present the day-to-day DTA models and the within-day DNL model correspondingly, the combination of them forms the doubly dynamic traffic assignment (DDTA) models. These DDTA models will be applied to the M&R planning modelling in this thesis, which could more accurately capture travellers' responses to M&R and more realistically simulate traffic flow dynamics under the network conditions with and without M&R. This chapter conducts numerical case studies on the proposed DDTA models for the purpose of examine the performance of the DDTA models in both long-term behaviour of traffic flow and short-term disequilibrium states derived by network disruptions (e.g. M&R). A battery of sensitivity and scenario-based analyses are conducted on the Sioux Falls network (530 O-D pairs, 6,180 paths, 30,000 trips) and Anaheim network (1,406 O-D pairs, 30,719 paths, 30,000 trips). Local capacity disruption and restoration are simulated to highlight the need for explicitly modelling SRDT choices in DTD dynamics, and understand the interaction between travellers' decision making and traffic dynamics with different levels of information availability and user behaviour. The findings in this chapter highlight the need for modelling network transient and disequilibriated states when M&R planning, which are often overlooked in equilibrium-constrained network design and optimisation.

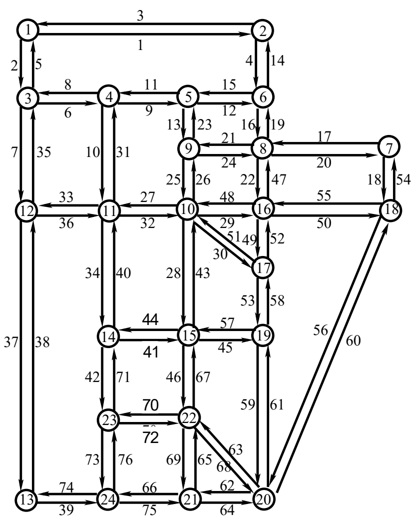
This chapter[*] first introduces the test networks and experimental settings used for the case studies in Section 4.1. The case studies begin by examining the long-term behaviour of the

[*] Part of the contents in this chapter has been published in *Transportation Research Part C* (Yu et al., 2020).

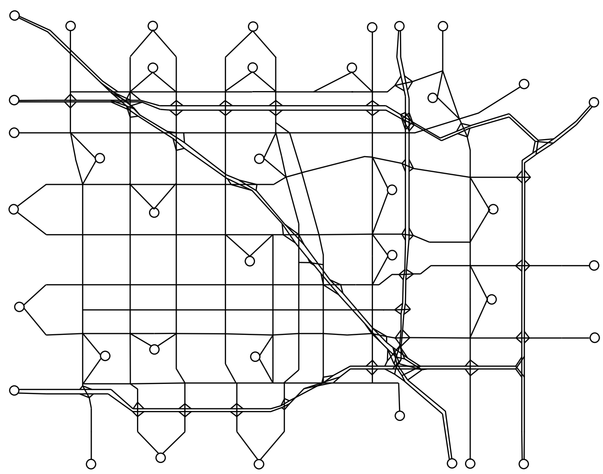
proposed DDTA models by performing a sensitivity analysis on the model parameters in Section 4.2. Then this chapter tests the route and departure time choices under network disruptions in Section 4.3. Section 4.4 further explore the variability and consistency of the model outputs with respect to some exogenous choices of modelling components. A summary made from the numerical studies in this chapter are given in Section 4.5.

4.1 Numerical Studies on Large-scale Road Networks

This chapter will illustrate the proposed DDTA models on two test networks: the Sioux Falls network with 528 O-D pairs, 30,000 trips and 6,180 routes, and the Anaheim network with 1,406 O-D pairs, 30,000 trips and 30,719 routes; see Figure 4.1. Unlike existing literature, which mainly uses small networks and static traffic flow model to illustrate the main features of the DTD learning and decision making on the demand side, this thesis use these reasonably large-scale networks to demonstrate the complexity arising from the interaction between DTD and within-day traffic dynamics, while demonstrating that the proposed models' capability to be readily applied for problems of realistic sizes. The within-day DNL procedure can capture shock wave, spillback, and the inter-link propagation of location congestion in space and time, which is an important feature of the DTD doubly dynamic model.



Sioux Falls network
(24 nodes, 76 links, 24 zones)



Anaheim network
(416 nodes, 914 links, 38 zones)

Figure 4.1. The test networks

The simulation horizon is a five-hour morning commuting period, split into 20 departure time windows (15 min each). In addition to analysing the long-term behaviour of the doubly DTD dynamics towards equilibrium, this chapter also investigate the effect of possible local network disruptions by reducing the capacities of some links before restoring them at the end of the disruption period. A range of DDTA models proposed in this thesis will be discussed and compared using sensitivity and scenario-based analyses.

Throughout the numerical tests in this chapter, the travel cost structure follows that of Equation (3-35) with the following parameters: in-vehicle value of time $\alpha = 1$, early arrival value of time $\beta = 0.8$, late arrival value of time: $\gamma = 1.8$. The unit of the travel cost is seconds. Note that, to be consistent with most of the traffic models that only consider travel time as travel cost, parameter α in this thesis is also set to be one unit. This thesis further adds early or late arrival penalty into travel cost, and sets parameters β and γ to be smaller and greater than one unit correspondingly. This is reasonable assumption to reflect the different values of time satisfying $\beta < \alpha < \gamma$ (Small, 1982). As the route and departure time choices made by the travelers within the same OD pair have a same target arrival time, the values of α, β, γ can be arbitrarily defined without changing the results, as long as they satisfied $\beta < \alpha < \gamma$.

4.2 Long-term Behaviour of the DDTA models

This section begins by examining the long-term behaviour of the proposed models by performing a sensitivity analysis on the model parameters. Note that the purpose of the analysis is not to seek any form of dynamic user equilibria, which are often viewed and studied as the asymptotic states of DTD dynamics. Rather, the DDTA models aim to capture realistic user and traffic behaviours and their interactions, noting that the proposed doubly dynamics may not converge to their steady states due to the highly complex and non-monotone delay operators (Han et al., 2015) associated with the dynamic network loading. Indeed, this study is partially driven by the expectation that idealized equilibria may not exist in real-world traffic systems.

This chapter first test four variants of the proposed DTD models:

1. Base Model I: multinomial Logit model (Section 3.5.2);
2. Base Model II: sequential-decision model with mixed multinomial and nested Logit model (Section 3.5.3);
3. Base Model I with bounded rationality (BR); and
4. Base Model II with information sharing (IS)

The level of daily oscillation is measured by the relative gap:

$$\text{Relative Gap: } \left(\frac{\sum_{r\in R}\sum_{t\in T}\left(f_{(r,t)}(\tau)-f_{(r,t)}(\tau-1)\right)^2}{\sum_{r\in R}\sum_{t\in T}\left(f_{(r,t)}(\tau-1)\right)^2}\right)^{1/2} \tag{4-1}$$

which represents the relative change of the departure flows in two consecutive days.

4.2.1 Long-term Behaviour on the Sioux Falls Network

Figure 4.2 and Figure 4.3 show the relative gaps for the four model variants with $M = 3$ and $M = 6$, respectively. Other relevant parameters are:

Base Model I: $\lambda = 0.7,\ \theta = 0.004$

Base Model II: $\lambda = 0.7,\ \theta = \theta_1 = 0.004,\ \eta = 400$

Base Model I + BR: $\lambda = 0.7,\ \theta = 0.004,\ \delta = 400$

Base Model II + IS: $\lambda = 0.7,\ \theta = \theta_1 = 0.004,\ \eta = 400,\ G(x) = x^n$

Here M denotes the number of past days that influence present day's perception. Given the learning process in Equation (3-12), which resembles a moving average, it is expected that M has a smoothing effect on the time series (in τ) of the perception of different alternatives, and therefore larger M tends to reduce the daily variations of path flows, hence the relative gaps. This is indeed the case by comparing Figure 4.2 ($M = 3$) and Figure 4.3 ($M = 6$). In addition, larger λ means that past days' experience carries less weight, which has a similar effect as small M. For this reason, in what follows the value of λ not changed, but to only consider different values of M.

It can be further observed from Figure 4.2 that: (1) Base Model I with bounded rationality has lower relative gaps than without, which is expected because of travellers reluctance to switch choices; (2) Base Model II with information sharing has larger gaps than without, which highlights the uncertainties in decision making due to lack of complete information (also see Figure 4.5).

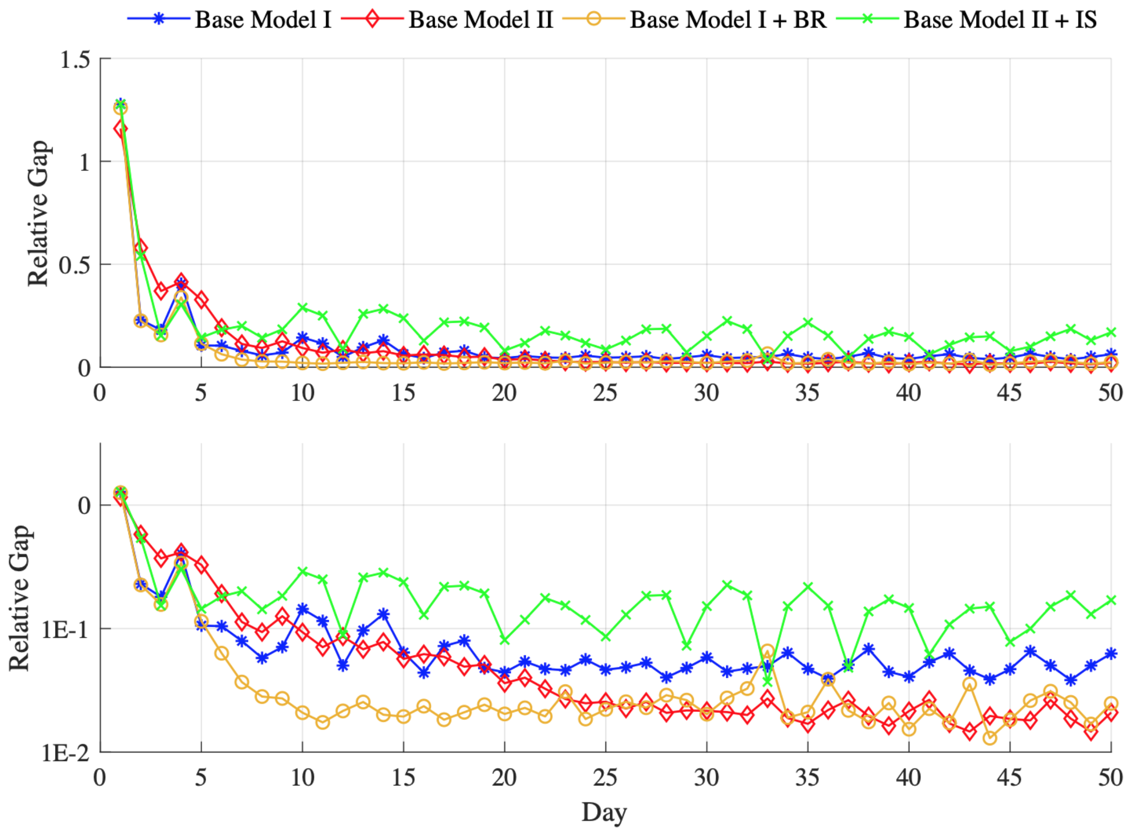


Figure 4.2. Relative gaps in 50-day simulation ($M = 3$) based on the Base Model I, Base Model II, Base Model I with bounded rationality (BR), and Base Model II with information sharing (IS). The lower figure displays the logarithmic scale.

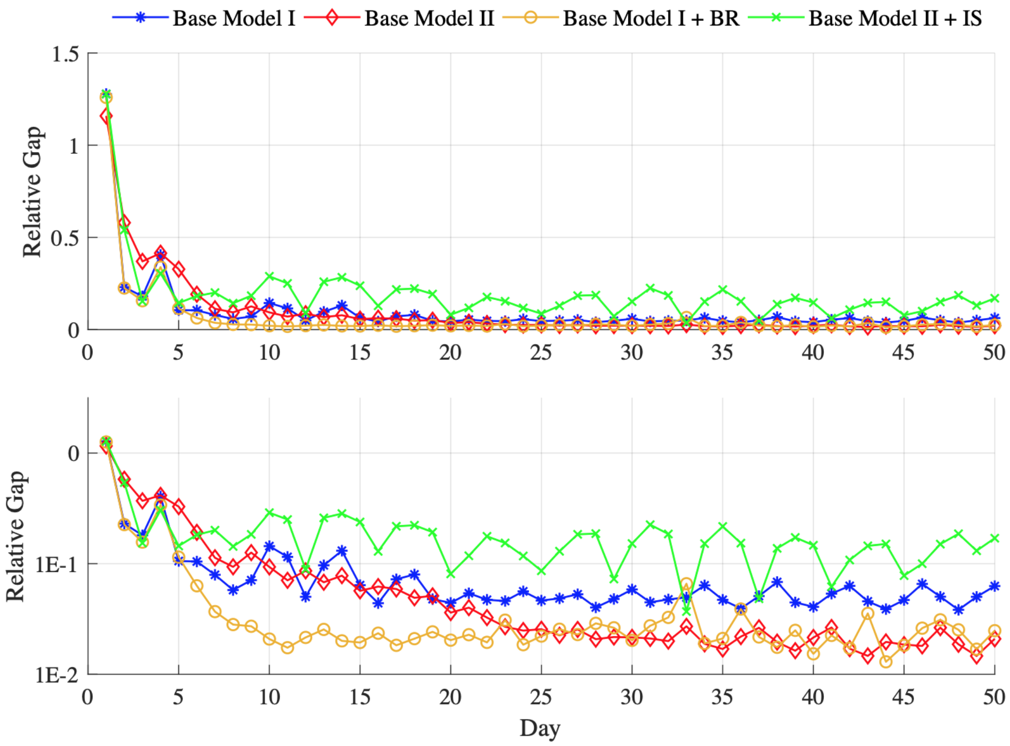


Figure 4.3. Relative gaps in 50-day simulation ($M = 6$) based on the Base Model I, Base Model II, Base Model I with bounded rationality (BR), and Base Model II with information sharing (IS). The lower figure displays the logarithmic scale.

Figure 4.4 compares the Base Model I + BR model with different indifference bands $\delta = 0$, 200, 400 and 800. It can be seen that a decreasing trend of the relative gaps as δ increases, which means that when the travelers are willing to accept larger cost differences, their route and departure time choices undergo less daily oscillation.

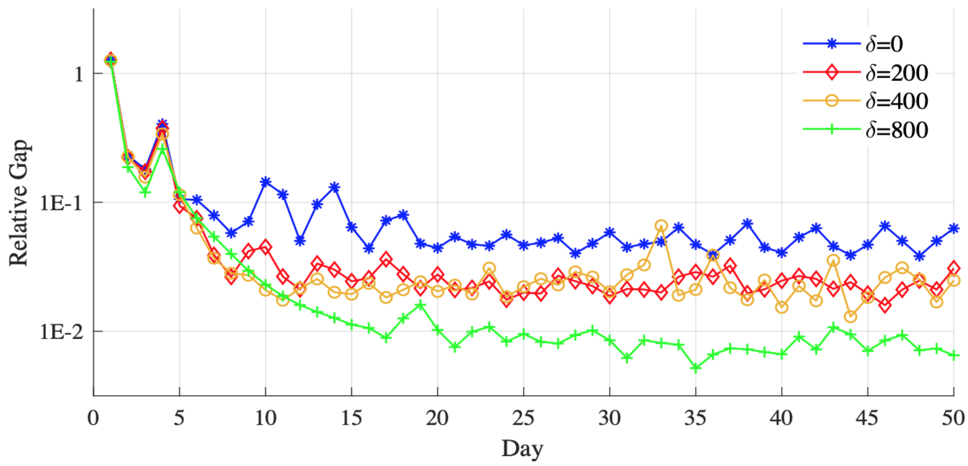


Figure 4.4. Comparison in terms of relative gaps (in logarithmic scale) of the Base Model I + BR with different values of the indifference band δ.

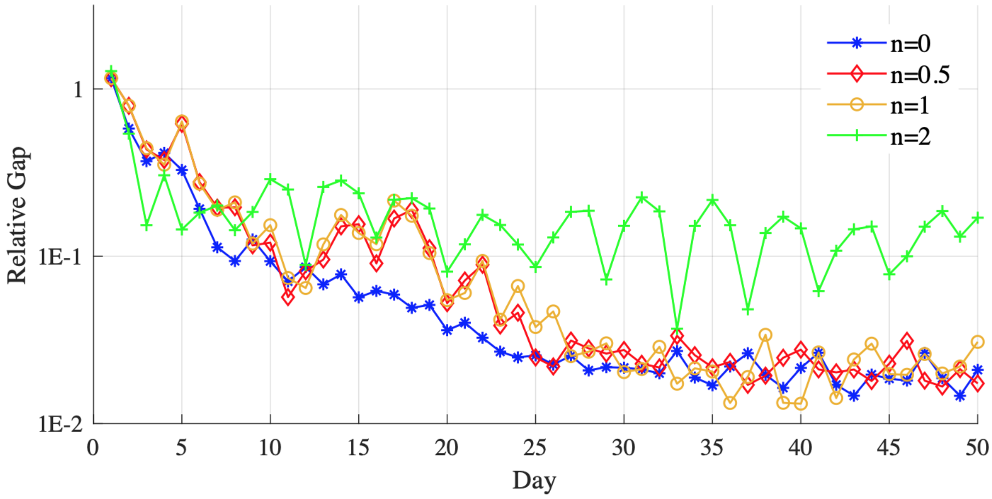


Figure 4.5. Comparison in terms of relative gaps (in logarithmic scale) of the Base Model II + IS with different values of n in the weighting function $G(x) = x^n$.

Figure 4.5 is used to illustrate the impact of information sharing strength, i.e. n in $G(x) = x^n$, on the variations of travel choices. It can be seen that $n = 2$ yields large relative gaps, which means that ignoring information reported by small crowds, however relevant they may be, tends to create much uncertainties in the decision-making process. However, note that this is likely the case in a real-world situation, where information provided either by individual travellers via social platforms or by a centralized information sharing entity (e.g. ATIS) tends to focus on those popular choices. Moreover, the other three cases ($n = 0, 0.5, 1$) seem to have reached the same level of relative gaps after 30 days.

4.2.2 Long-term Behaviour on the Anaheim Network

The similar analysis is performed on the Anaheim network. Figure 4.6 compares the relative gaps produced by Base Model I with different scale parameters $\theta = 0.001, 0.002, 0.003$. Note that larger θ means that travellers are more sensitive to the cost different between alternatives. It can be seen that the relative gaps correspond to higher values of θ, which means that higher sensitivity towards the perceived cost difference causes traffic to constantly switch routes and departure times.

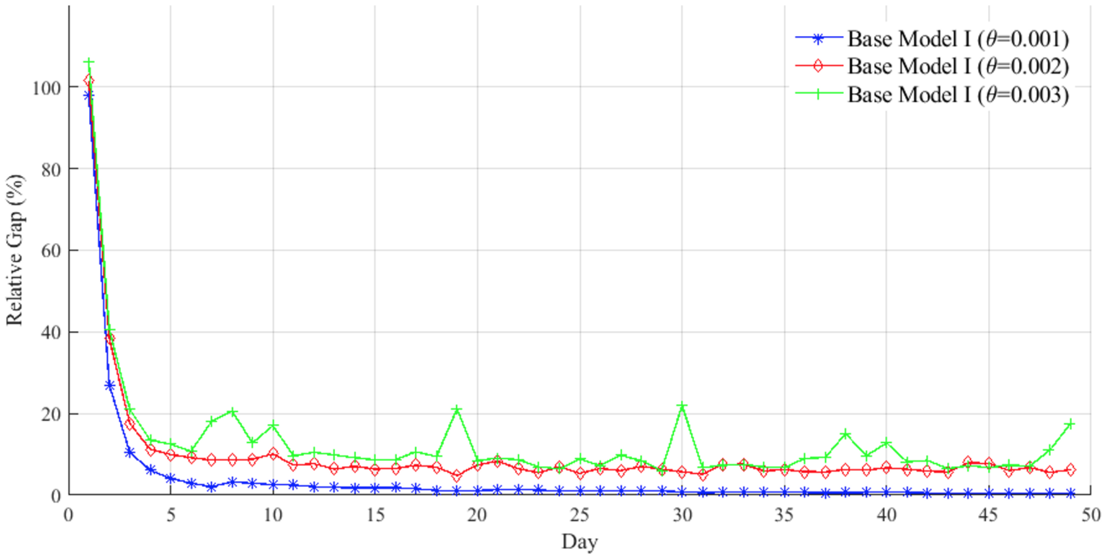


Figure 4.6. Relative gaps on the Anaheim network produced by Base Model I ($\theta = 0.001, M = 6$).

Next, this section examines the effect of information sharing on network performance. Simulations are performed on the network dynamics using Base Model II without information sharing (IS), as well as with IS ($n = 1, 2$). The relative gaps and total network costs are shown in Figure 4.7. It is interesting to see that Base Model II, which is assuming complete traffic information, actually yields the largest relative gap and also highest network total cost compare to the case with incomplete information. In particular, the sums of network costs over the period $[10, 50]$ (day) are:

- 3.4451×10^9 (Base Model II),
- 3.4400×10^9 (Base Model II + IS $n = 1$), and
- 3.4393×10^9 (Base Model II + IS $n = 2$).

This suggests that limiting access to information of certain alternatives could in fact stabilize traffic and reduce congestion associated with daily SRDT choice switches. This can be viewed as a generalized Braess paradox where information transparency is working against the network performance.

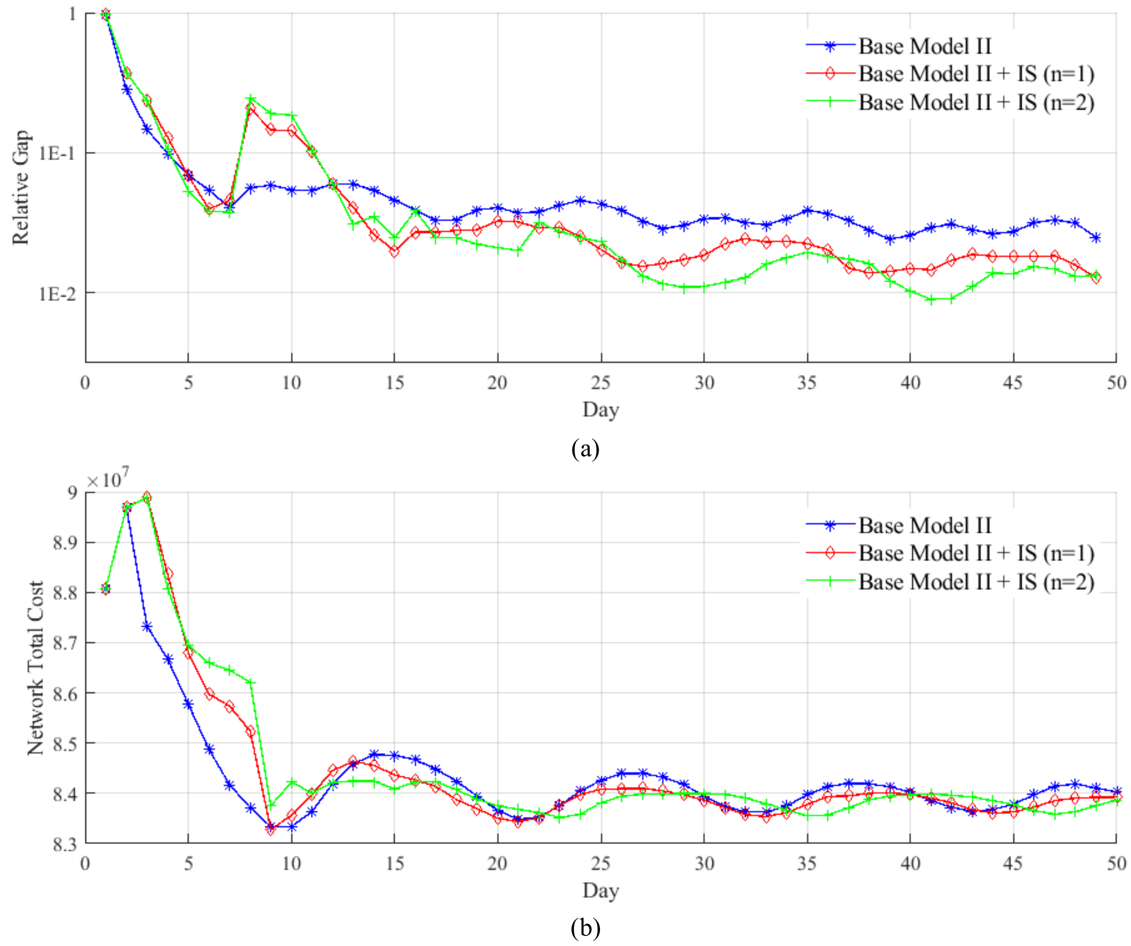


Figure 4.7. Relative gaps (in logarithmic scale) and network total costs corresponding to Base Model II ($n = 0$) and Base Model II with information sharing ($n = 1, 2$). The other parameters are chosen to be ($\theta = \theta_1 = 0.001, M = 6, \eta = 600$).

Consider a given O-D pair $w \in W$, which has a route set ranging from #39-#219. For each day of simulation, the average perceived travel cost is calculated corresponding to each departure window $t \in \{1, 2, \dots, 20\}$ as

$$\bar{C}_t^w(\tau) \doteq \frac{1}{|R^w|} \sum_{r \in R^w} \bar{C}_{(r,t)}(\tau)$$

Figure 4.8 shows the daily evolution of such average perceived costs for four cases: Base Model II + information sharing with $n = 0, 0.5, 1, 2$, respectively. Note that $n = 0$ corresponds to the complete information case. It can be seen that the lowest perceived costs are concentrated between departure windows 8 and 11 in all four cases. However, the difference lies in the departure windows 12-15, where $n = 0$ yields clear daily oscillations of the perceived cost, while such oscillations diminish as n gets larger. This means that the lack of complete information tends to have a smoothing effect on the daily profile of the perceived cost, which conforms with Figure 4.7(a).

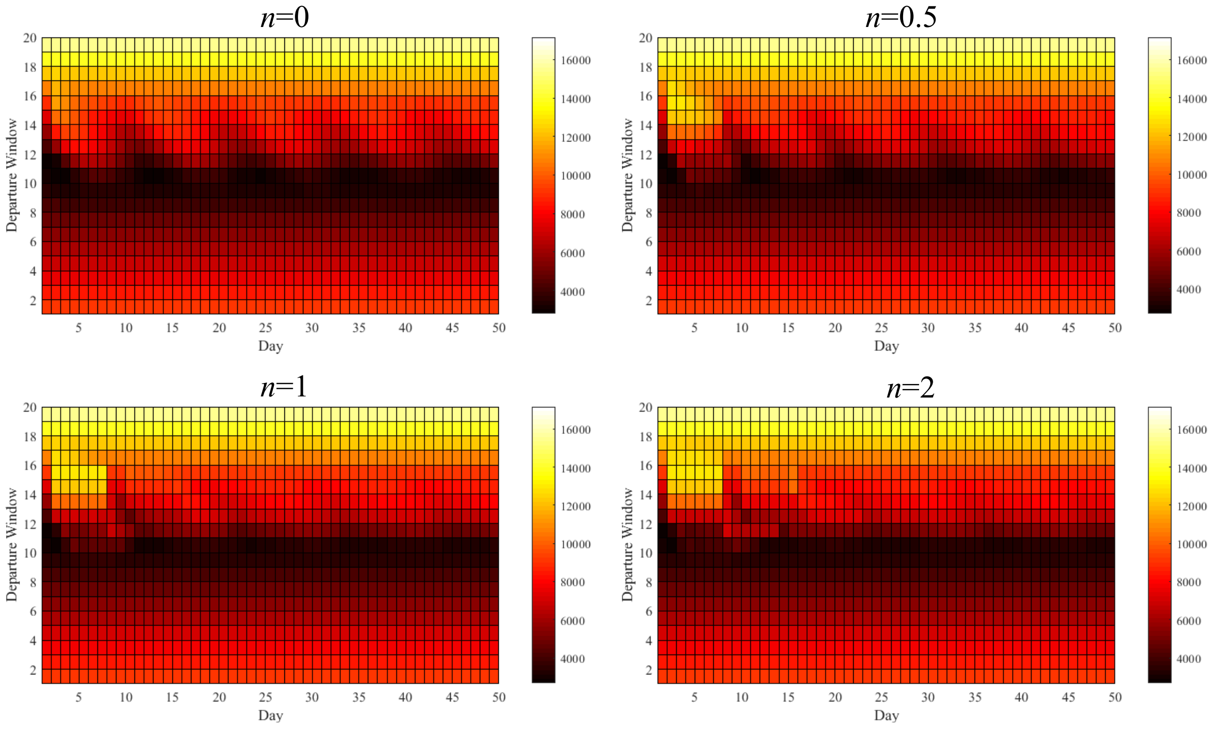


Figure 4.8. Average perceived travel costs between O-D pair #4 (routes #39-219) for each departure window for a 50-day simulation.

4.3 Route and Departure Time Choices under Network Disruptions

This section simulates a local disruption in the Sioux Falls network by reducing 1/3 of the flow capacity of link #68 (see Figure 4.1) between day 51 and day 100. After the 100th day, its capacity is restored. Link 68 is chosen as it carries the highest traffic volume in the DTD simulation reported in Section 4.2.1, and is therefore considered a critical component of the network supply. The Base Model II + IS from Section 4.2.1 is used to illustrate the SRDT choices in the DTD dynamics.

Figure 4.9 illustrates the change in SRDT choices after the disruption took place. Figure 4.9(a) shows two departure peaks around 8th-9th window and 12th-13th window, respectively before the disruption. After the 51st day, there is a clear shift of departure times towards earlier windows in response to the congestion created by the local disruption. Figure 4.9(b) shows the route choice switches caused by the local disruption. In this figure, paths #3321-3335 and #3336-3346 belong to two different O-D pairs. When disruption occurs, it can be clearly observed that travellers switching routes and, more interestingly, on certain days they switch back to their original routes, displaying a periodic switching pattern.

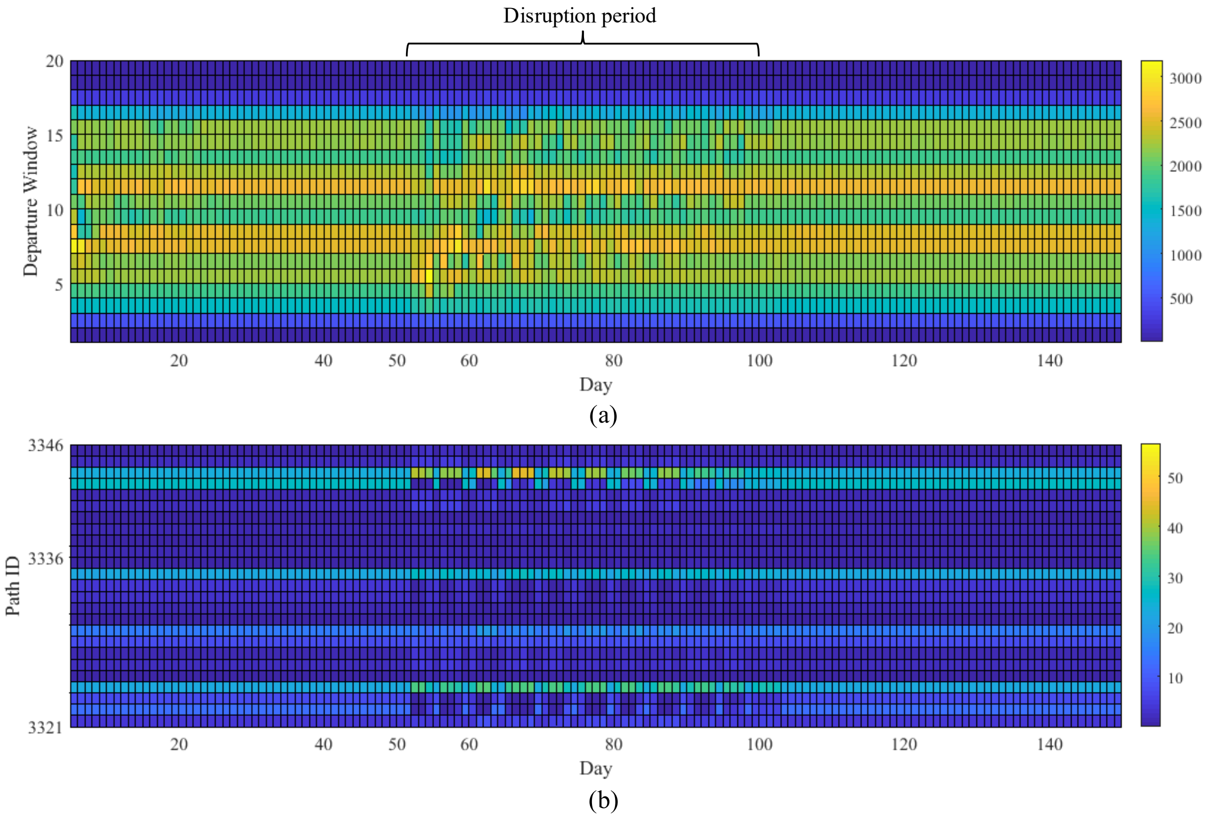


Figure 4.9. (a): the total departure volumes in each departure window on different days. (b): the total departure volumes along routes 3321-3346 on different days.

This section further analyse O-D pairs directly impacted by the disruption. Hereafter, consider an O-D pair directly impacted by the disruption if the O-D contains at least one route that traverses the disrupted link. Figure 4.10 shows the daily departure volumes along four routes in one such O-D pair. It can be seen that for routes # 3355 and # 3358, which both traverse link 68, there is a drastic decrease of route volumes at window 6 between day 51 and 100. Those flows are switched to routes #3354 and #3357, which circumvent link 68. This clearly shows the route switching behaviour within the impacted O-D pair. Furthermore, some traffic is seen to switch to departure window 5 during the disrupted period for all the four routes, which is captured by the proposed SRDT choice model.

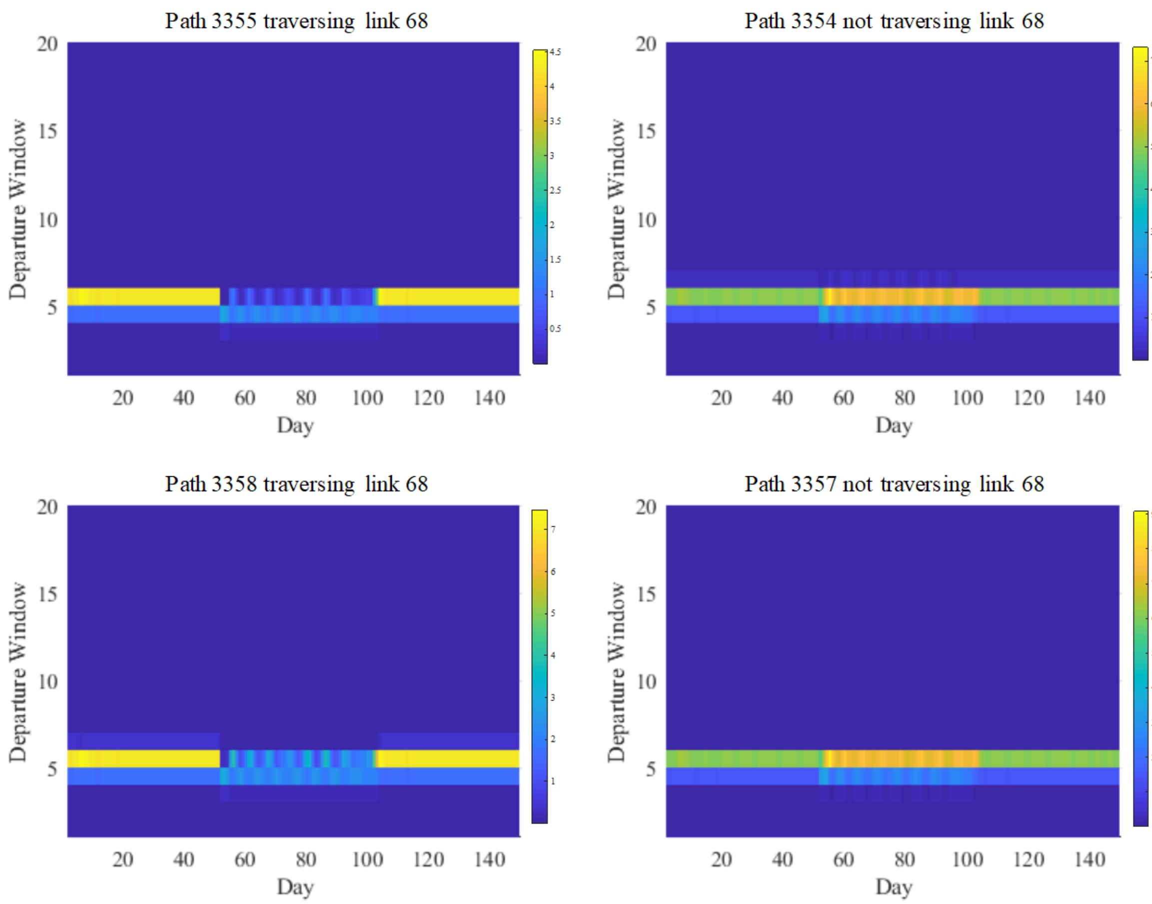


Figure 4.10. Changes in the SRDT choices after local disruption on day 50.

To further illustrate the departure time shifts, Figure 4.11 is used to show the cumulative departures of all O-D pairs directly impacted by the disruption, within four days since the disruption first took place. Both Base Model II with and without information sharing (IS) predict higher cumulative departures at any point in time, which suggests a shift towards earlier departures for these O-D pairs. This is likely caused by the spatial propagation of congestion triggered by vehicle spillback, rendering alternative routes within the same departure period unattractive. In addition, such a trend of earlier departure is more pronounced in the absence of complete information (Base Model II + IS). This suggests that incomplete information produces higher uncertainties in travellers' perceived costs, and hence induces earlier departures to accommodate the expected congestion and uncertainties. Such an interaction between travel information uncertainty and departure time choices is not captured by existing models in the literature. This highlights the need to (a) simultaneously model route and departure time choices; and (b) accurately represent congestion propagation with realistic vehicle queuing dynamics.

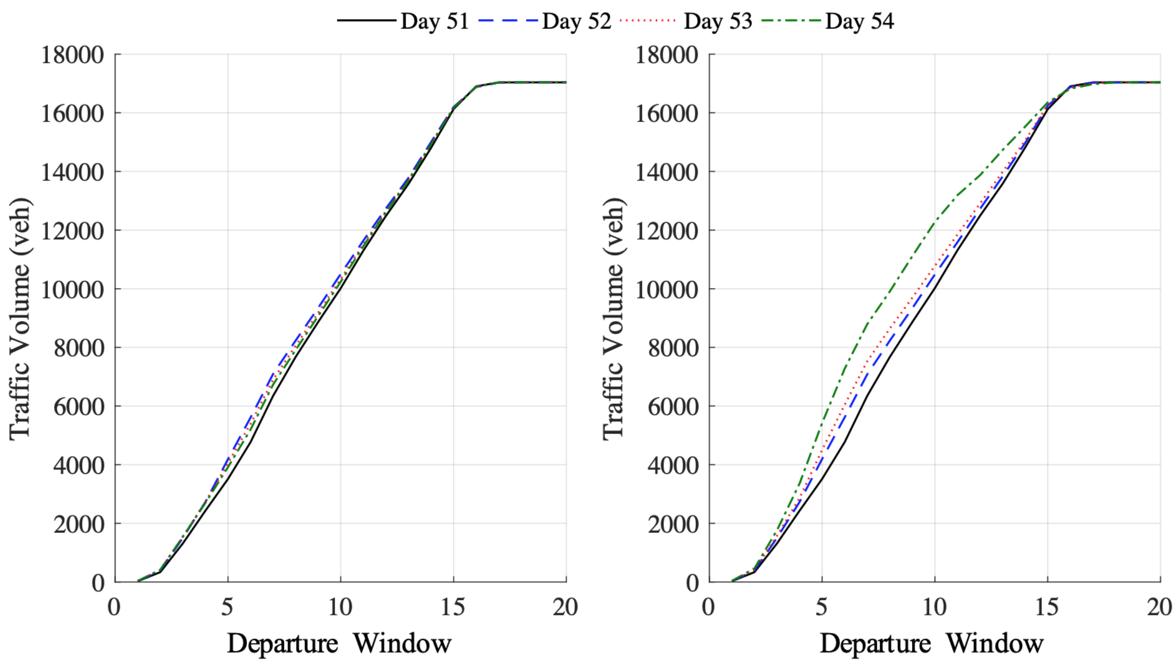


Figure 4.11. Cumulative departure volume for O-D pairs directly impacted by the local disruption. Left figure: Base Model II, right figure: Base Model II with information sharing.

Finally, for the simulated network disruption, Figure 4.12 compares Base Model II with and without information sharing, where $n = 2$ for information sharing. As suggested in Figure 4.5, having access to complete information on every alternative tends to reduce traffic oscillations due to uncertainties, and this remains the case for network disruption, as shown in the top figure of Figure 4.12: both models predict an increase of the relative gaps when the network is undergoing disruption. Moreover, the traffic does not return to an approximate stationary state for the entirety of the disruption, as the travellers are constant switching routes and departure times, as confirmed by Figure 4.9.

In terms of the travel costs encountered by all the travellers in the network, both models predict a drastic increase during the disruption period; see the middle figure of Figure 4.12. It is interesting to observe that having incomplete information also introduces inefficiencies to the entire network. However, the cost gap between the two models diminishes in time and almost vanish right before the 100th day. This means that the lack of complete information leads to a transient state with larger daily traffic variations and higher network-wide cost, and it may take a long time before the system returns to an approximate stationary state.

The bottom picture of Figure 4.12 shows that the traffic that uses the disrupted link #68 experiences daily oscillations under both models. The magnitude of oscillation predicted by Base Model II is in general lower than that of Base Model II + IS, and tends to be stabilized since around day 70. In contrast, Base Model II + IS is associated with cyclic oscillatory patterns between 600 (veh) and 1000 (veh).

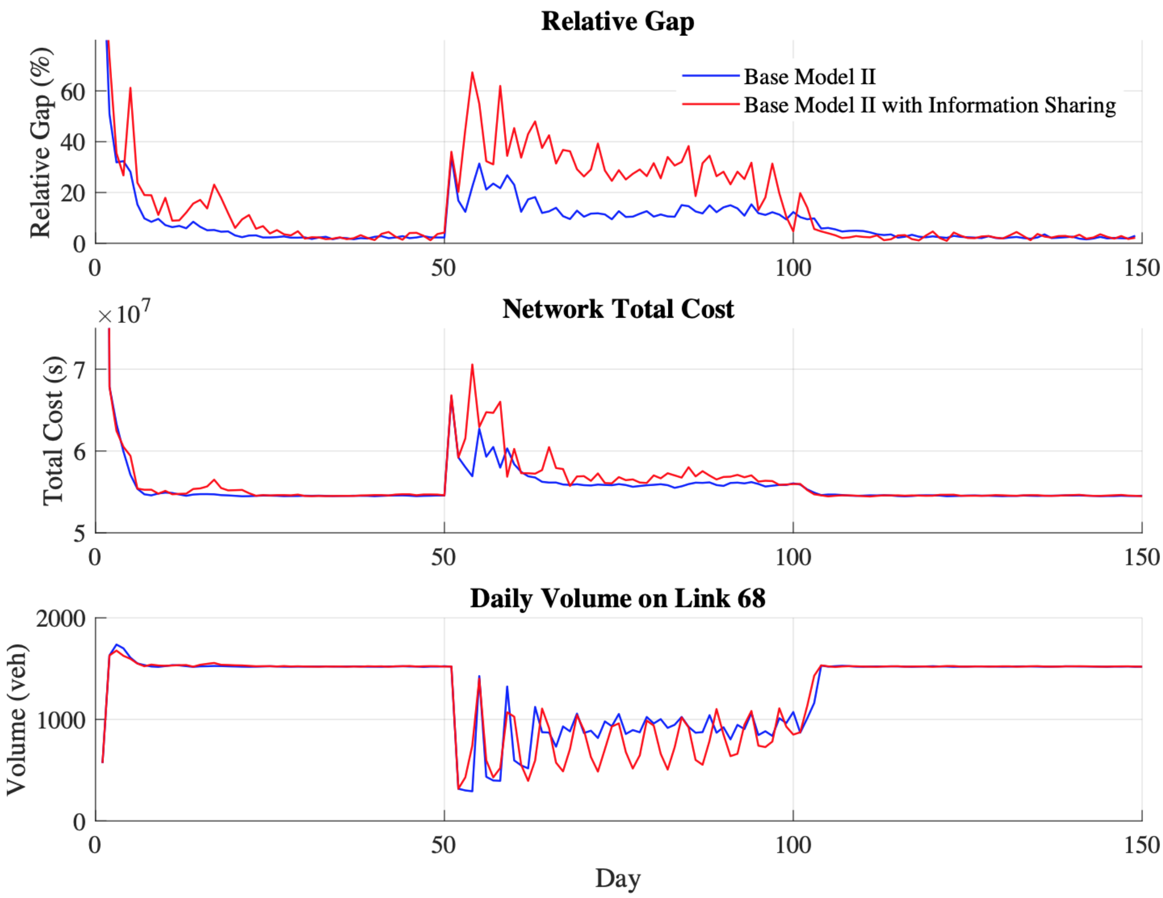


Figure 4.12. Comparison of Base Model II and Base Model II with information sharing. Top: relative gaps when the network is locally disrupted during 51st -100th day. Middle: total network cost. Bottom: daily traffic volume.

4.4 Discussion on Model Variants

The previous numerical demonstrations have tested the model's sensitivity with respect to some of the endogenous parameters such as the scale parameter of the multinomial Logit model, the indifference band, and the information communication parameter n (as in $G(x) = x^n$). This section further explore the variability and consistency of the model outputs with respect to some relatively exogenous choices of modelling components, including the route set, the choice of $G(x)$ and the weights described in the departure time choice model (3-17) and (3-20).

As mentioned in the remark at the end of Section 3.4, the set of routes (of size 6180) is generated via the Frank-Wolfe algorithm. To illustrate the model performance with different route sets, three additional route sets are considered with decreasing sizes: 5537, 5270 and 4895. The link disruption experiment in the Sioux Falls network is repeated for these cases (with Base Model II, $\theta = \theta_1 = 0.004, \eta = 400, N = 3$), and the results in terms of network total cost and relative gaps. It can be seen from Figure 4.13 that all four cases (including the original case) show qualitatively similar trends in network evolution, suggesting that different route sets lead to similar behaviour of the model. It is interesting to note that the overall network cost increases as the number of routes (choice alternatives) reduces, which makes sense as travellers are competing for resources (road capacity) on more stringent choice spaces. The fact that the cases of 5270, 5537 and 6180 routes do not differ significantly suggests that the current choice of 6180 routes is reasonable in representing attractive routes associated with the given travel demands.

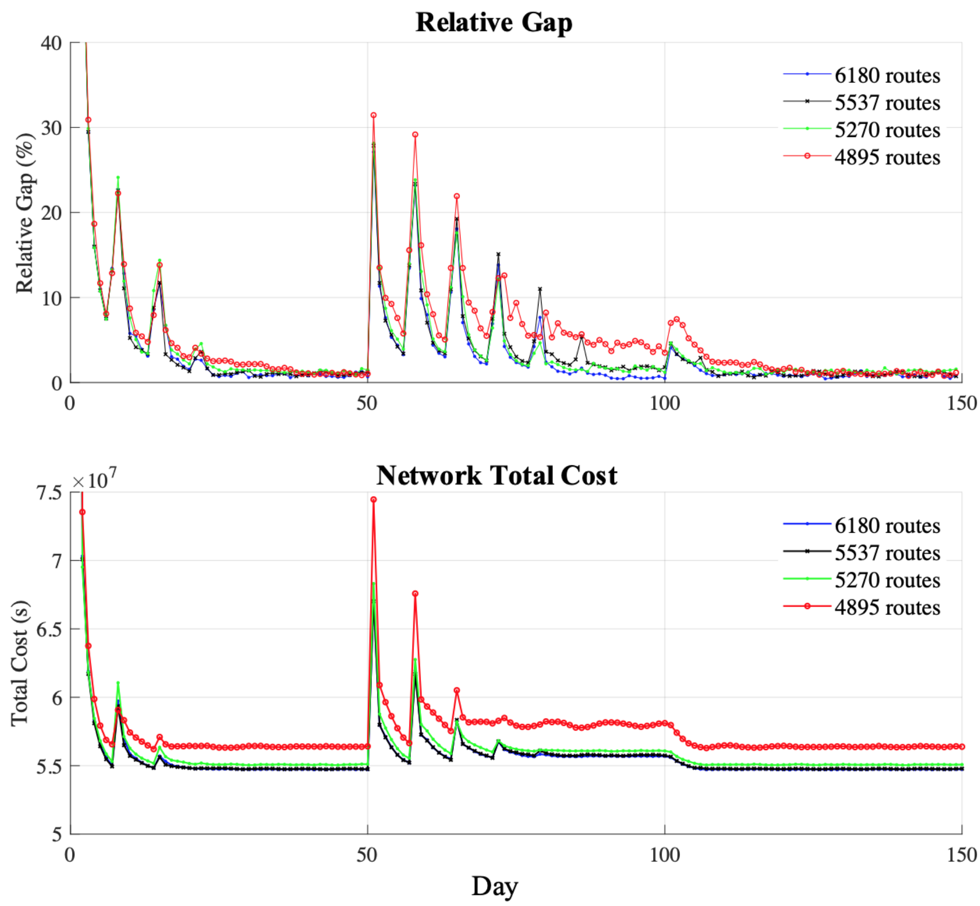


Figure 4.13. Comparison of different route sets in the Sioux Falls network under link disruption (Base Model II)

Next, this section considers two additional forms of $G(x)$ in the information sharing model. The purpose is to demonstrate consistency of the model outputs with regard to different functional forms of $G(x)$, as long as they satisfy the minimum requirement of being monotonic, and $G(0) = 0, G(1) = 1$. In deriving the following functional forms, $G(x) = x^2$ is used as the benchmark.

1. **Piecewise affine**. The following formula is proposed:

$$G(x) = \begin{cases} \frac{2}{3}x & x \in [0, 0.75] \\ 2x - 1 & x \in (0.75, 1] \end{cases}$$

2. **Trigonometric functions.** The following formula is considered:

$$G(x) = \tan(1.2x)/\tan(1.2) \qquad x \in [0, 1]$$

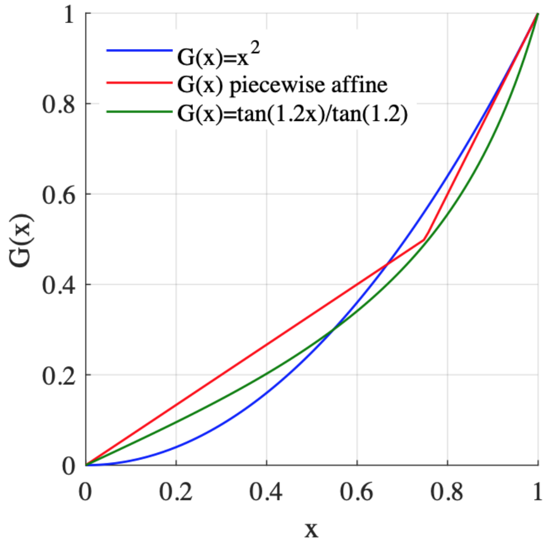


Figure 4.14 Different forms of $G(x)$.

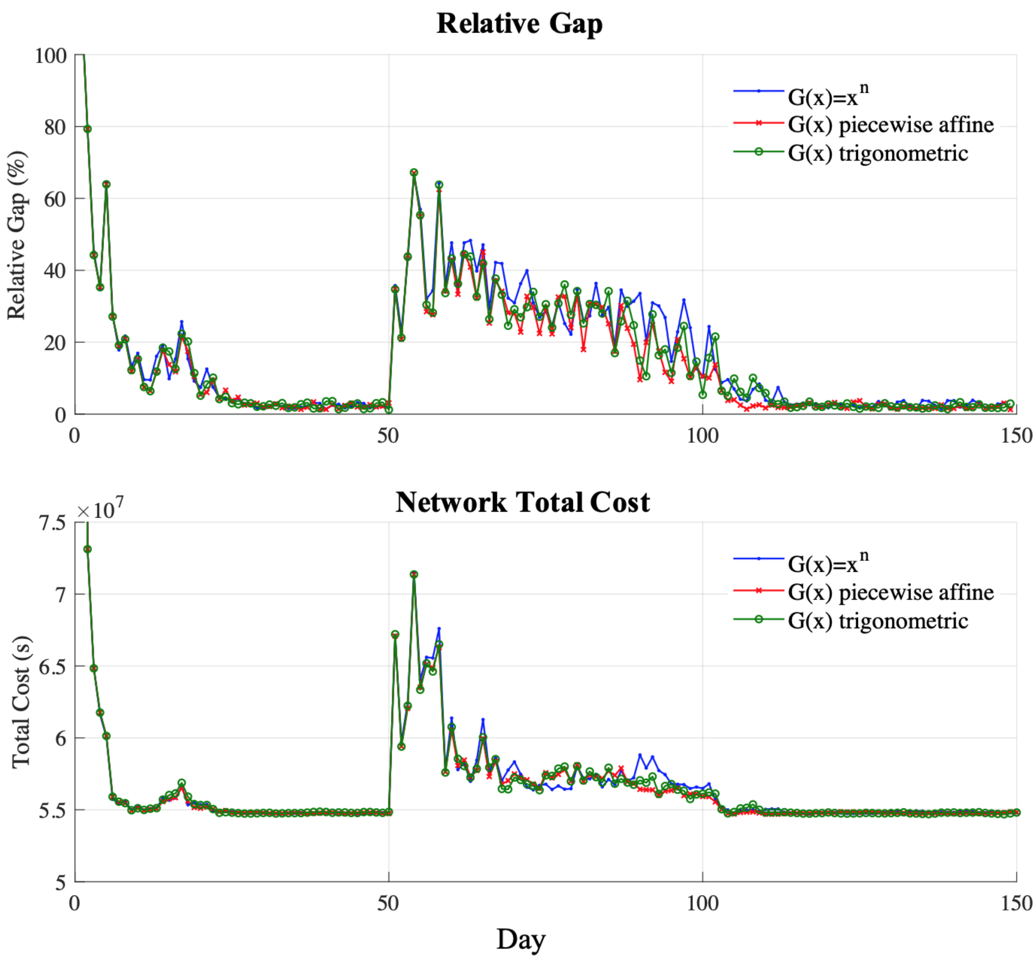


Figure 4.15 Comparison of different functional forms of $G(x)$ in the Sioux Falls network under link disruption (Base Model II with information sharing)

The two new functions are compared with $G(x) = x^2$ in Figure 4.14. Next, simulations are run on the models (Base Model II with information sharing) and compare the results in Figure 4.15. It can be seen that despite the different forms of $G(x)$, the resulting daily trajectories in terms of relative gap and network total costs are quite similar. This verifies the model's consistent performance, which is not significantly affected by the choice of $G(x)$ as long as it satisfies $G(0) = 0, G(1) = 1$ and being monotonically increasing.

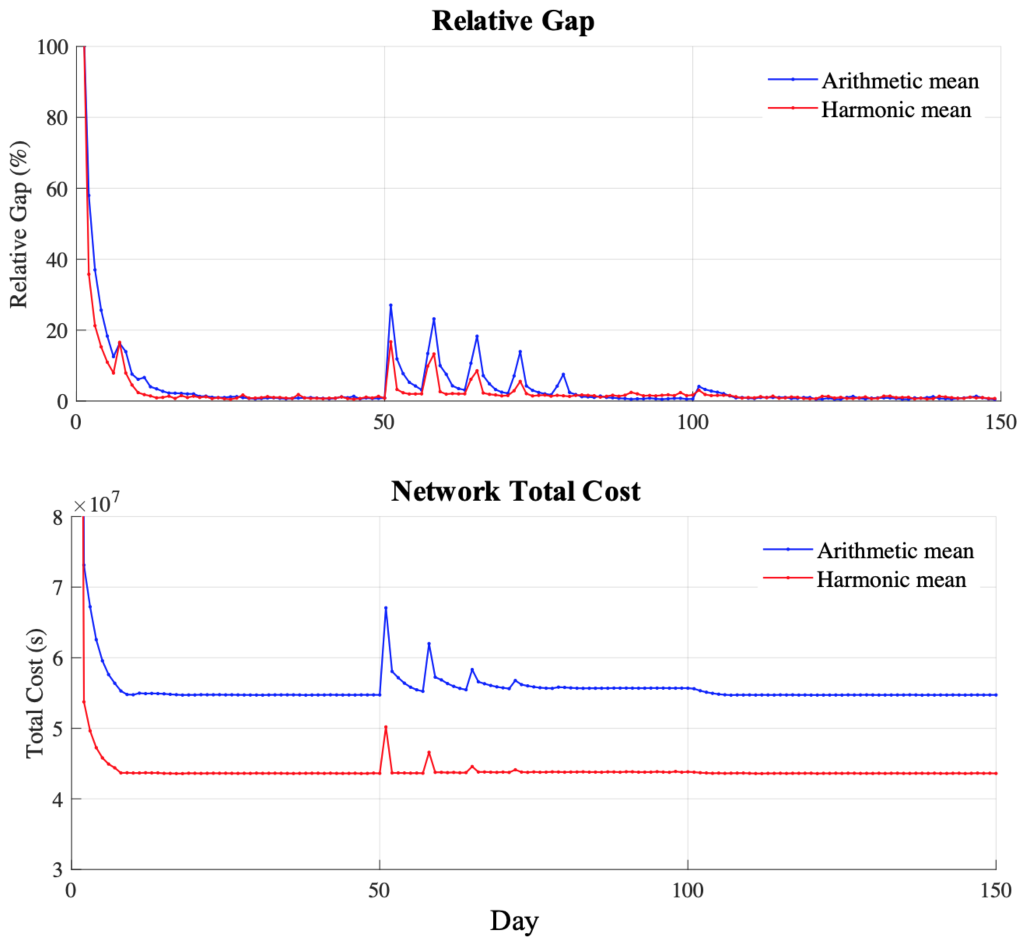


Figure 4.16 Comparison of Base Model II with different departure time choice models.

Finally, this section compares the departure time window choice models within Base Model II. Two variants, based respectively on arithmetic mean (3-17) and harmonic mean (3-20) of the route costs within the same time window, are proposed. The arithmetic mean considers all the route costs with equal weights, while the harmonic mean places more weights on the more efficient routes. As can be seen in Figure 4.16, the two cases differ in that

1. The case with harmonic mean leads to reduced total network costs at both equilibriated and disequilibriated conditions. This may be due to travellers' perception of a departure window being influenced by a few attractive routes, instead of all the possible routes. This allows travellers to more effectively explore the spatial-temporal network capacity.

2. The case with harmonic mean results in less oscillations in the network during the disruption period. A possible cause is that their decisions on departure time window are influenced by only a subset of all possible routes.

4.5 Summary

The previous chapters propose doubly dynamic traffic assignment (DDTA) models with realistic user behaviour and network dynamics. The analytical and deterministic model is flexible in incorporating further model extensions such as bounded rationality, and incomplete information. The proposed DDTA models could serve as the traffic model in the road network M&R planning models proposed in Chapter 6 and 7 for a more realistic capturing of travellers' behaviour and network traffic dynamics during the M&R planning period.

In this chapter, the proposed DDTA models has been implemented in large-scale networks including the Sioux Falls (528 O-D pairs, 6,180 routes) and Anaheim (1,406 O-D pairs, 30,719 routes) networks. The following conclusions are made from the numerical results:

1) Daily oscillation of traffic flow, measured by the relative gap, depends on the strength of information communication, which is parameterized by $n \in [0,1]$ in the function $G(x) = x^n$ (Section 3.7). In particular, in the Sioux Falls network, the relative gaps increase with n (Figure 4.5), which means that network traffic undergoes larger daily oscillation when the travellers only have access to information of a few popular choices; such oscillation is minimised when the travellers have complete information of every alternative.

2) The size of the indifference band (δ) has an impact on the daily oscillation. Larger δ reduces the relative gaps, which conforms with intuition that travelers' reluctance to switch

choices has a stabilizing effect on the daily dynamics.

3) Under certain network conditions, the absence of complete information on every single alternative tends to smooth the daily variations of perceived costs, and hence could stabilize daily traffic and reduce congestion cost associated with constant SRDT choice switches (Section 4.2.2). Note that this contradicts the observations made in 1) concerning the Sioux Falls network, which suggests that this type of network behaviour is case-dependent.

4) Local disruption (in the form of link capacity reduction in this chapter) tends to induce earlier departures for relevant O-D pairs. This is likely caused by the spatial propagation of congestion triggered by vehicle spillback, rendering alternative routes within the same departure window unattractive. This highlights the need to (a) simultaneously model route and departure time choices; and (b) accurately represent congestion propagation with realistic vehicle queuing dynamics.

5) Relating to 4), the amount of shift towards earlier departure windows depends on the information shared among travellers. In particular, larger n (as in $G(x) = x^n$) leads to more shift. This is caused by travelers' conservative behavior when facing uncertainties in the absence of complete and accurate travel information.

6) Relating to 5), the model displays similar behaviour when the functional form of $G(x)$ undergo minor perturbations. For example, assuming that $G(x)$ is increasing, convex and satisfies $G(0) = 0, G(1) = 1$ (examples include $G(x) = x^2$, piecewise affine and trigonometric functions), the model results are exhibit qualitatively similar patterns.

7) Under local disruption, the network may undergo a significant transient period before reaching the (approximate) stationary state. This has been corroborated by Figure 4.12. The transient state may be associated with daily traffic variations and considerable congestion and social cost. Unfortunately, such transient states have been overlooked in many equilibrium-based traffic network design and optimisation approaches, such as those based

on Stackelberg games and Mathematical Program with Equilibrium Constraints.

8) When making departure time choices in Base Model II, travellers (with complete information on alternative routes in a particular window) may evaluate different routes with equal weighting (Eqn (3-17)), or give higher weights to the better routes (Eqn (3-20)). Numerical experiment suggests that the latter leads to less network oscillation and higher efficiency, as travellers' perception of a time window depends only on a few efficiency routes instead of all possible ones.

9) Although the proposed models comprise numerous components and parameters, which makes it difficult to derive theoretical results on their performances and behaviour, it is shown through numerical examples and extensive sensitivity analyses that the model outputs remain consistent and stable with respect to different choices of their parameters and components. In addition, the model behaviour coincides with intuition. This makes these models desirable to study and predict complex traffic phenomena such as network disequilibria, for which no existing modelling tools are available.

In this chapter, simulations on large-scale networks illustrate the interactions between users' adaptive decision making and network conditions (including local disruption) with different levels of information availability and user behaviour. The proposed doubly dynamics contribute to state of the art by presenting a unified framework for modelling realistic user and traffic dynamics under transient or non-equilibrium states, which offers useful tools for network management and policy appraisal, such as M&R planning.

5 Day-to-Day Road Quality Model and M&R Modelling

In Chapter 3 , a day-to-day dynamic traffic assignment model is proposed, which serves as a network traffic flow modelling platform for M&R planning and optimisation problems. The model is capable of capturing realistic traffic dynamics and responses under various M&R planning decisions. In addition, long-term road M&R planning problems are conditional on the estimation of road quality dynamics among networks as well as modelling of M&R effectiveness. For M&R decisions, it is necessary to apply realistic road quality models for evaluating road deterioration process and M&R performance. This chapter presents a deterministic road quality model, in conjunction with the DTD DTA model, to capture DTD road deterioration and M&R effectiveness. Traffic loads in different parts of the road network, which can be computed within the proposed DTD DTA models in Chapter 3 is considered as an important factor affecting the DTD deterioration of road surface. Furthermore, this chapter presents the DTD evolution of road flow capacity and free flow time influenced by the dynamic change of road quality, which will in turn affect traffic loads via the DTD DTA model. This forms the 'quality-usage' feedback mechanism between road quality and traffic loading, which partially reveals the complexity of M&R planning problems.

This chapter first describes road deterioration process, reviews road deterioration modelling in M&R, and introduces the road roughness index in Section 5.1. The description of the 'quality-usage' feedback mechanism framework is provided in Section 5.2. The DTD road quality model is presented in Section 5.3, including the modelling of road deterioration and M&R effectiveness. Then, the model of DTD road flow capacity during and between M&R

actions is presented in Section 5.4. Section 5.5 presents a numerical example for illustrating how road quality and traffic dynamics can be factored into each other by the models proposed in this thesis. A summary of this chapter is given in Section

5.1 Road Deterioration and Roughness Index

Road are designed for a particular service lifetime and will deteriorate over time. The main factors that affects road performance are traffic loading on roads, weather conditions, and road maintenance actions.

- *Traffic.* Traffic is the primary factor contributing to road performance. Road deterioration is majorly influenced by the repetitive traffic loading on the roads, especially heavy vehicles that carry higher loading magnitude.
- *Weather.* Weather condition is another important factor affecting road quality. Especially moisture and high temperature of roads can weaken the support strength of pavement materials and damage road structure, which could also intensify the road deterioration due to traffic loading.
- *Maintenance.* Road performance also dependent on when, what, and how the maintenance work carried out on roads. It is very important to plan the timing of road maintenance work, since postponed M&R limited by budget could significantly increase user costs due to fair road quality.

The effects of road deterioration can be mitigated or even converted by applying effective road M&R actions, which could reduce the current and future operating costs consequently (Durango & Madanat, 2002).

5.1.1 Road Deterioration

M&R planning evaluation and decision-making is based on the predictions of road performance in the network as well as the effectiveness of M&R actions. It is critical to select the appropriate road deterioration models for long-term M&R planning problems.

Road deterioration process can be modelled both deterministically and stochastically. Deterministic models use empirical curves for the descriptions of road condition evolutionary dynamics, with explicit quantification of the relationship of road condition and influencing factors. Deterministic road deterioration models have been widely applied in the M&R studies (Tsunokawa & Schofer, 1994; Li & Madanat, 2002; Ouyang & Madanat, 2006; Ouyang, 2007; Maji & Jha, 2007; Chu & Chen, 2012; Gao & Zhang, 2013). Stochastic road deterioration models are capable to capture the stochastic nature of road deterioration and quantify the uncertainty in the road performance predictions. Markov Decision Process (MDP) is often utilized to solve road M&R planning problems (Guignier & Madanat, 1999; Smilowitz & Madanat, 2000; Guillaumot et al., 2003), but it requires sufficient data of road conditions and needs more computational effort than the deterministic models, especially for large-scale problems (Bellman, 1957). The road deterioration model employed in this thesis is a deterministic road roughness model.

There is an increasing demand for improved M&R planning techniques, which requires the realistic modelling of road quality for evaluating road deterioration process and the M&R performance on roads. The majority of the road deterioration models only consider road deteriorates with time by defining the deterioration rates. Friesz and Fenandez (1979) used linear expression of road deterioration with time. Tsunokawa and Schofer (1994), Li and Madanat (2002), Ouyang and Madanat (2004; 2006), Gao and Zhang (2013) modelled the road deterioration process as an exponential deterioration function of time, taking roughness as the indicator of road conditions. Maji and Jha (2007) applied parabolic equations in modelling road deterioration with time. The deterioration rates of these studies are assumed to be dependent only on the current road conditions. Traffic flow is assumed to be an exogenous factor that influences road deterioration in these studies. However, traffic loading on the road is a major factor that contributes to road deterioration (Chu & Chen, 2012), which is necessary to be quantified in modelling road quality dynamics in M&R planning problems. A few M&R studies (Uchida and Kagaya, 2006; Ouyang, 2007; Chu & Chen, 2012) considered traffic loading in road deterioration models. Ouyang (2007) added a linear component of traffic flow into the exponential road deterioration rate function, which is the reference model for the DTD road deterioration model in this thesis for a more accurate and realistic capturing of road quality dynamics.

The modelling of M&R effectiveness is also critical since the prediction of road quality after M&R depends on the estimation of M&R effects. Majority of the related M&R studies (Tsunokawa & Schofer, 1994; Li & Madanat, 2002; Ouyang & Madanat, 2004, 2006; Ouyang, 2007; Sathaye & Madanat, 2011) modelled the M&R effectiveness as a performance jump. Paterson (1990) presented that the effectiveness of pavement M&R is a function of the road condition before M&R and the M&R intensity. Ouyang and Madanat (2004) proposed a M&R effectiveness model based on this empirical study and modelled the effect of M&R as an instantons performance jump, the discontinuous version of which is applied to quantify M&R effectiveness in this thesis.

5.1.2 Road Roughness Index

Road roughness is broadly defined as an indication of the un-smoothness of pavement surface so that adversely affects the riding quality of vehicles thus has an impact on user costs. Roughness will increase as the road deteriorates. The higher the roughness value, the worse the road quality is (see Figure 5.1). Roughness is a key factor in determining road quality as well as quantifying the benefits from road M&R and is thus a critical measurement of road conditions (Paterson, 1990). Road roughness, the negative expression of road quality, is taken as the indicator for modelling the road condition in this thesis. Road roughness deterioration process is always assumed to follow a saw-tooth-like time trajectory curve as roads deteriorate and receive M&R actions (Tsunokawa & Schofer, 1994). As illustrated in Figure 5.1, roughness increases continuously between consecutive M&R actions, where road M&R actions cause discrete reductions on road roughness. Many existing studies on M&R planning (Li and Madanat, 2002; Ouyang and Madanat, 2004; 2006; Ouyang, 2007; Maji and Jha, 2007; Ng et al., 2009; Zhang et al. 2010; Lee and Madanat, 2014) assume that the M&R took place instantly as shown in Figure 5.1, this thesis considers an explicit M&R period for the purpose of modelling the impact of M&R activities on network traffic, see Section 5.3.

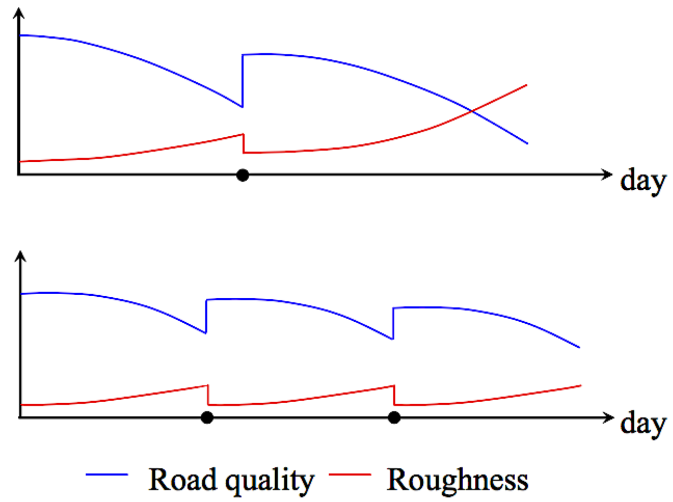


Figure 5.1 Sawtooth trajectory curve of road roughness compared with road quality

Various measurements of road roughness are applied in different countries. International Roughness Index (IRI), established from the International Road Roughness Experiment (IRRE) by the World Bank in 1980s, is a transferable reference of roughness. Paterson (1990) discussed various roughness index and their relationships with IRI. This thesis applies Quarter-car Index (QI) rather than IRI for quantifying road roughness so as to be consistent with the index of numerous studies on road quality models in M&R (Li and Madanat, 2002; Ouyang and Madanat, 2004; Ouyang and Madanat, 2006; Ouyang, 2007). QI is a profile-based statistic defined by the reaction of a single tire on a vehicle suspension (quarter-car) to roughness of the pavement surface, traveling at 55 mph, which is calculated as the filtered ratio of a standard vehicle's accumulated suspension motion (in counts) divided by the distance travelled by the vehicle during the measurement (in km). Figure 5.2 provides QI scale regarding different road conditions as well as the associated normal use speed, in which data are transformed from IRI scale by The World Bank (Sayers, et al. 1986). The transformation formula between QI and IRI is $QI = 13 \times IRI$ (Paterson, 1990).

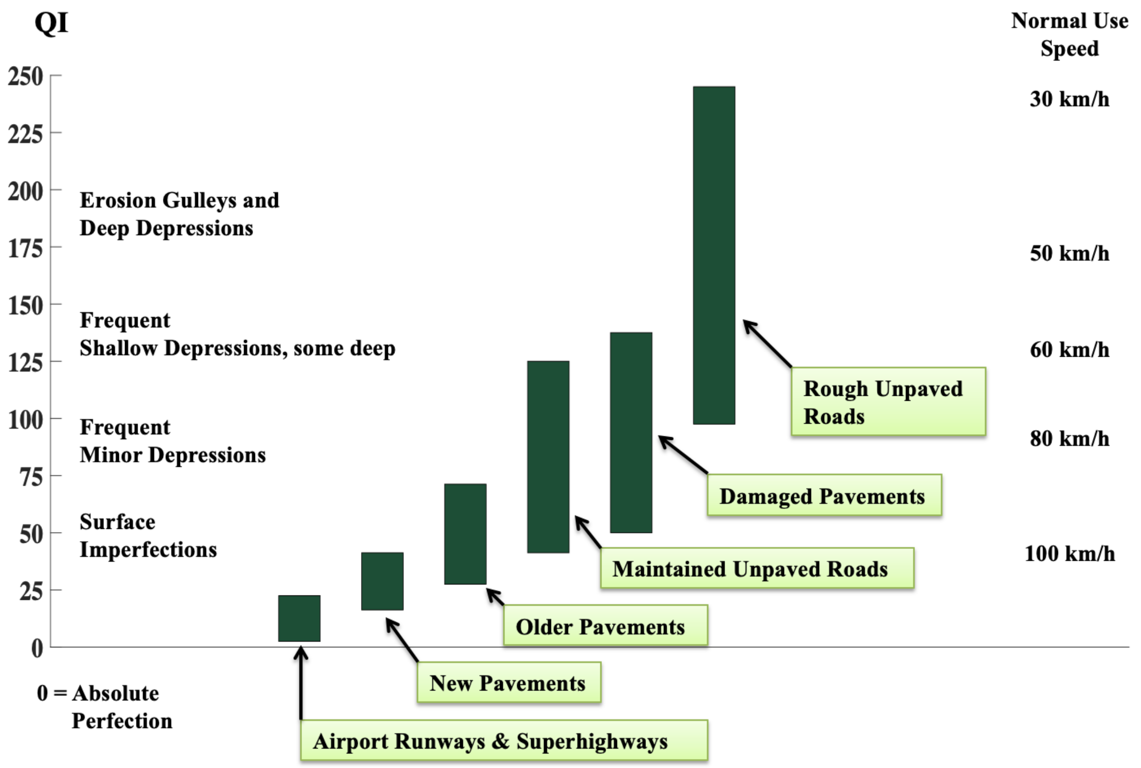


Figure 5.2 QI index scale

5.2 Quality-Usage Feedback Mechanism

The most important maintenance-relevant state variables are link-specific and path-specific traffic flows as well as road quality. M&R studies, including Friesz and Fernandez (1979), Guignier and Madanat (1999), Ouyang and Madanat (2006) and Sathaye and Madanat (2011), have recognized that M&R planning problems are intrinsically dynamic due to a variety of phenomena including the interactions between traffic, road quality and M&R actions. Except for the influence of traffic loading on road deterioration that discussed in Section 5.1.1, road condition is in turn a significant factor that influence adaptive traffic choices thus responsive traffic flow among road network (Hawas, 2004).

The road quality and traffic usage (Quality-Usage) feedback mechanism, as shown in Figure 5.3, illustrates the interdependencies between road quality and road traffic usage, leading to the complexity of M&R planning problems in this thesis. Intuitively, the traffic load on the road causes road deterioration, which in turn affects the road capacity and subsequently the traffic load (via the selfish routing mechanism). Decision-making on M&R plans are partially determined based on road deterioration, and M&R would reduce road capacity during the road works in relevant parts of the network. Traffic flow dynamics on each road segment throughout the entire network are a critical factor for estimating DTD road quality, which informs M&R decisions. The DTD road quality model in this chapter presents the process of traffic-induced road deterioration as well as quality recovery after M&R actions.

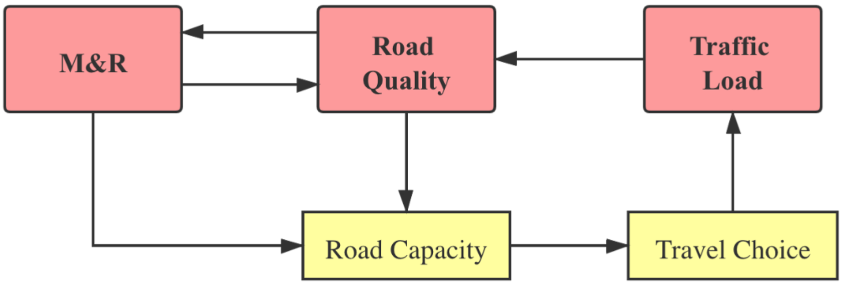


Figure 5.3 Quality-usage feedback mechanism

This feedback mechanism will be investigated in the bi-level M&R planning framework in Chapter 6 and 7 ,which simultaneously minimise M&R expenditure and road traffic congestion. The underlying lower-level problem is the day-to-day dynamic traffic network model, which consists of two components: (1) the evolution of traffic in response to both on-going M&R activities and road quality dynamics; and (2) the evolution of road quality as a result of traffic loads and M&R actions. These dynamics are combined to interact with an upper-level M&R model, which captures realistic phenomena associated with short-term and long-term effects of M&R, including road capacity reduction, physical queuing and spillback, temporal-spatial shift of congestion due to on-going M&R activities, the tendency to converge to an equilibrium after M&R projects, and scheduled disruption of the equilibrium due to M&R activities.

5.3 Day-to-Day Road Quality Model

This section presents the day-to-day road quality model, where the evolutionary dynamic of road roughness over time follows a saw-tooth like trajectory as the road deteriorates and receives M&R. Figure 5.4 gives an illustration of the DTD road quality model, which consists of two parts: (1) the road deterioration process between two consecutive M&R actions, where an increase in roughness is seen from $Q(\tau_1)$ to $Q(\tau_2)$; and (2) road roughness decrease after M&R, from $Q(\tau_2)$ to $Q(\tau_3)$. Unlike many existing studies on M&R, which assume that the M&R took place instantly, this work considers a non-empty M&R interval (e.g. $\tau_2 - \tau_3$), where the impact of M&R activities on traffic is explicitly modelled.

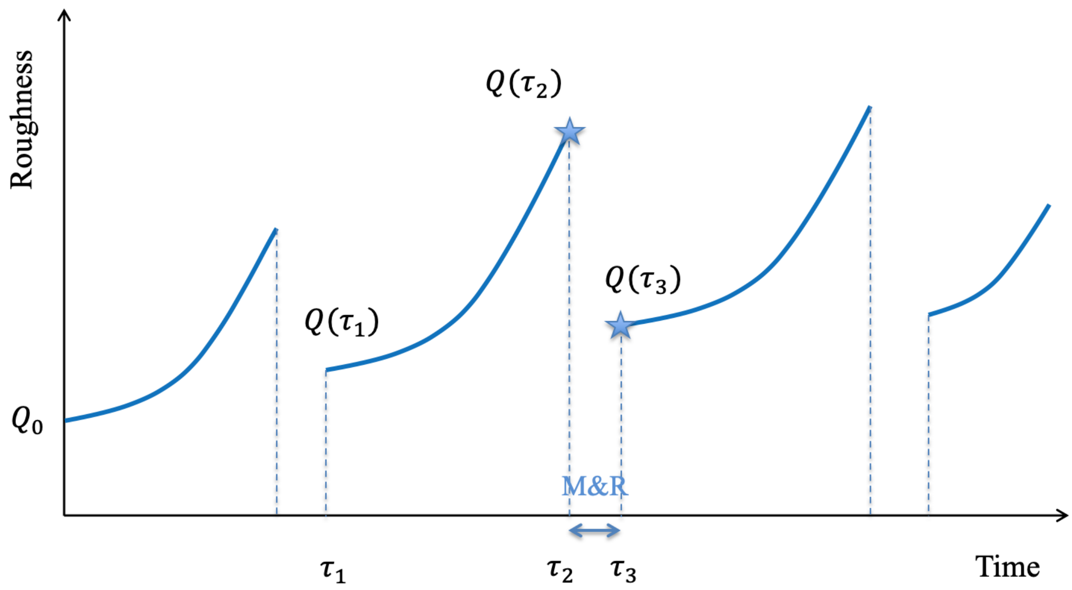


Figure 5.4 An illustration of the DTD road quality model

The model formulations of these two parts of the DTD road quality model are given in this section respectively. The key notations employed in this chapter are listed below.

Parameters/variables

τ:	Day-to-day time parameter
a:	Link in the road network
$Q_a(\tau)$:	Road quality (e.g. roughness) of link $a \in A$ on day τ
$w_a(\tau)$:	M&R intensity of link $a \in A$ of M&R action on day τ
$CC_a(\tau)$:	Flow capacity of link $a \in A$ on day τ
$FFT_a(\tau)$:	Free flow time of link $a \in A$ on day τ

Sets

A: Set of links in the road network

A^m: Set of links in the road network subject to M&R

5.3.1 Road Deterioration Model

Roughness deteriorates continuously between consecutive M&R actions. The road deterioration rate is generally modelled as a function of road condition with time only (e.g. Tsunokawa and Schofer, 1994; Li and Madanat, 2002; Ouyang and Madanat, 2004; Ouyang and Madanat, 2006), such as a simple linear deterioration rate in Tsunokawa and Schofer (1994):

$$\frac{dQ}{dt} = b \cdot Q \tag{5-1}$$

where, t is continuous time, Q is road quality, b is deterioration parameter.

The assumption in Equation (5-1) is not realistic, since traffic loading is expected as a key factor that influences road quality (Ouyang, 2007). This thesis further considers the impact of time varying traffic loads on the road deterioration process. To achieve this, a linear traffic flow component is added to the deterioration rate, which is akin to Ouyang (2007):

$$\frac{dQ_a(t)}{dt} = [b_{a0} + b_{a1} \cdot h_a(t)] \cdot Q_a(t) \ , \qquad \forall a, t \tag{5-2}$$

where $Q_a(t)$ is road quality of link a at time t, $b_{a0} > 0$ and $b_{a1} > 0$ are link-specific deterioration parameters, $h_a(t)$ denotes traffic flow of link a at time t. This deterioration rate allows the modelling of road deterioration with the increase of road traffic loads.

This thesis applies an exponential function of time for modelling road deterioration process, which is commonly assumed in the literature (e.g. Tsunokawa and Schofer, 1994; Li and Madanat, 2002; Ouyang and Madanat, 2004; Ouyang and Madanat, 2006; Ouyang, 2007). Thus, Equation (5-2) can be represented as the exponential deterioration function as follows:

$$Q_a(t_n) = Q_a(t_0) \cdot \exp\left\{\int_{t_0}^{t_n} [b_{a0} + b_{a1} \cdot h_a(t)]dt\right\}, \qquad t_0 \le t_n, \forall a \tag{5-3}$$

If time is discretized as a day-to-day time parameter τ, Equation (5-3) can be converted into the DTD road deterioration model in this thesis as shown in Equation (5-4). The road roughness of link a on day τ, denoted $Q_a(\tau)$, is determined on the road roughness of the previous day as well as the traffic loading on the road in the previous day.

$$Q_a(\tau) = Q_a(\tau - 1) \cdot \exp[b_{a0} + b_{a1} \cdot f_a(\tau - 1)], \qquad \forall a \in A \tag{5-4}$$

where, $f_a(\tau - 1)$ is the traffic volume loading on link a of day $\tau - 1$. The term $[b_{a0} + b_{a1} \cdot f_a(\tau - 1)]$ is increase with link traffic volume $f_a(\tau - 1)$. $b_{a0} > 0$ and $b_{a1} > 0$ are link specific deterioration parameters regarding to various road classes and road types.

As can be seen from Equation (5-4), DTD traffic volume is a major endogenous factor that contributes to DTD roughness deterioration process in this thesis. The traffic loading on each path r at each departure window t on each simulation day τ, that is $f_{(r,t)}(\tau)$, is provided by the DDTA models (see Section 3.5.2, 3.5.3, 3.6.2, 3.7.2). Thus, the total traffic volume loading on path r on day τ, denoted $f_r(\tau)$, can be calculated as:

$$f_r(\tau) = \sum_t f_{(r,t)}(\tau) \cdot k , \qquad \forall (r,t) \in R \times T \tag{5-5}$$

where, k is a converting factor in order to convert the path traffic volume of the simulation horizon to the traffic volume of a simulation day. For the case studies in this thesis, the simulation horizon within a day is a five-hour morning commuting period and the simulation day refers to a calendar month. Thus, $k = 1/0.4 \times 6 \times 4$ is applied to convert the simulated five-hour travel cost to the network travel cost of a calendar month, assuming that five-hour morning commuting period consists of 40% traffic of a calendar day, each commuting day consist of 1/6 traffic of a week, and each month contents 4 weeks.

Then, the traffic volume of link a on day τ, denoted $f_a(\tau)$, can be calculated as the cumulated path traffic volume that uses the link:

$$f_a(\tau) = \sum_r z_{ar} \cdot f_r(\tau) \ , \qquad \forall a \in A \tag{5-6}$$

where, z_{ar} is indicator variable that equals 1 if path r passing through link a, and equals 0 otherwise.

Therefore, the DTD link traffic volumes $f_a(\tau)$ derived from the DDTA model can be used in the DTD road deterioration model in Equation (5-4) to calculate the DTD road roughness.

5.3.2 M&R Effectiveness Model

Paterson (1990) developed parametric models for the physical effects of various M&R activities, which are functions of M&R intensity and the road condition right before M&R action. M&R effectiveness is the amount of road condition improvement due to M&R action, represented by roughness reduction after M&R and measured by QI index. M&R intensity is the strength or depth of a M&R construction work, measured in millimetre (mm). According to the empirical data from Paterson (1990), Ouyang & Madanat (2004) fit the estimated relationships between M&R effectiveness and M&R intensity for different conditions of roughness before M&R. Figure 5.5 is taken from Ouyang & Madanat (2004). It can be seen that, given a road roughness condition before M&R, the M&R effectiveness (roughness changes) can be represented by a linear relationship with M&R intensity, and there is an upper limit of M&R intensity, beyond which additional M&R work does not have a noticeable reduction on roughness. This indicates that M&R with intensity larger than this upper limit will be sub-optimal in M&R planning problems as it generates more expenditure.

Therefore, for modelling M&R effectiveness, same to Ouyang and Madanat (2004), this thesis assumes that, before the roughness change reached a maximum value, there is a linear relationship between M&R effectiveness and M&R intensity, which is different according to road conditions before M&R. In addition, a maximum intensity constraint is added into the model to restrict the intensity to be lower than the certain upper limit. Compared with formulating the piecewise functions of M&R effectiveness, modelling in this way could simplify the computational difficulty of the M&R planning model without changing the optimal M&R solution.

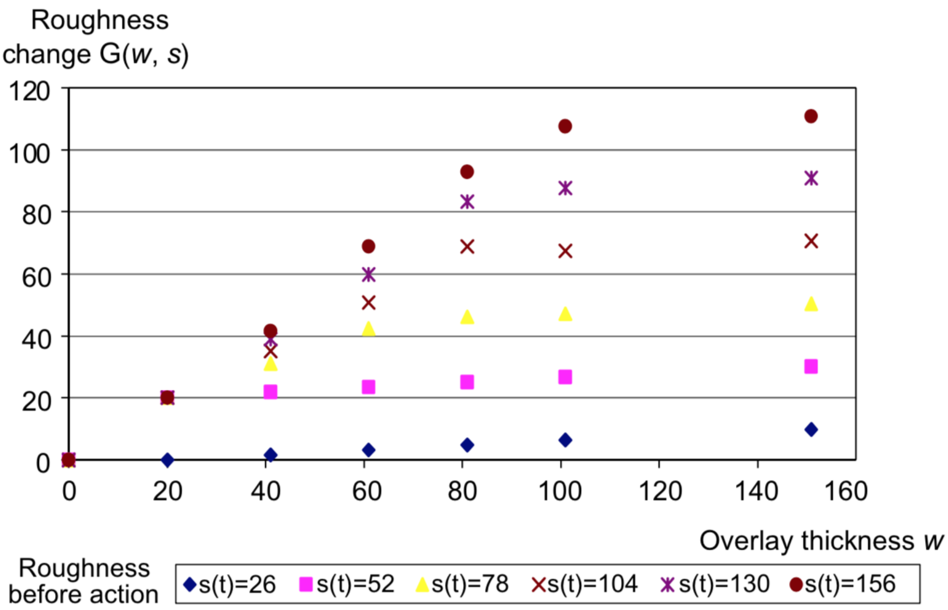


Figure 5.5 M&R effectiveness from Paterson (1990) in QI index (Ouyang and Madanat, 2004)

According to this approach, the effectiveness of the M&R action on link a on day τ then can be represented as the functions below. As shown in Figure 5.5, the intensity limit as well as the maximum M&R effectiveness are depending on the roughness before M&R.

$$G[Q_a(\tau-1), w_a(\tau)] = \frac{G_{max}\big(Q_a(\tau-1)\big)}{w_{max}\big(Q_a(\tau-1)\big)} \cdot w_a(\tau) \qquad \forall a \in A^m \qquad (5\text{-}7)$$

$$w_a(\tau) \leq w_{max}\big(Q_a(\tau-1)\big) \qquad (5\text{-}8)$$

where, G_{max} is the maximum M&R effectiveness and w_{max} is the upper limit of intensity, $Q_a(\tau-1)$ is the roughness of link a on the day before M&R. The amount of roughness reduction, that is M&R effectiveness, is assumed to be dependent on M&R intensity as well as roughness before M&R action.

Ouyang and Madanat (2004) use data from Figure 5.5 to estimate the functions of G_{max} and w_{max} of the roughness before M&R. Figure 5.6 is taken from Ouyang and Madanat (2004) that shows the regression results, which see clear linear relationships.

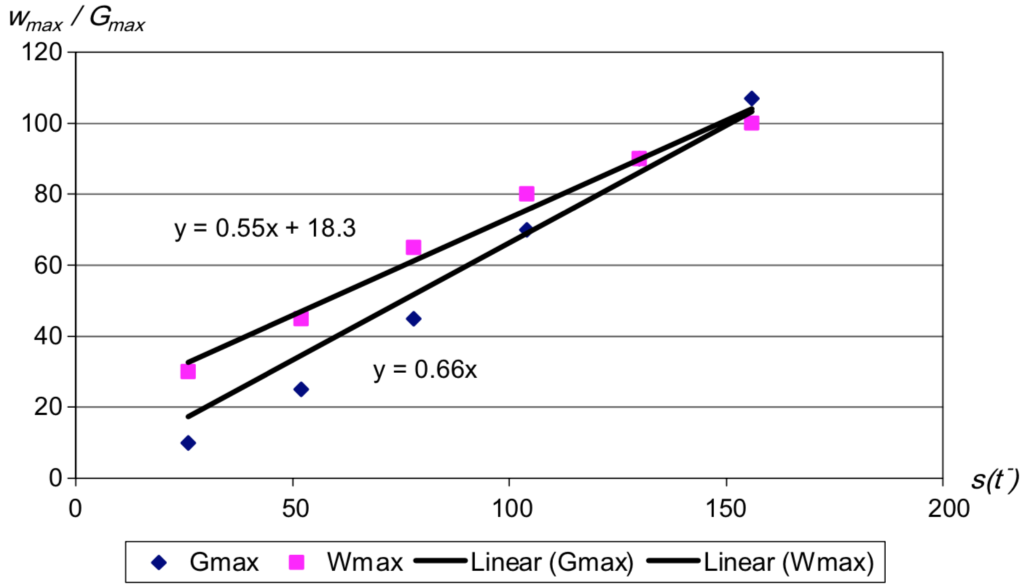


Figure 5.6 Regression of G_{max} and w_{max} (Ouyang and Madanat, 2004)

This thesis applies the models proposed in Ouyang and Madanat (2004) for M&R effectiveness modelling. Thus, applying the linear relationships shown in Figure 5.6 into Equation (5-7) and (5-8), for a M&R action on link a on day τ with M&R intensity $w_a(\tau)$ and the M&R duration of D_a days, the M&R effectiveness is formulated as:

$$Q_a(\tau-1)-Q_a(\tau+D_a)=G[Q_a(\tau-1),w_a(\tau)] \\ =\frac{g_1\cdot Q_a(\tau-1)}{g_2\cdot Q_a(\tau-1)+g_3}\cdot w_a(\tau) \qquad \forall a\in A^m \tag{5-9}$$

$$w_a(\tau)\le g_2\cdot Q_a(\tau-1)+g_3 \tag{5-10}$$

where, $g_1=0.66$, $g_2=0.55$, $g_3=18.3$. $Q_a(\tau-1)$ is the roughness of link a on the day before M&R. $Q_a(\tau+D_a)$ is the roughness of link a after M&R. Although the data for deriving g_1, g_2, g_3 have not been updated, if the functions of $G_{max}\big(Q_a(\tau-1)\big)$ and $w_{max}\big(Q_a(\tau-1)\big)$ satisfy monotonicity, it will not change the establishment of the results made on M&R effectiveness even it could have a difference in the direct values.

So far, The DTD road quality dynamics in this thesis can be modelled by the Equation (5-4), (5-9), and (5-10) above.

5.4 Day-to-day Road Flow Capacity Model

Section 5.3.1 presents the impacts of traffic loads on road quality on a day-to-day time scale, which forms one branch of the quality-usage feedback mechanism (see Figure 5.3). This section presents another branch: how day-to-day road deterioration in turn influence day-to-day road capacity and affects the evolution of traffic loading on the road network. The modelling of road capacity reduction due to M&R actions is also presented.

5.4.1 LWR Model and Fundamental Diagram

This thesis employs an LWR-based DNL procedure (see Section 3.8.4) for modeling traffic loading on the road. Traffic dynamics within-link in the road network are modeled by the Lighthill-Whitham-Richards (LWR) model (Lighthill and Whitham, 1955; Richards, 1956), which describes the temporal-spatial evolution of traffic density on a link via the partial differential equation below.

$$\frac{\partial \rho(t,x)}{\partial t} + \frac{\partial F(\rho(t,x))}{\partial x} = 0, \qquad x \in [i,j], t \in [t_0, t_f] \tag{5-11}$$

where, the link studied is represented as a spatial interval $[i,j]$. $\rho(t,x)$ denotes the vehicle density. The function $F(\rho(t,x))$ is a description of the flow-density relationship, known as the fundamental diagram. The fundamental diagram satisfies $F(0) = F(\rho_{jam}) = 0$ where ρ_{jam} denotes the jam density (maximum density). There also exists a critical density ρ_{crit} at which $F(\rho_{crit}) = CC$ where CC denotes the link flow capacity (maximum flow). LWR-type models have been widely used in traffic flow modelling since they are capable to describe shock waves phenomena as well as capture vehicle queues and spillback.

There are some widely adopted forms of the fundamental diagram, such as the Greenshields (Greenshields, 1935), the triangular (Newell 1993) and the trapezoidal (Daganzo, 1994, 1995). This thesis considers a triangular fundamental diagram formulated as:

$$F(\rho) = \begin{cases} v\rho & \rho \in [0, \rho_{crit}] \\ -w(\rho - \rho_{jam}) & \rho \in (\rho_{crit}, \rho_{jam}] \end{cases} \tag{5-12}$$

Furthermore, the DNL model in this thesis assumes the following relationship between jam density and critical density in the fundamental diagram.

$$\rho_{jam} = 4\ \rho_{crit} \tag{5-13}$$

This fundamental diagram is illustrated in Figure 5.7. It shows that traffic flow has two states: the uncongested (free-flow) state and the congested state. Flow increase with density at forward propagating wave speed v that equal to free-flow speed (FFS) until flow reach capacity at critical density ρ_{crit}, after this point flow decrease with density at backward propagating wave speed w, and reduce to zero when density reach jam density ρ_{jam}.

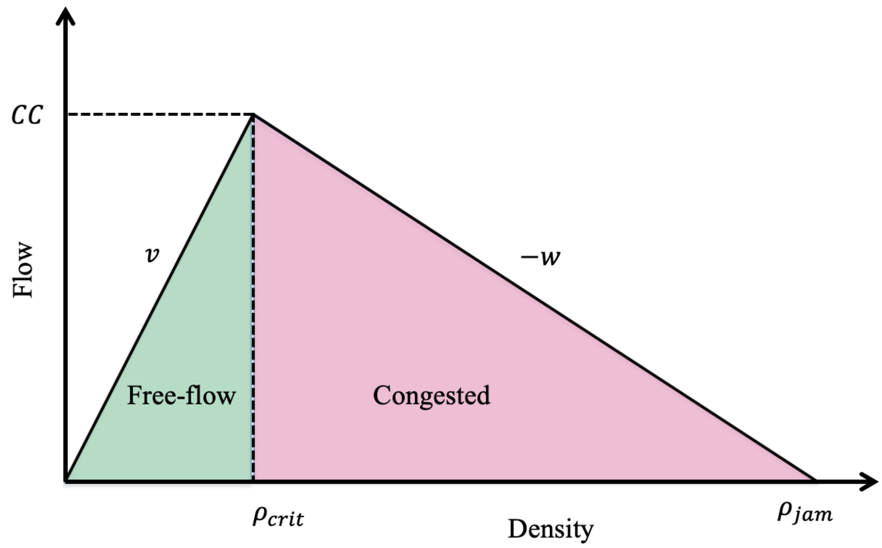


Figure 5.7 Triangular Fundamental Diagram

5.4.2 Road Capacity Reduction without M&R Actions

This section considers the effect of road quality on road flow capacity dynamics. Between successive M&R actions, the modelling of DTD road capacity reduction due to road deterioration is given in the following formula:

$$CC_a(\tau) = CC_a(\tau - 1) - (Q_a(\tau) - Q_a(\tau - 1)) \cdot \kappa\ , \qquad \forall a \in A \tag{5-14}$$

where κ is capacity reduction rate due to road deterioration. $CC_a(\tau)$ denotes the road flow capacity of link a on day τ, $Q_a(\tau)$ denotes the road quality of link a on day τ. In terms of the rate κ, this thesis applies the value estimated by Chandra (2004) that, for unsignalized two-lane roads, the flow capacity reduction is 300 PCU/h for an increase of 1m/km (one unit of IRI index) of the road roughness.

Throughout the numerical studies in this thesis, the test networks are composed by signalized two-lane roads. It can be assumed that the amount of capacity reduction could be reduced by half for signalized roads, providing 150 PCU/h of capacity reduction per IRI (Chu and Chen, 2012). The unit of flow capacity in the DNL model is in PCU/s, thus this value equals to 0.04 PCU/s. Since QI index, which equals to $13\square IRI$ (Paterson, 1990), is used as the roughness index in this thesis, the modelling of DTD capacity updates of link a when no M&R action is undertaken, takes the form:

$$CC_a(\tau) = CC_a(\tau-1) - \frac{\big(Q_a(\tau) - Q_a(\tau-1)\big)}{13} \times 0.04, \qquad \forall a \in A \tag{5-15}$$

Figure 5.8 illustrates the change of fundamental diagram due to road deterioration. As the road quality deteriorates (without M&R), the jam density of the road ρ_{jam} remain unchanged, and the critical density ρ_{crit} also remain unchanged due to assumption (5-13). This leads to a well-defined and unique triangular fundamental diagram.

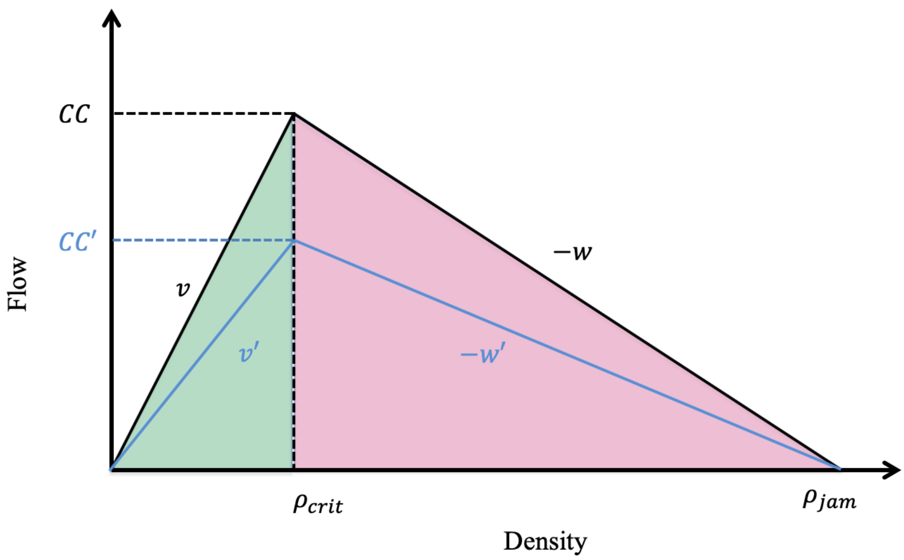


Figure 5.8 Illustration of capacity reduction due to road deterioration

In Figure 5.8, the road change from the condition $[CC, FFT, v]$ in black lines to the condition

$[CC', FFT', v']$ in blue lines due to road quality deterioration, where the corresponding notations denotes [capacity, free flow time, free flow speed]. It can be seen from Figure 5.8 that, as the road capacity reduce from CC to CC', the free flow speed of the road decrease from v to v'. The following two equations must hold:

$$\rho_{crit} = \frac{CC \times FFT}{L} = \frac{CC}{v} \tag{5-16}$$

$$\rho_{crit} = \frac{CC' \times FFT'}{L} = \frac{CC'}{v'} \tag{5-17}$$

where, L denotes road length. Combining these two equations,

$$v' = \frac{CC'}{CC} \cdot v \tag{5-18}$$

$$FFT' = \frac{CC}{CC'} \cdot FFT \tag{5-19}$$

Given this, during the road deterioration process without M&R actions, after DTD road capacity dynamics modelled by Equation (5-15), DTD evolution of road free flow time of link a can be formulated as:

$$FFT_a(\tau) = \frac{CC_a(\tau - 1)}{CC_a(\tau)} \cdot FFT_a(\tau - 1), \quad \forall a \in A \tag{5-20}$$

The roughness-dependent capacity and free flow time is incorporated in the DTD dynamic traffic assignment model to capture the user response to road deterioration. Therefore, the modelling of the impacts of road deterioration on traffic usage is achieved.

5.4.3 Road Capacity Reduction due to M&R actions

Road M&R construction works in this thesis refer to closing one lane of the two-lane link during maintenance (see Figure 5.9); that is, only one lane is in use during M&R. Thus, M&R actions are assumed to be modelled by reducing 50% of the flow capacity of the M&R links.

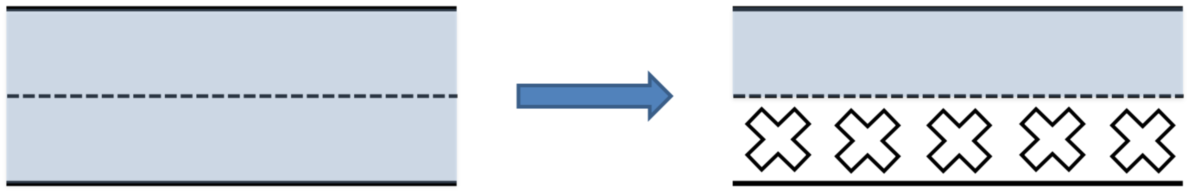


Figure 5.9 Link topology change due to M&R implementation

For a M&R construction on link a started on day τ and lasting for D_a days, the link flow capacity during M&R can be formulated as:

$$CC_a(\tau) = \cdots = CC_a(\tau + D_a - 1) = \phi \cdot CC_a(\tau - 1), \quad \forall a \in A_m \tag{5-21}$$

where, $\phi = 0.5$ is the capacity reduction rate due to M&R construction.

After M&R, the amount of link capacity increase is according to the amount of roughness decrease due to M&R effectiveness, and based on the same principle with Equation (5-15). This gives,

$$CC_a(\tau + D_a) = CC_a(\tau - 1) + \frac{\big(Q_a(\tau - 1) - Q_a(\tau + D_a)\big)}{13} \times 0.04, \forall a \in A_m \tag{5-22}$$

where, $Q_a(\tau - 1) - Q_a(\tau + D_a)$ is the roughness reduction due to M&R effectiveness, which can be achieved by Equation (5-9).

Figure 5.10 illustrates the changes of the fundamental diagram of modelling the capacity reduction due to M&R. Assume that the road change from the condition $[CC', FFT', v']$ in blue lines to the condition $[CC'', FFT'', v'']$ in red lines due to M&R action, where the corresponding notations denotes [capacity, free flow time, free flow speed]. The following two equations are hold:

$$\rho_{crit} = \frac{CC' \times FFT'}{L} = \frac{CC'}{v'} \tag{5-23}$$

$$\rho_{crit}'' = \frac{CC'' \times FFT''}{L} = \frac{CC''}{v''} \tag{5-24}$$

where, L denotes road length.

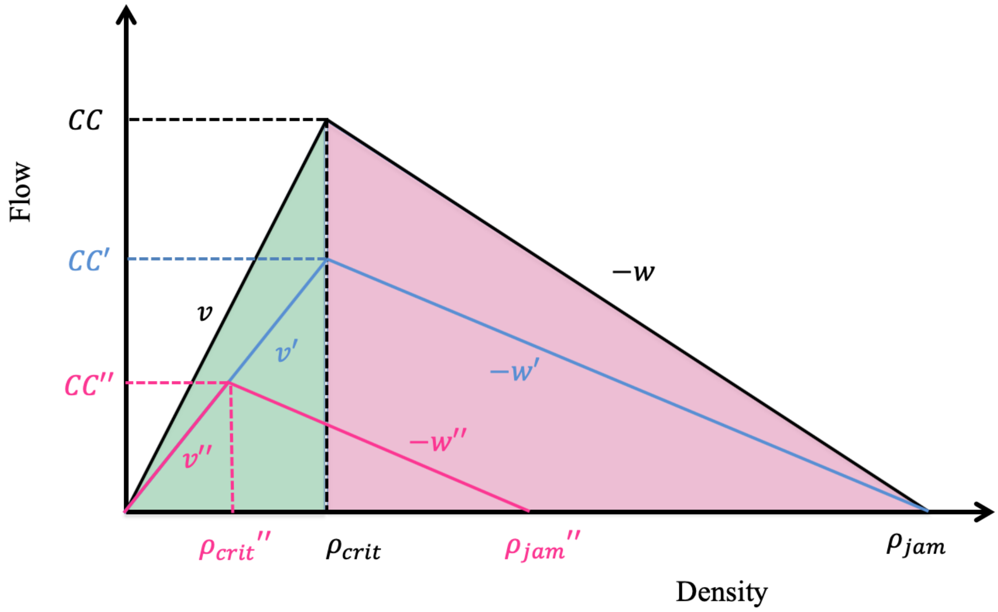


Figure 5.10 Illustration of capacity reduction due to M&R

Also, the M&R is modelled by 50% capacity reduction, gives:

$$CC'' = \frac{1}{2}\ CC' \tag{5-25}$$

As shown in Figure 5.9, during the M&R construction, the area of the road reduces by half thus the jam density of the road $\rho_{jam}'' = \frac{1}{2}\ \rho_{jam}$. Equation (5-13) is still satisfied in the fundamental diagram, thus the critical density satisfies:

$$\rho_{crit}'' = \frac{1}{2}\ \rho_{crit} \tag{5-26}$$

Combine Equation (5-23), (5-24), (5-25), (5-26), then get

$$v'' = v' \tag{5-27}$$

$$FFT'' = FFT' \tag{5-28}$$

This is shown in Figure 5.10 that, as the road capacity reduce from CC' to CC'', the free flow speed of the road is the same.

Therefore, for a M&R work on link a start on day τ and lasting for D_a days, the road free flow time of link a during the M&R construction time remain unchanged:

$$FFT_a(\tau) = \cdots = FFT_a(\tau + D_a - 1) = FFT_a(\tau - 1), \qquad \forall a \in A_m \tag{5-29}$$

Figure 5.11 shows the changes of fundamental diagram right after M&R, which is in green lines. After the M&R construction completed, the road reopens to its origin area. Thus, the jam density recovers to ρ_{jam} and the capacity increase to a value of CC'''.

Therefore, given the capacity increase calculated by Equation (5-22), the free flow time decrease of link a after the M&R can be calculated by:

$$FFT_a(\tau + D_a) = \frac{CC_a(\tau + D_a)}{CC_a(\tau - 1)} \cdot FFT_a(\tau - 1), \qquad \forall a \in A_m \tag{5-30}$$

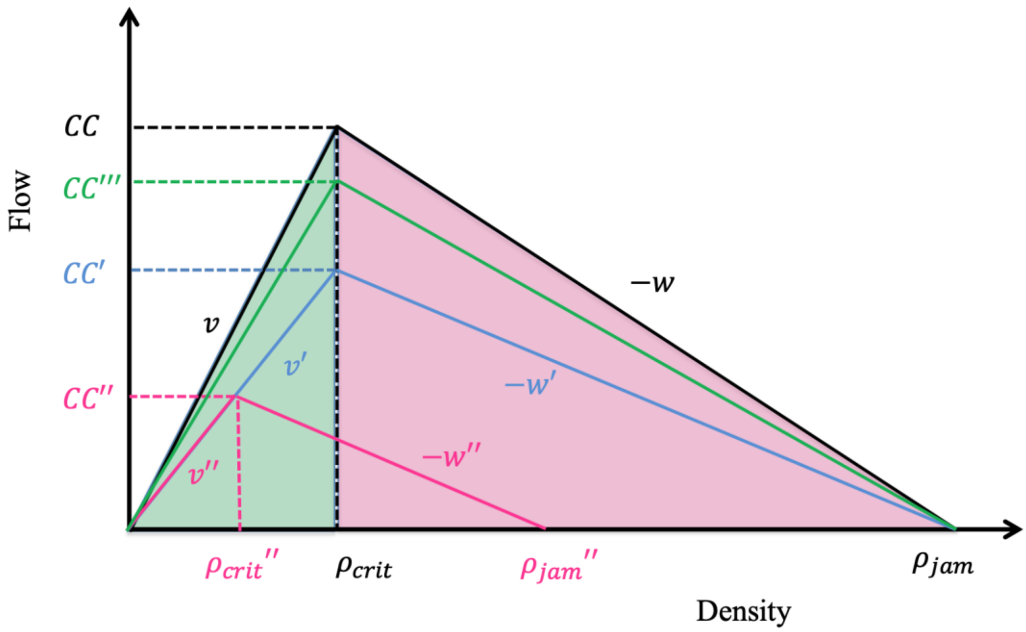


Figure 5.11 Illustration of capacity increase right after M&R

Till now, the modelling of DTD flow capacity dynamics are given by Equation (5-15), (5-21), and (5-22) for circumstances between, during and right after M&R respectively; the modelling of corresponding DTD free flow time evolution is given by Equation (5-20), (5-29), and (5-30). Both DTD road capacity and DTD road free flow time for all links in the road network will be the inputs of the DNL model (see Section 3.8.4) for computing DTD traffic loading on the road network. Therefore, the modelling of the impacts of road deterioration as well as M&R actions on DTD traffic assignment on the road network can be achieved.

5.5 Numerical Examples of the DTD Road Quality and DTD Road Capacity Dynamics and Interactions

This section provides numerical examples for the illustration of the DTD road quality model (see Section 5.3) and the DTD road capacity model (see Section 5.4) as well as how they factored into each other, under the conditions with and without M&R.

The numerical examples are conducted on the Sioux Falls network. The simulation horizon is 6 years with the simulation day referring to a calendar month. An M&R action is simulated on link #68 beginning at year 3 and lasting for 2 months, by reducing 50% of the flow capacity of link #68 on simulation day 36 and day 37 (see the third picture of Figure 5.12). Base model II with information sharing (IS) proposed in Section 3.7.2 is used as the modelling platform for DTD traffic dynamics. The travel cost structure follows that of Equation (3-35) with the following parameters: in-vehicle value of time $\alpha = 1$, early arrival value of time $\beta = 0.8$, late arrival value of time: $\gamma = 1.8$. The unit of the travel cost is in seconds. Other relevant parameters are:

Base Model II + IS:	$\lambda = 0.7,\ \theta = \theta_1 = 0.004,\ \eta = 400,\ M = 3,\ G(x) = x^2$

In the first example, all links in the Sioux Falls network are modelled with DTD road deterioration according to the traffic loading, as well as DTD flow capacity dynamics influenced by its road quality evolution. The relevant parameters regarding the DTD road quality model, the DTD road capacity model, and the M&R modelling are:

$$b_0 = 0.02,\quad b_0 = 2E-7,\ g_1 = 0.66,\quad g_2 = 0.55,\ g_3 = 18.3,\ \phi = 0.5,\ \kappa = \frac{1}{13} \times 0.04$$

The numerical results of the DTD traffic loading, DTD roughness, DTD flow capacity as well as DTD free flow time dynamics of link #68 are given in Figure 5.12. for the illustration of the 'quality-usage' feedback mechanism.

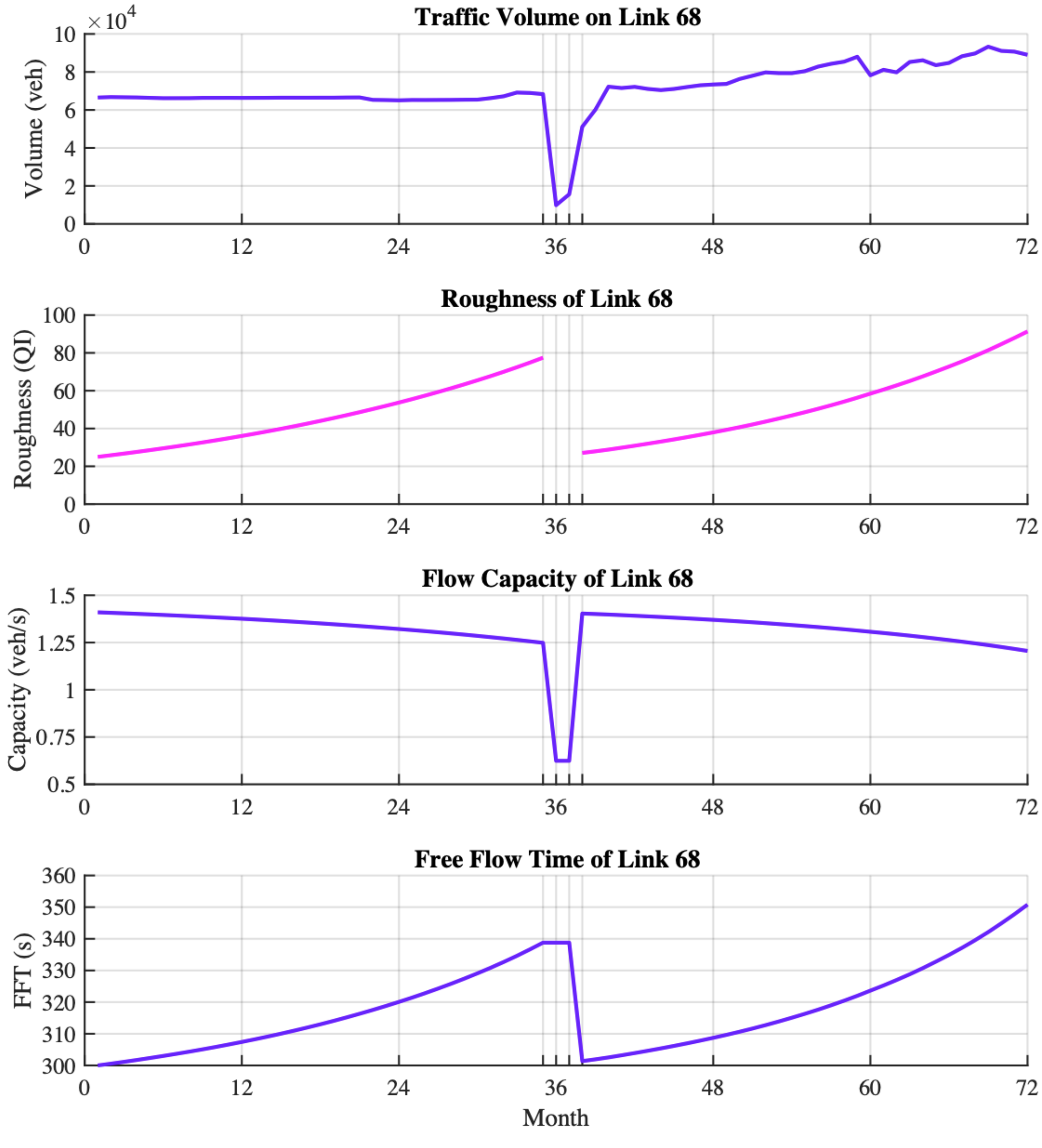


Figure 5.12 Illustration of the interaction between DTD road quality and DTD road capacity

During the time without M&R (day 1-35 and day 38-72), as shown in the top two pictures of Figure 5.12, the roughness increases exponentially with the traffic loading on link #68 and the increasing rate between day 38-72 is greater than between day 1-35, which indicates that more traffic usage of the road could induce its faster road deterioration. In the corresponding time periods, as the road deteriorates, the flow capacity of link #68 decreases (see the third picture of Figure 5.12) and its free-flow time increases (see the bottom picture of Figure 5.12), which influences traffic dynamically loading on the road network (see the top picture of Figure 5.12). The aforementioned quality-usage feedback mechanism can be captured by the DTD road quality and the DTD flow capacity models proposed in this chapter.

During the M&R action (day 36 and day 37), the flow capacity of link #68 reduces by 50 % (see the third picture of Figure 5.12) and the free-flow time of link #68 remain unchanged (see the bottom picture of Figure 5.12), which causes obviously decrease of the traffic volume on link #68 due to the M&R construction (see the top picture of Figure 5.12). After the M&R on day 38, the roughness of link #68 decreases to a much lower level (see the second picture of Figure 5.12), which indicates improved road quality due to M&R effectiveness. According to this M&R effectiveness, as shown in the bottom two picture of Figure 5.12, the flow capacity of link #68 increases and the corresponding free flow time decreases to a certain level. The top picture of Figure 5.12 shows that the traffic loads on link #68 gradually increases after M&R, which is caused by more traffic switching from other routes (with continuously degraded road conditions without M&R) to the routes containing link #68.

The second example conducts a similar experiment, but without modelling DTD flow capacity dynamics under the impact of DTD road deterioration. A comparison of the simulation results with and without modelling DTD flow capacity is illustrated in Figure 5.13. It can be observed from the upper picture of Figure 5.13 that the traffic volume is steady before and after M&R under the scenario without modelling DTD capacity, indicating that the network traffic was at equilibrium before, and converges to an equilibrium quickly afterwards. In contrast, under the scenario with modelling DTD capacity, the traffic load on link #68 increases after M&R. This is expected because the flow capacity of link #68 is restored after M&R (see the third picture of Figure 5.12), but other links in the network continue to deteriorate with flow capacity reduction, which draws more traffic to link #68. The lower picture of Figure 5.13 shows that network total cost follows an increasing trend before and after M&R with DTD capacity modelling, which means that the deterioration of the road quality brings negative effects to the network performance. By comparison, without modelling DTD capacity could significantly underestimate network travel costs, which is usually ignored by the existing M&R studies. Therefore, it is necessary to modelling DTD flow capacity in the M&R planning problems for a more realistic representation of traffic dynamics under the condition with and without M&R, which could be achieved by the quality-usage feedback models in this thesis.

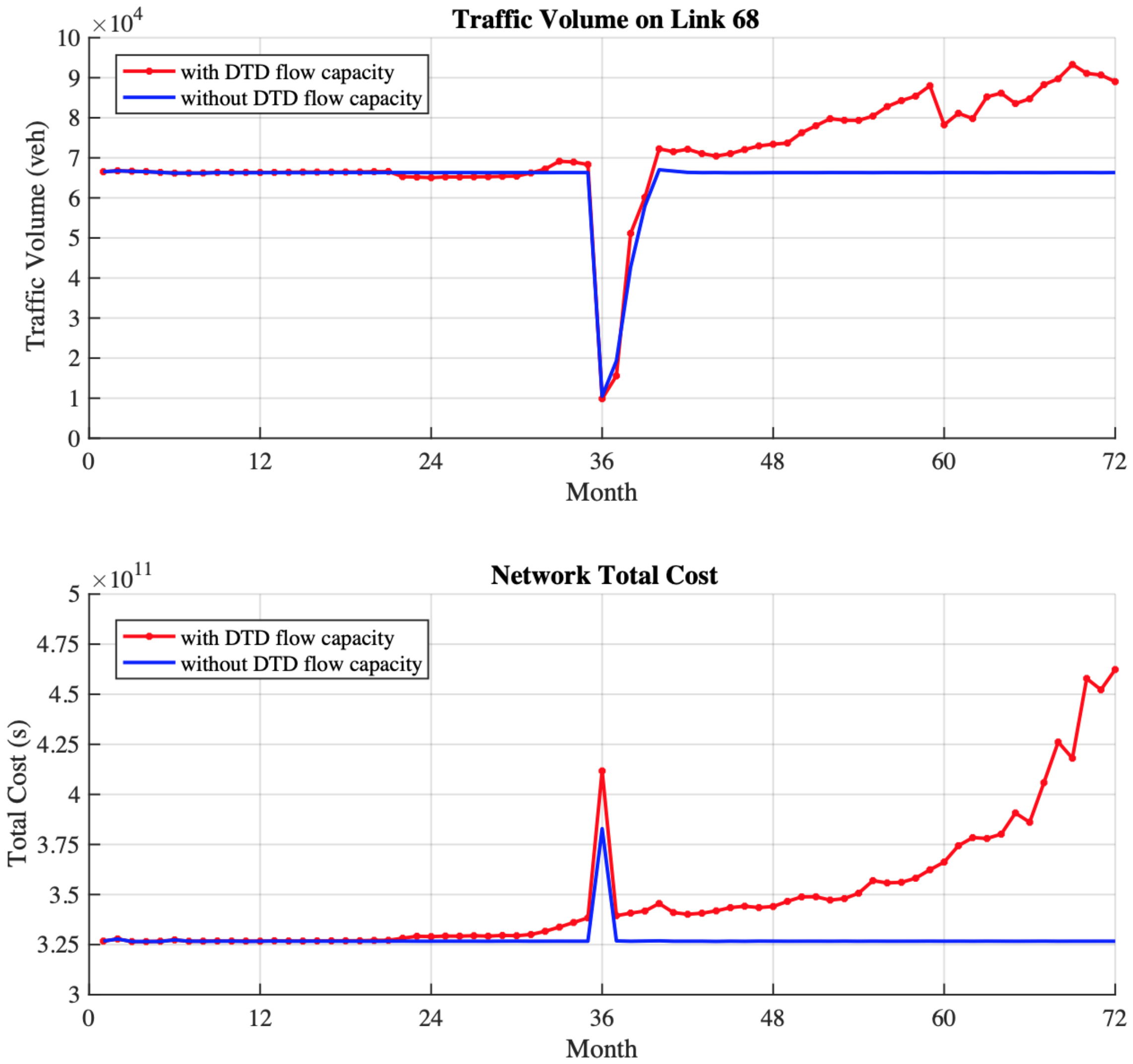


Figure 5.13 Comparison of with and without modelling DTD road capacity

5.6 Summary

This chapter proposes the DTD road quality model and the DTD road flow capacity model, which interacts with each other and forms the 'quality-usage' feedback mechanism. The following modelling counterparts are formulated in this chapter:

- **Modelling of DTD road deterioration.** DTD road deterioration is modelled with an exponential function of time, and traffic loading on roads is factored into the function for a realistic modelling of road deterioration process.
- **Modelling of road quality improvement due to M&R.** M&R effectiveness is modelled with a deterministic formulation based on empirical studies. Unlike many existing literatures assuming that the M&R took place instantly, this thesis considers a non-empty M&R interval for an explicitly modelling of M&R activities.
- **Modelling of DTD road capacity.** DTD road flow capacity is modelled with a reduction rate of the DTD road quality, which will be inputted into the DNL model and affects DTD traffic loading among road networks.
- **Modelling of road capacity reduction due to M&R.** M&R constructions are assumed as close one lane of the two-lane roads during M&R, which causes 50% reduction of the road capacity. Despite this, the model is also suitable for other percentage of capacity reduction according to different assumptions on M&R worksites.

The applicability of the aforementioned models was demonstrated by numerical examples on the Sioux Falls network, which highlights the necessity of modelling quality-usage feedback mechanism in M&R planning.

This chapter together with Chapter 3 could output the DTD dynamics of road quality and road traffic, which will incorporate into the M&R planning and optimisation models in the following Chapter 6 and Chapter 7 for studying long-term M&R planning problems.

6 Road Network M&R Planning Considering Day-to-day Traffic Dynamics and Transient Congestion

Road infrastructure maintenance and repair (M&R) can be broadly defined as a set of activities intended to retain or restore road transportation facilities, especially pavement segments, within a satisfactory level, so that road systems will operate in the desired performance level. Road M&R consists of various functional and structural treatments involving surface dressing, resurfacing and partial or total reconstruction. Road M&R tends to become one of the most costly activities in transportation infrastructure system management (Deshpande et al., 2010). According to the report provided by Department for Transport UK (DfT, 2016), the expenditure for the maintenance of local authority managed roads in England of the year 2015 is higher than the previous four years. Under this circumstance, it is necessary to make optimal use of available M&R budgets, intending to maintain and repair road networks efficiently and cost-effectively.

M&R-derived disruptions to the road networks could produce significant social costs in the form of transient congestion, which is essential to be captured by appropriate traffic modelling in M&R planning. A hallmark of existing long-term M&R planning studies is the use of traffic equilibrium models to capture the response of travellers to road conditions at certain point in time. However, such work does not address other types of M&R costs and benefits that may produce profound physical, social and economic impacts, such as:

i. value of time lost due to delays induced by M&R activities on a within-day time scale;

ii. disequilibrated network states or transient congestion that may follow irreversible and chaotic trajectories as a result of M&R-derived disruptions on a day-to-day time scale;

iii. the potential for network paradoxes to make maintenance actions globally detrimental.

This thesis addresses these gaps by introducing day-to-day dynamic traffic assignment (DTD DTA) model into long-term M&R planning, which is able to capture traffic disequilibrium states as well as transient congestion induced by M&R disruptions to the road networks.

This chapter develop a long-term road M&R planning model at the network level, which is advantage in accurately modelling within-day and day-to-day traffic flow dynamics under different road conditions with or without M&R as well as capturing M&R derived transient congestion. Chapters 3-5 developed the three sub-models (e.g. the DTD traffic dynamic model, the DNL model, the DTD road quality model) that will be implemented into the M&R planning model in this chapter to support the road network M&R planning problems. The applicability of the proposed M&R planning model is then demonstrated by numerical case studies on a large-scale network (e.g. Sioux Falls network) of both threshold-based M&R and periodic M&R approaches.

This chapter is organized as follows. Section 6.1 develop a M&R planning framework and formulates the objective cost functions of network travel cost, M&R expenditure and salvage M&R cost. This together with the three sub-models (e.g. the DTD traffic dynamic model, the DNL model, the DTD road quality model) forms the long-term road M&R planning model. The proposed M&R planning model is then tested on the Sioux Falls network, and Section 6.2 gives the preliminary settings of model parameters before the numerical case studies. Section 6.3 conducts case studies on threshold-based M&R problems for both a single road segment and a system of road segments of various threshold values. Modelling parameters, including road deterioration rate and information sharing strength, are discussed by the numerical studies. Case studies are also conducted on periodic M&R methods in Section 6.4 , and the result is compared with the threshold-based M&R solution. Also, the M&R planning under the proposed DDTA model is compared with the solution under the DUE model in Section 6.4, which will demonstrate the necessity of M&R planning under DTD traffic dynamics.

6.1 Long-term Road Network M&R Planning Model

Long-term road M&R planning problems are to schedule the M&R actions temporally and spatially among the road network for the purpose of maintaining the road segments above certain service levels, and the planning horizons often lasting for years. As for long-term M&R planning problems that consider travel costs into the objective, majority of the studies introduce user cost parameters without modelling traffic assignment among road networks (Guignier and Madanat, 1999; Smilowitz and Madanat, 2000; Li and Madanat, 2002; Ouyang and Madanat, 2004). Recent research that apply traffic assignment models to quantify the network travel cost are mostly via solving static traffic assignment (Uchida and Kagaya, 2006; Ouyang, 2007; Chu and Chen 2012). Ng et al. (2009) among the first introduce dynamic traffic assignment by applying cell transmission model to quantify user costs in the long-term M&R planning. According to the literature review in Section 2.4, all traffic assignment models for estimating travel costs in long-term M&R planning are in the form of static or dynamic user equilibrium (UE). As UE models tend to underestimate travel costs by ignoring M&R derived transient congestion, this thesis proposes DTD DTA models in long-term M&R planning for more realistically represent traffic dynamics for richly detailed time-varying flow scenarios, and hence more accurately quantify travel costs when planning long-term M&R.

This section formulates a M&R planning model for long-term road network planning problems that account for day-to-day traffic dynamics and M&R derived transient congestion. The underlying traffic assignment model is a doubly dynamic traffic assignment (DDTA) model that is proposed in Chapter 3 . This dual-time-scale M&R planning model allows simultaneously capture the long-term effects of M&R under traffic dynamics towards equilibria, and the maintenance-derived transient congestion using day-to-day traffic evolutionary dynamics. The proposed road network long-term M&R planning model aims to search for the M&R plans with lower M&R expenditure as well as network travel costs while maintaining satisfactory level of the road quality.

6.1.1 M&R Planning Model Framework

This thesis intent to develop a computable theory of infrastructure network M&R with modelling of day-to-day traffic dynamics and transient congestion, which will then be specialized to study the M&R of vehicular road networks. The modelling of traffic network under M&R in this thesis consists of three major sub-models:

1) **The DTD traffic dynamic model**, which modelling the day-to-day evolution of adapted travellers' route and departure time choices, where the notion of 'day' is arbitrarily defined (e.g. weeks or months). This model is developed in Chapter 3 .

2) **The dynamic network loading (DNL) model**, which refers to the within-day modelling of link and junction traffic dynamics, flow propagation and travellers' experienced cost, according to the demand matrix and network conditions within a conceptual 'day'. This model is given in Section 3.8.

3) **The DTD road quality evolution model**, which captures the adjustment of day-to-day road quality due to traffic loads, maintenance actions as well as natural deterioration. This model is proposed in Chapter 5 .

The interdependencies between the above three sub-models as well as the enabling mechanisms are illustrated in the Figure 6.1 below.

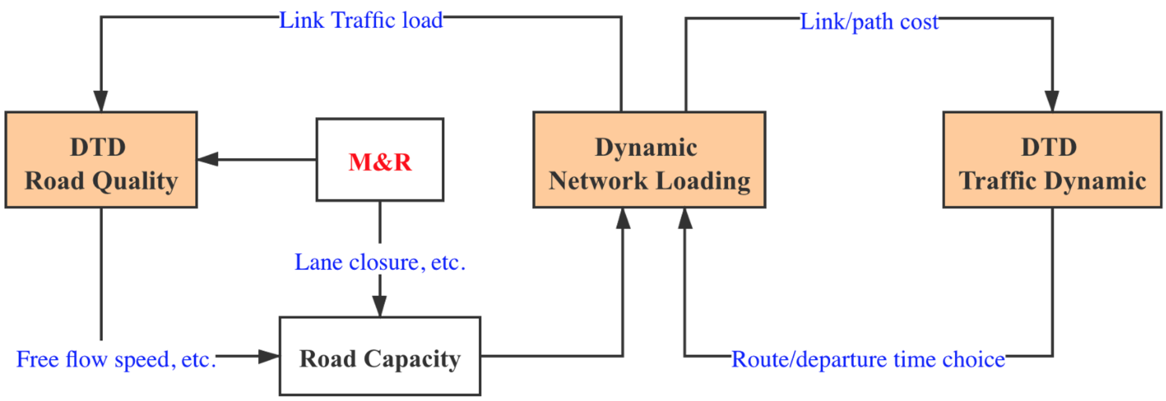


Figure 6.1 Overall modelling framework

The proposed family of M&R planning models in this thesis is bi-level problems. The upper level is to decide network-level M&R plans (e.g. where, when, how) based on network travel cost and M&R expenditure. The lower level problem is the combination of the three sub-models: DTD road quality dynamics, dynamic network loading, and DTD traffic dynamics. Each M&R model to be developed will take the form of dynamic Stackelberg game, where an omniscient leader (e.g. planning organization) makes decisions by anticipating the reactions of the followers (e.g. road network users) who are competitors in a dynamic Nash game. As such, the proposed M&R models will be complex and computationally demanding.

According to the systematic literature review in Chapter 2 , this is among the first in the literature to account for day-to-day traffic dynamics and transient congestion into M&R planning theory. The doubly dynamic traffic assignment (DDTA) models proposed in this thesis are employed to describe time-varying traffic flows on networks and constrain the optimal design of M&R plans, which could more realistically modelling dynamic routing and departure time choice so that capture travellers' reactions to M&R plans and estimate maintenance-derived transient congestion. Such a decision support tool does not presently exist for metropolitan networks and makes the contribution of this thesis quite unique.

6.1.2 M&R Performance Model Formulation

For the decision-making of long-term road network M&R planning problems in this chapter, two objectives (e.g. network travel cost, M&R expenditure) are assumed for the decision-maker in judging between different M&R plans. It is noted that other factors (e.g. emission, fuel consumption, etc.) could also be the objectives for M&R planning depending on different goals of the planning organizations. As M&R cost and travel cost are the most considerable objectives for M&R planning problems, this thesis assumes that the planning agency focus on these two objectives when deciding M&R plans, and the specifications of the cost functions are given in this section as follows.

6.1.2.1 Network Travel Cost

In each simulation day, the path travel costs $C_r(s)$ for each time step s of the simulation horizon can be achieved by the DDTA model, which is a weighting sum of travel time and early/late arrival penalty defined in Equation (3-35) and is recalled here.

$$C_r(s) = \alpha \cdot \mathrm{TT}_r(s) + \beta \cdot \mathrm{EP}_r(s) + \gamma \cdot \mathrm{LP}_r(s) \ , \qquad \forall r \in R \tag{6-1}$$

where, α, β, γ are positive weighting parameters of travel time, and early/late penalties.

The network travel cost for the simulation horizon of simulation day τ can be calculated as a sum of the travel costs for all routes r and all time steps s of that day:

$$C(\tau) = \sum_r \sum_s C_r(s) \ \ , \forall r \in R, \qquad for\ \ all\ \ simulation\ \ day\ \ \tau \tag{6-2}$$

Thus, total network travel cost of the M&R planning period of n simulation days is a sum of the network travel cost of each simulation day, and is formulated as:

$$TTC\_sd = \sum_{\tau=1}^{n} C(\tau) \cdot k \tag{6-3}$$

where, k is a converting factor in order to convert the travel cost of the simulation horizon to the network travel cost of a simulation day. Note that the unit of TTC_sd is in seconds.

Afterwards, Equation (6-4) convert TTC_sd in Equation (6-3) into monetary network total travel cost TTC to be able to compared with M&R expenditure.

$$TTC = \sum_{\tau=1}^{n} C(\tau) \cdot k \cdot vot \cdot e^{-r\tau} \tag{6-4}$$

where, vot is value of time. According to 2010 UK market prices and values, vot is £10.79 per hour (DfT, TAG, 2018). Parameter r is discount rate, this thesis assumes an exponential decay $e^{-r\tau}$ to discount the travel costs to the present values.

For the purpose of focusing more on M&R derived travel cost, this thesis also considers an incremental travel cost, which is the network total travel cost TTC minus the baseline travel cost TTC_0 as the network has no disruptions. This M&R derived network travel cost is represented as:

$$MTC = TTC - \ TTC_0 \tag{6-5}$$

TTC_0 can be calculated by the same process of TTC as the DTD simulation without M&R action. In the numerical case studies in this chapter, the resulted travel costs refer to MTC, unless stated otherwise.

6.1.2.2 M&R Expenditure

The M&R expenditure consists of two components: a fixed cost and a variable cost, akin to many studies (Li and Madanat, 2002; Ouyang and Madanat, 2004; Ouyang 2007). The fixed component represents M&R setup costs, such as labour, machine rental and operation fees. The variable component is the construction costs proportional to the M&R intensities, which is related to the material usage.

Therefore, the undiscounted M&R expenditure for an M&R activity of intensity $w_a(\tau)$ on link a at simulation day τ can be represented by the function below, given that a subset of links A^m in the road network is the subject of M&R.

$$M_a\big(w_a(\tau)\big) = \begin{cases} m_{a0} + m_{a1} \cdot w_a(\tau), & w_a(\tau) > 0 \\ 0, & w_a(\tau) = 0 \end{cases}, \qquad \forall a \in A^m \tag{6-6}$$

where, $m_{a0} \geq 0$ and $m_{a1} \geq 0$ are fixed and variable M&R parameters, which are link-specific and depends on the M&R area. The M&R intensity $w_a(\tau)$ should satisfy the maximum intensity constraint given in Equation (5-10) and is recalled here.

$$0 \leq \ w_a(\tau) \leq g_2\big(Q_a(\tau - 1)\big) + g_3 \tag{6-7}$$

where, $Q_a(\tau - 1)$ is the roughness value of link a of the previous day before M&R, and parameters $g_2 = 0.55, \quad g_3 = 18.3$.

Then, the total discounted M&R expenditure for a planning horizon of n simulation days for all links subject to M&R can be formulated as the following function:

$$MC = \sum_{a} \sum_{\tau=1}^{n} M_a\big(w_a(\tau)\big) \cdot e^{-r\tau} \quad , \qquad \forall a \in A^m \tag{6-8}$$

where, r is discount rate and the exponential decay $e^{-r\tau}$ discounts the maintenance expenditure to the present values.

6.1.2.3 Salvage M&R Cost

This thesis considers a boundary condition that the road should be maintained above a certain quality at the end of the planning horizon, accounting for the roughness level when the M&R planning period ends. To measure this final roughness level, this thesis includes an additional M&R cost, named salvage M&R cost, into the objective function of M&R expenditure, by assuming that another M&R activity is conducted at the end of the planning horizon to bring the roughness to a satisfactory level that could be predetermined by the planning agency.

It can be derived from Equation (5-9) that the M&R intensity of the salvage M&R on link $a \in A^m$ at the end of planning horizon day n can be represented as below, with a target final roughness value of Q_f.

$$w_a(n) = \begin{cases} \dfrac{\big(Q_a(n) - Q_f\big) \cdot g_2 + {g_3}/{Q_a(n)}}{g_1}, & Q_a(n) > Q_f \\ 0 \ , & Q_a(n) \le Q_f \end{cases} \tag{6-9}$$

where, $Q_a(n)$ is the roughness value of link a at the end of planning period on day n, and parameters $g_1 = 0.66$, $g_2 = 0.55$, $g_3 = 18.3$.

Given this intensity, the salvage M&R cost for each M&R link $a \in A^m$ can be achieved by Equation (6-6). Thus, the total discounted salvage M&R cost for all links subject to M&R is given by:

$$SMC = \sum_{a} M_a\big(w_a(n)\big) \cdot e^{-rn} \quad , \qquad \forall a \in A^m \tag{6-10}$$

where, r is discount rate and the exponential decay e^{-rn} discounts the salvage cost to the present values.

6.1.3 M&R Duration Model

The M&R duration is considered to be calculated as a fixed set-up time and a variable duration. The fixed component represents the time for setting up the worksite. Since this thesis studies about long-term M&R, the set-up time is short enough to be omitted in the long-term M&R planning. Therefore, the M&R duration in this thesis is modelled as variable duration representing the time required for M&R constructions, which is assumed to be proportional to the link length thus is link specific.

Then, the M&R duration for each time M&R on link a is modelled as:

$$D_a = d_a \cdot l_a \quad , \qquad \forall a \in A^m \tag{6-11}$$

where, d_a is M&R duration parameter for 1-km of link a, which is specific for road type and M&R type. l_a is road length of link a in kilometres.

Table 6.1 M&R duration for each M&R action and different road types (days/1km)

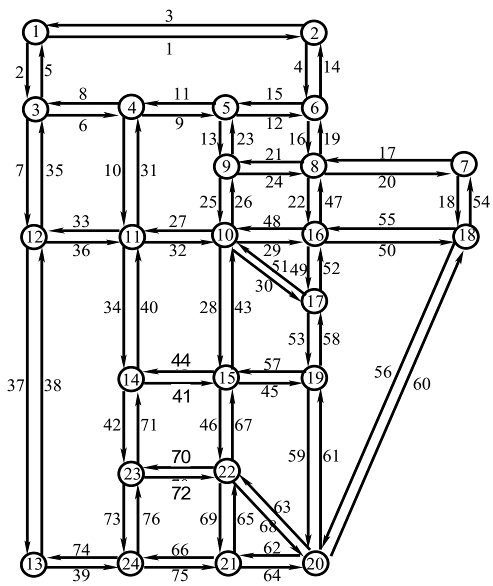
M&R Type	Single Carriageway	Dual 2 Lane Carriageway	Dual 3 Lane Carriageway
Patching	2	3	4
Surface Dressing	4	5	6
Resurfacing	8	14	18
Overlay	16	23	30

*Note: Durations are for 1km of road, that is, both carriageways.

For the value of d_a, this thesis applies the data given in the *Design Manual for Roads and Bridges (DMRB)* by Highway England (DfT, DMRB, 2019). According to this, the maintenance duration associated with different road types and maintenance actions for 1km of road are given in Table 6.1. Resurfacing is considered as the M&R type in the numerical studies in this chapter, but the proposed M&R model is suitable for any types of M&R actions.

6.2 Numerical Case Studies Configurations

For illustration, numerical case studies will be conducted on threshold-based M&R approach as well as periodic M&R approach in Section 6.3 and Section 6.4 respectively by applying the proposed M&R planning model. This section gives the simulation network data as well as modelling parameters setup for the numerical case studies in the following sections.



Sioux Falls network

Figure 6.2 The test network

The case studies in this chapter are conducted on the Sioux Falls network (see Figure 6.2), which is a large-scale network with 528 O-D pairs, 30,000 trips and 6,180 routes. This test network consists of 76 dual-lane one-directional pavement segments with a range of road characteristics such as road length, flow capacity and free flow time, and there are 24 intersections in the road network. The network data (e.g. link characteristics, OD information, traffic demand) are provided in Appendix III.

Throughout the numerical studies in this chapter, the parameter values assumed for the M&R planning model are given in Table 6.2. Road roughness is measured in QI index and the M&R intensity is in millimetres (mm). It is assumed that initial road conditions are $Q_0 = 25$ QI for all links and the links subject to M&R should be maintained above $Q_f = 40$ QI at the end of the planning horizon. The road deterioration parameters b_0 and b_1 are selected so that a pavement with a good quality of 25 QI will deteriorate to a poor condition of 150 QI over 5 years with traffic load of 5×10^4 veh/month, which is a reasonable deterioration process. The rate κ of DTD capacity reduction due to DTD road deterioration is based on the data reported in Chandra (2004). Under this condition, the links in the test network could suffer a speed of approximately $1/3$ decrease of road capacity after 5 years without M&R. M&R actions are modelled by reducing 50% of the flow capacity of the M&R links. The model parameters g_1, g_2 and g_3 for M&R effectiveness are according to the model in Ouyang and Madanat (2004). M&R expenditure model parameters m_0 and m_1 for every 1km of road are taken from Li and Madanat (2002), and M&R duration model parameter d is extracted from the Design Manual for Roads and Bridges (DMRB) by DfT (2019) for resurfacing of dual two lane carriageway. The value of time vot is based on the data from Transport Analysis Guidance (TAG) by Department for Transport UK (DfT, 2018). The financial discount rate r is selected so that the cost could be discounted approximately 7% after one year. It assumes that network travel cost and M&R expenditure have same weight in the M&R decision-making in the case studies.

The case studies in this chapter consider only one type of M&R activity (e.g. resurfacing). However, the proposed M&R planning model is also capable to accommodate multiple M&R types with heterogeneous effects by defining different threshold level, M&R intensity and M&R expenditure for different types of M&R. The M&R actions will be automatically chosen according to the road conditions and different threshold or M&R time, and the intensity values will be selected based on the type of M&R actions and react in different M&R effects.

Table 6.2 Parameters used for the M&R planning model

Parameter	Value	Units	Parameter	Value	Units
$\boldsymbol{m_0}$	150000	\$/km	$\boldsymbol{Q_0}$	25	QI
$\boldsymbol{m_1}$	3000	\$/mm/km	$\boldsymbol{Q_f}$	40	QI
$\boldsymbol{d}$	7	days/km	$\boldsymbol{b_0}$	0.02	-
$\boldsymbol{vot}$	13.7033	\$/h	$\boldsymbol{b_1}$	2E-7	-
$\boldsymbol{r}$	0.006	-	$\boldsymbol{g_1}$	0.66	-
$\boldsymbol{\phi}$	50%	-	$\boldsymbol{g_2}$	0.55	-
$\boldsymbol{\kappa}$	0.04	/IRI	$\boldsymbol{g_3}$	18.3	-

For each M&R plan, simulations are performed for within-day and day-to-day traffic dynamics as well as day-to-day road quality during the planning period based on their interactions with different M&R strategies. Throughout the numerical studies in this chapter, the DDTA model proposed in Chapter 3 , which is the DTD Base Model II with information sharing together with the within-day DNL model, is employed for the traffic simulation in the M&R planning problems. In the DTD timescale, a simulation 'day' refers to a month. For each simulation day over the M&R planning horizon, the simulation horizon is a five-hour morning commuting period that splits into 20 departure time windows. Thus, the converting parameter $k = 1/0.4 \times 6 \times 4$ is applied to convert the five-hour simulated results (e.g. traffic volumes, travel costs) to the results of a calendar month, assuming that five-hour morning commuting period consists of 40% traffic of a calendar day, each commuting day consist of 1/6 traffic of a week, and each month contents 4 weeks. The corresponding modelling parameters for the DDTA model (see Section 3.5.3 and Section 3.7.2 for details) applied in the case studies are listed in Table 6.3 below.

Table 6.3 Parameters used for the DDTA model

$\boldsymbol{\alpha}$	$\boldsymbol{\beta}$	$\boldsymbol{\gamma}$	$\boldsymbol{\lambda}$	$\boldsymbol{\theta}$	$\boldsymbol{\theta_1}$	$\boldsymbol{\eta}$	$\boldsymbol{G(x)}$	$\boldsymbol{M}$
1	0.8	1.8	0.7	0.04	0.04	400	x^2	3

Unlike existing studies on M&R planning problems, which mainly uses historical traffic data or static traffic flow model for estimating travel costs, this thesis uses the proposed DTD doubly dynamic traffic model for numerical studies on large-scale networks, aiming to capture the realistic user behaviour and traffic dynamics in response to network conditions with and without M&R. This allows modelling of traffic disequilibrium and transient congestion derived by M&R activities, and hence an accurate estimation of travel cost and M&R expenditure for the M&R planning decision-making. Furthermore, the quality-usage feedback mechanism is considered: on one hand by applying a more realistic road quality model that could capture the impact of day-to-day traffic loading on road roughness; on another hand by modelling day-to-day road capacity reduction due to road deterioration. The proposed models and algorithms are coded in the Matlab R2019b.

6.3 Threshold-based Road M&R Planning at the Network Level

Threshold-based M&R planning is to conduct M&R actions when the road segment deterioration reaches a certain threshold, that is a specific roughness level. This section conducts numerical case studies to demonstrate the proposed M&R planning model in solving the threshold-based M&R planning problems at the network level for both a single road segment and a collection of road segments subject to M&R activities. First, the M&R strategy with different threshold values and their expenditure, as well as impacts on network-level travel costs are compared. Then, the interactions between the M&R solutions and travel behaviours as well as network dynamics are illustrated.

6.3.1 Threshold-based M&R Planning for a Single Road Segment

As a proof of concept, this section begins by conducting numerical studies on threshold-based M&R planning for a single road segment, to be followed by more substantial computational results in Section 6.3.2 of M&R for a collection of road segments. This section considers two cases, that is link #68 and link #49 of the Sioux Falls network are tested for threshold-based M&R planning separately. It assumes that only the road subjects to M&R is modelled as DTD roughness evolution with traffic loading on the road as well as DTD flow capacity reduction with road deterioration. In this section, the M&R planning horizon is 10 years, that is $T = 120$, for both cases.

6.3.1.1 Threshold-based M&R Planning for Link #68

In the first example, an 8.0467 km-long dual-lane pavement (link #68) is subject to threshold-based M&R planning. This link is chosen as it experiences the most traffic flow fluctuations when disrupted in the DTD simulation, and is therefore considered as a critical road segment with notable impact on the network traffic when M&R activities occurred. According to the assumptions in Table 6.2, the fix and variable parameters for M&R expenditure for a resurfacing on link #68 are calculated as $m_0 = 1{,}207{,}008\$$, $m_1 = 24{,}140.16\$/mm$; and the M&R duration is assumed to be $d = 2$ simulation days. Resurfacing actions are conducted on link #68 whenever the pavement deteriorates to the threshold level, with maximum intensity defined by the constraint in Equation (6-7). Simulations are performed on M&R plans with different threshold values from low to high between 40–460 QI, and the results of each plan are shown in Figure 6.3. Also note that the threshold greater than 300QI are unlikely for real-world implementation. They are presented here for the illustration of the network response to extreme cases for a comprehensive illustration of its trends.

The top picture of Figure 6.3 compares the maintenance-derived network travel cost of different threshold-based M&R plans. Since the planning horizon is fixed (e.g. 10 years), when the threshold increases, the number of M&R activities performed within the horizon decreases. When threshold is between 40 and 110 QI, three M&R activities are performed; when the threshold is between 110 and 300 QI, two M&R activities are required; when the threshold is greater than 300 QI, one M&R activity is conducted. For more clearly illustration, three colour zones are used to represent these different number of M&R times N in the planning period (e.g. green $N = 3$, blue $N = 2$, orange $N = 1$).

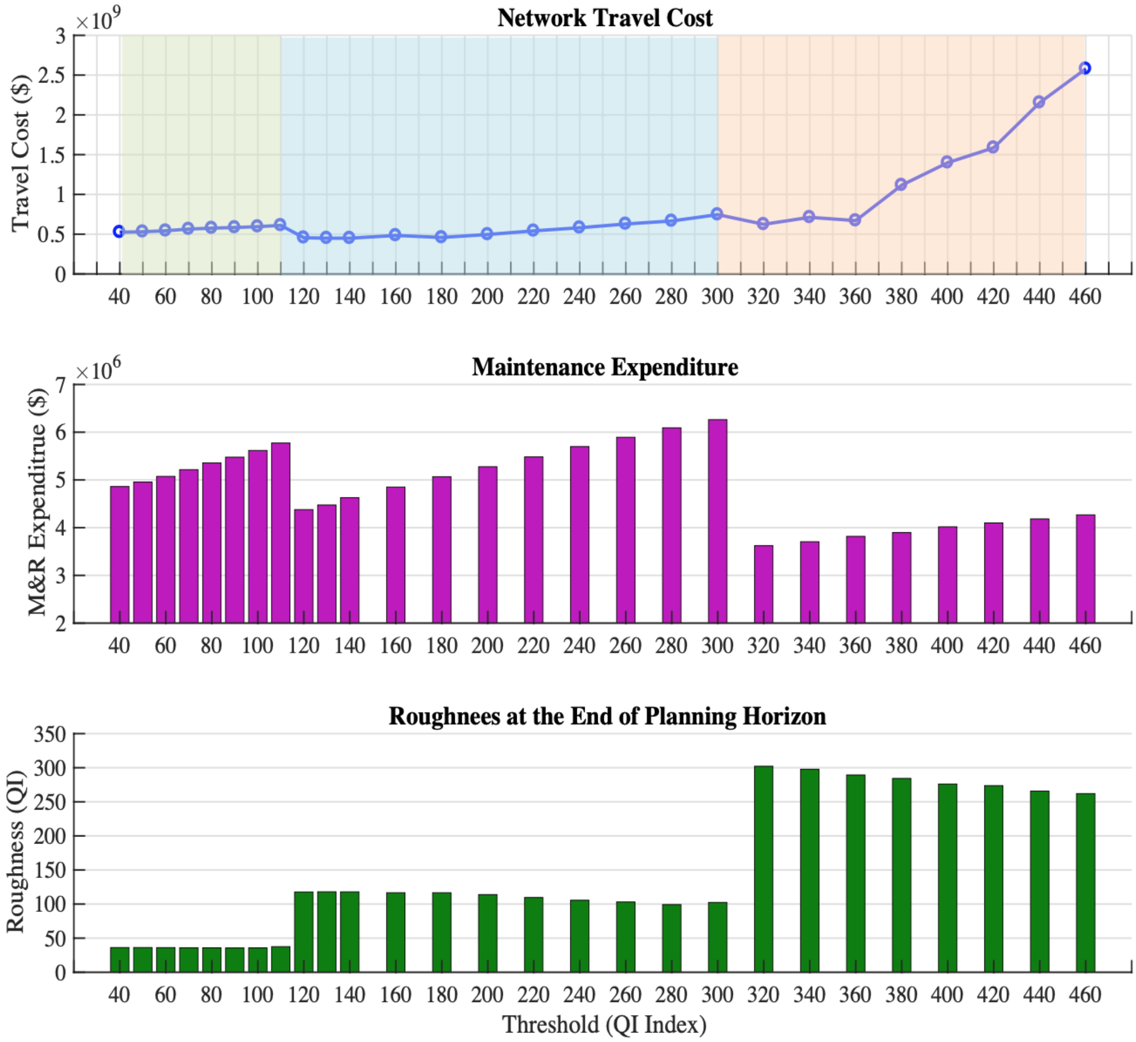


Figure 6.3 Comparison of different threshold-based M&R plans for link #68

It can be observed from top picture of Figure 6.3 that: (1) The frequency of M&R decreases as threshold increases, which is intuitive that it takes longer time to reach the higher threshold for M&R actions; (2) There is an increasing trend of network travel cost as threshold increases, which is expected that pavement will deteriorate more before reaching the higher threshold, causing more road capacity reduction and traffic congestion on the network; (2) There is a reduction of network travel cost when the number of M&R times decreases, which means that less M&R could reduce the level of disruptions to the network traffic; however, this could be overpowered by the increasing travel cost induced by deteriorated network roads as threshold growths; (4) The magnitude of the increase of travel cost due to road deterioration is small when the road is under good conditions (e.g. threshold is relatively low), and it becomes greater as the road condition getting worse (e.g. threshold getting large); especially when the road condition is very poor and not receive M&R promptly (e.g. threshold is very high as shown in the orange zone), the network will undergo sharply increase on its travel costs. Therefore, a very low threshold value could generate greater number of M&R disruptions, while a very high threshold value could cause more traffic delay due to poor road condition; both could result in higher network travel cost.

The middle picture of Figure 6.3 shows that there is a similar trend of M&R expenditure with threshold values. It is defined in Equation (6-6) that M&R expenditure is determined by the intensity of M&R activity, and larger threshold requires higher intensity hence the M&R expenditure. This is indeed illustrated in the figure that the M&R expenditure increases with the increasing of threshold when the number of M&R activities is the same. In addition, it can be seen that relatively low threshold values, that is more frequent M&R, tend to increase M&R expenditure. This means that M&R more frequently with lower threshold could keep the road in a better condition but costs more for the construction works. This observation serves as motivation to optimise the threshold to minimise traffic costs while maintaining a reasonable budget level.

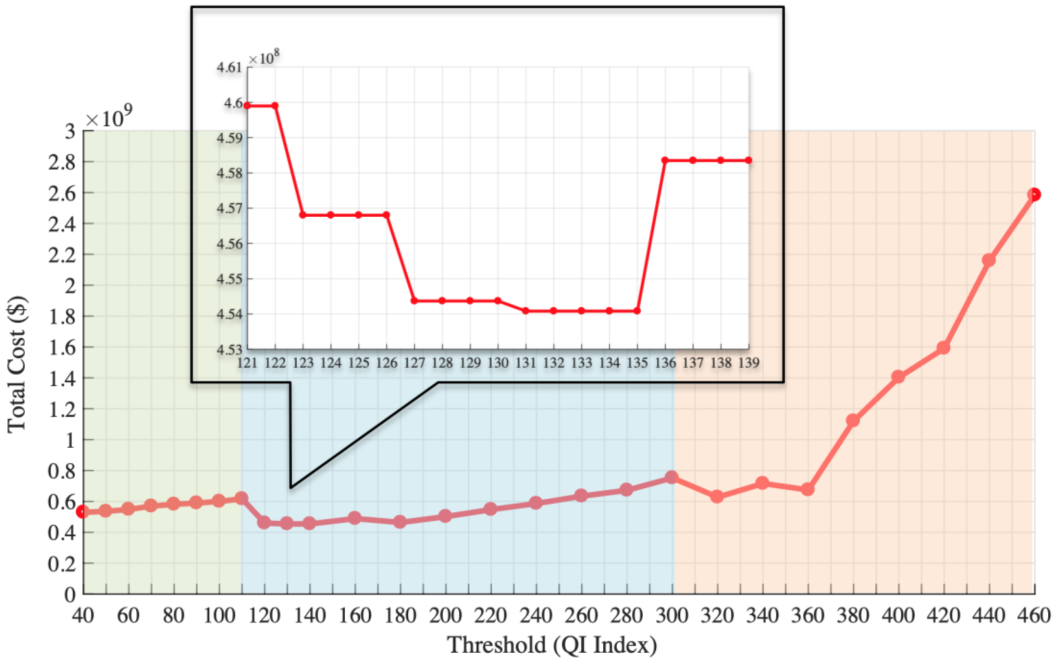


Figure 6.4 Discounted total cost of M&R plans with different threshold values for link #68

Corresponding to the above results, the total cost (e.g. a sum of network travel cost and M&R expenditure) of different threshold-based M&R plans are compared in Figure 6.4. It indicates that a threshold value between 120-140 QI is a better choice for resurfacing planning on link #68, which generates lower total cost during the planning period. I further test in more details between threshold 120-140 QI and the simulation results are illustrated in the zoom window of Figure 6.4. In this case, the best threshold value for resurfacing on link #68 as shown is 131 QI and the post-M&R roughness is at a medium level of 118.15 QI (see the bottom picture of Figure 6.3). This plan results in the lowest travel cost to the road network as well as the minimum total cost.

The corresponding resurfacing plan for link #68 is given in Table 6.4, where MC (maintenance cost) and MTC (M&R derived travel cost) are discounted values. According to this plan, there are two resurfacing activities at month 53 and 89 respectively. Assuming that the roughness at the end of the planning horizon is constrained to be lower than 40 QI, there should be another resurfacing action conducted at $T = 120$ and the salvage M&R cost is calculated as 1,568,241.4 \$. Included this salvage cost, the plan shown in Table 6.4 is still the optimal M&R plan with a discounted total cost of 455,650,083.2 \$, compared with other threshold values. This result is based on the assumptions that there is no budget constraint, MC and MTC have same weight in decision-making, and the roughness constraint at the end of planning horizon is 40 QI. It is expected that various budget constraint, roughness constraint and the weighting parameters between two costs could result in different optimal M&R plans, which will be further tested in the M&R optimisation problems in Chapter 7 .

The roughness trajectory of this M&R plan is plotted in Figure 6.5, together with the network travel cost, and the traffic volume and capacity evolutions of link #68 under this plan. It shows that there is a clear oscillation of the traffic on link #68 due to its capacity reduction by 50% when M&R is conducted, which means that the traffic flow propagates from link #68 to the alternative links in the network. This therefore breaks the steady state of the network flow pattern and produce transient congestions, which induces a drastic increase of the network travel cost. This indeed highlights the need for modelling traffic disequilibrium states and transient congestion derived by M&R activities, as it could generates significant travel costs that should not be ignored.

Table 6.4 Optimal resurfacing plan for link #68

Action i	Threshold (QI)	t_i (month)	$s_i(t-1)$ (QI)	R_i (mm)	w_i (mm)	$s_i(t+1)$ (QI)	MC_i (10^6\$)	M&R Cost (10^6\$)	Travel Cost (10^8\$)	Total Cost (10^8\$)
1	131	53	135.3147	92.72	92.72	46.0070	2.5069	4.5247	4.4956	4.5565
2		89	135.0602	92.58	92.58	46.9312	2.0179			
salvage	-	120	118.1490	83.28	83.26	40	1.5682	1.5682	-	

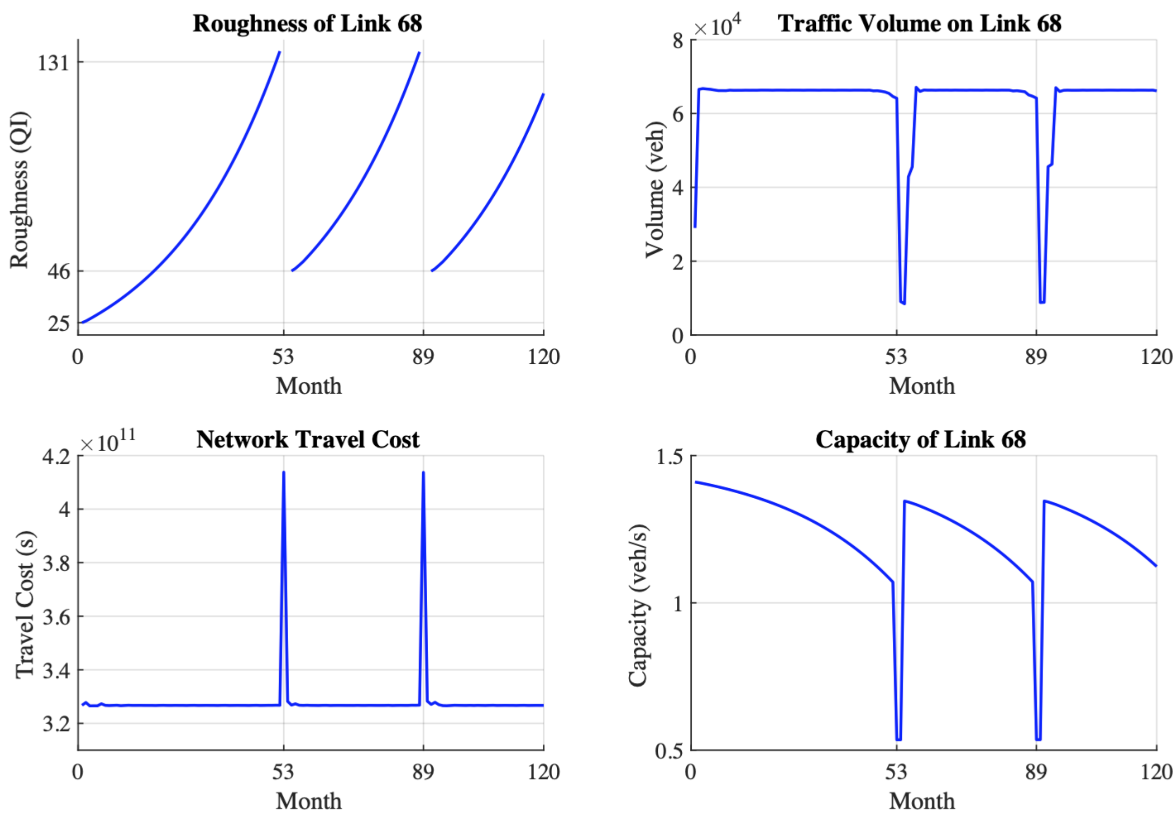


Figure 6.5 Illustration of the optimal resurfacing plan for link #68

6.3.1.2 Threshold-based M&R Planning for Link #49

In the second example, another critical link #49 of the Sioux Falls network, which is a 3.2187 km-long dual-lane pavement, is chosen for the M&R planning. Link #49 is the most flow saturated road segment (e.g. maximum flow/capacity ratio) among all links in the network under the DUE simulation, and it carries more traffic volume than link #68. Based on Table 6.2, for resurfacing on link #49, M&R expenditure parameters are calculated as $m_0 = 482{,}803.2\ \$$, $m_1 = 9{,}656.06\ \$/mm$; and the M&R duration is $d = 1$ month. The same simulations of threshold-based M&R plans are performed on link #49, and the resulted optimal resurfacing plan is shown in Table 6.5 and illustrated in Figure 6.6.

It can be observed from Table 6.5 that the optimum threshold for the M&R planning on link #49 is 88 QI and the discounted total cost is 109,975,605.01 \$. This plan could generate the minimum M&R-derived travel costs to the road network. Under this threshold, there are three resurfacing activities at month 34, 63 and 93 respectively, and another M&R action at the end of planning horizon for the purpose of bringing the roughness to the satisfactory level of 40 QI. Compared with link #68, link #49 has a greater number of M&R times, which is expected that the road with higher traffic volume will accelerate its deterioration process so that increase the M&R frequency to maintain road quality. Also, link #49 has a lower threshold value, which suggests that the road carries more traffic should be kept in better road condition in order to reduce the travel costs induced by road deterioration.

Table 6.5 Optimal resurfacing plan for link #49

<table>
<tr><th>Action i</th><th>Threshold (QI)</th><th>t_i (month)</th><th>$s_i(t-1)$ (QI)</th><th>R_i (mm)</th><th>w_i (mm)</th><th>$s_i(t+1)$ (QI)</th><th>MC_i (10^5\$)</th><th>M&R Cost (10^6\$)</th><th>Travel Cost (10^8\$)</th><th>Total Cost (10^8\$)</th></tr>
<tr><td>1</td><td rowspan="3">88</td><td>34</td><td>90.0788</td><td>67.84</td><td>67.84</td><td>30.6268</td><td>9.2792</td><td rowspan="3">2.3553</td><td rowspan="3">1.0714</td><td rowspan="4">1.0998</td></tr>
<tr><td>2</td><td>63</td><td>88.5415</td><td>67.00</td><td>67.00</td><td>30.1041</td><td>7.7413</td></tr>
<tr><td>3</td><td>93</td><td>90.7306</td><td>68.20</td><td>68.20</td><td>30.8484</td><td>6.5326</td></tr>
<tr><td>salvage</td><td>-</td><td>120</td><td>85.6544</td><td>65.41</td><td>52.82</td><td>40</td><td>4.8329</td><td>0.4833</td><td>-</td></tr>
</table>

Figure 6.6 shows that, for the threshold-based M&R planning, the interval between each M&R activity is relatively constant (e.g. about 30 months for link #49) and the roughness trajectory is at a relative steady state after first M&R. Compared with link #68 in Figure 6.5, the daily volume on link #49 suffers less oscillations when M&R and results in less increase in the network travel cost. It indicates that choice change behaviour of great number of travellers in response to M&R for avoiding the congestion (e.g. link #68) may lead to more transient congestion at the network level, which can be viewed as a lack of complete information when individual making travel choices.

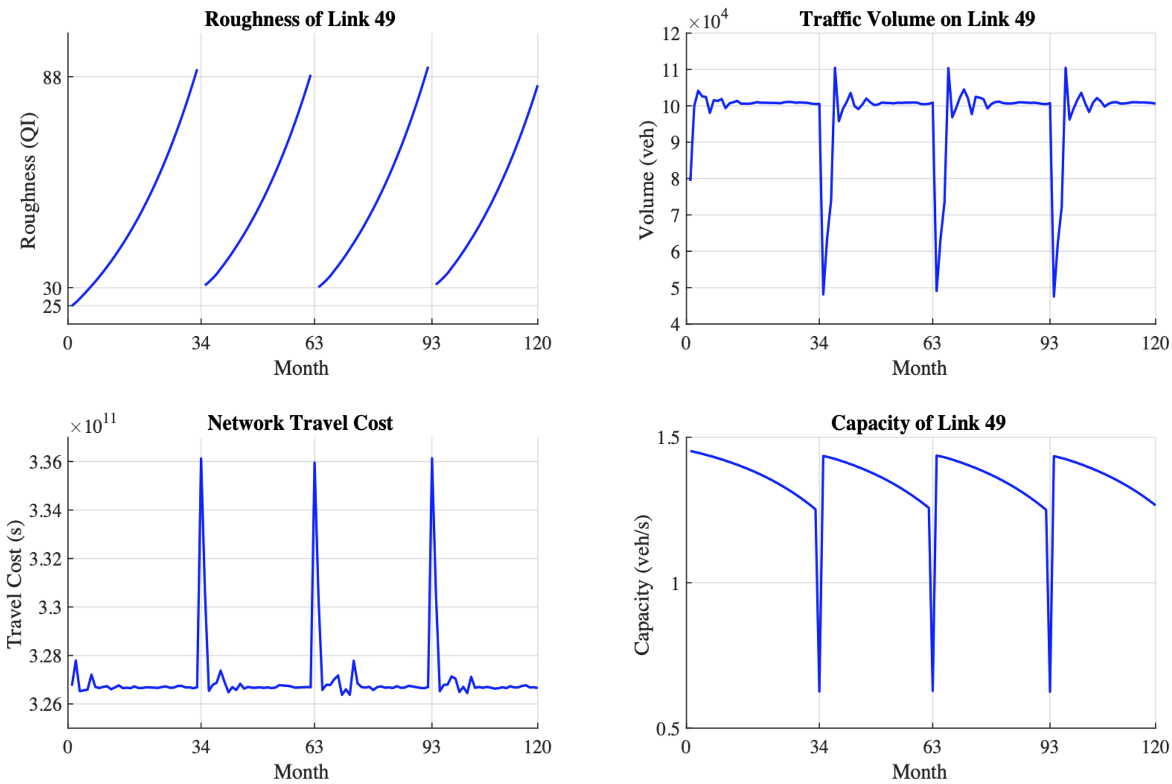


Figure 6.6 Illustration of the optimal resurfacing plan for link #49

Next, this M&R plan is used to test the network dynamics under different level of road deterioration according to traffic loading on links, that is the deterioration rate b_1 in Equation (5-4). Figure 6.7 compares roughness trajectory and flow capacity evolution of link #49 as well as network travel costs under different deterioration rate of $b_1 = 0,\ 1 \times 10^{-7}, 2 \times 10^{-7}$, where $b_1 = 0$ is the case that traffic has no impact on road quality. It can be seen from the top picture that link #49 deteriorates much faster under the cases $b_1 = 1 \times 10^{-7}, 2 \times 10^{-7}$ than $b_1 = 0$, which indicates that traffic loading on the road has an obviously influence on road deterioration thus need more M&R actions. There is an accelerating trend of road capacity reduction between M&R as b_1 increases, as illustrated in the middle picture, which is expected that faster road deterioration could cause more reduction on flow capacity. The number of M&R actions increases with the increase of b_1 and causes more disruptions to the network inducing more network travel costs, see the bottom picture of Figure 6.7. Therefore, the impact of traffic loading on road deterioration should be captured in DTD road quality modelling for properly deciding M&R plans.

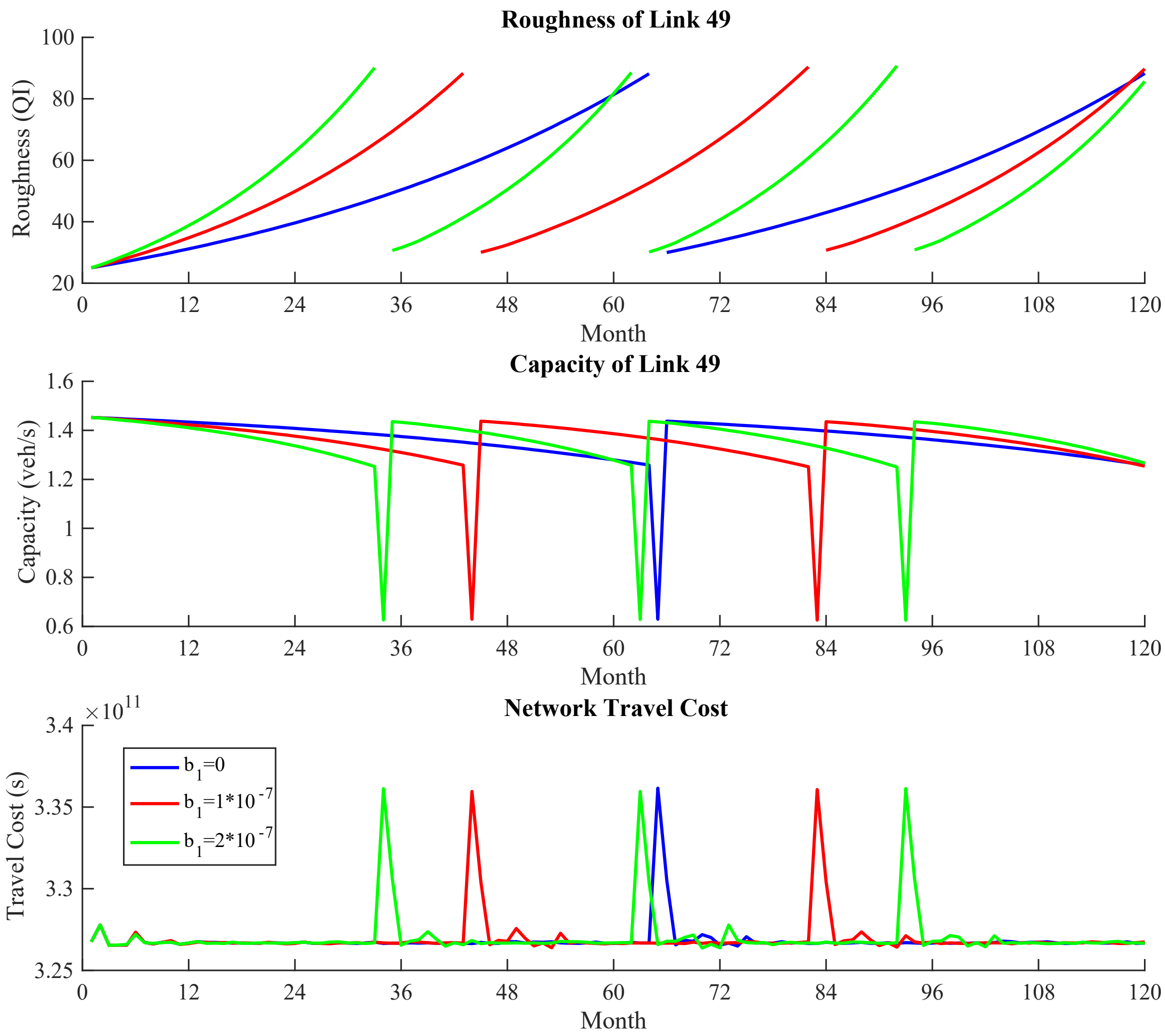


Figure 6.7 Comparison between different deterioration rates

6.3.2 Threshold-based M&R Planning for a Collection of Road Segments

This section further conducts numerical studies that all road segments in the Sioux Falls network are considered for threshold-based M&R. Simulations are performed on different M&R plans with threshold values from 30 QI to 145 QI with an increment of 5 QI. This section considers a planning horizon of 6 years, and the M&R activities are conducted at maximum intensity defined in Equation (6-7) based on the roughness values before M&R. The roughness constraint at the end of planning horizon is assumed to be below 40 QI. Figure 6.8 shows the results of the network travel cost, M&R expenditure and total cost of different threshold-based M&R plans for the road network.

As shown in the top picture of Figure 6.8, the changing of total network travel cost with M&R threshold has a similar trend with the case for a single road segment in Figure 6.3. It suggests that: (i) As the threshold increase from 70 to 80 QI , the number of M&R actions needed in the network greatly decreases over the planning horizon, causing much less disruption to the traffic network; (ii) In other cases, the total number of M&R actions in the network is gradually decrease with the increase of threshold, and there is no significant difference of the M&R amount between thresholds. Under this condition, as the threshold increase, sometimes the network travel costs decrease due to the decreased M&R disruptions to the network traffic; but more usually this could be overpowered by more deteriorated road conditions and cause the increase of the network travel cost. See the middle figure of Figure 6.8, in terms of M&R expenditure, there is a decreasing trend of total M&R cost and an increasing trend of salvage M&R cost as threshold increase. This is expected that M&R expenditure decrease as the total number of M&R actions decrease with the increase of threshold, and higher threshold will keep the roads under less satisfactory conditions and result in more salvage M&R cost to bring the road network roughness back below 40 QI (terminal constraint) at the end of planning horizon. It can be seen from the bottom picture of Figure 6.8 that a preliminary result of the optimal resurfacing threshold adapting to all road segments in the Sioux Falls network should be around 80-95 QI, which have lower total costs.

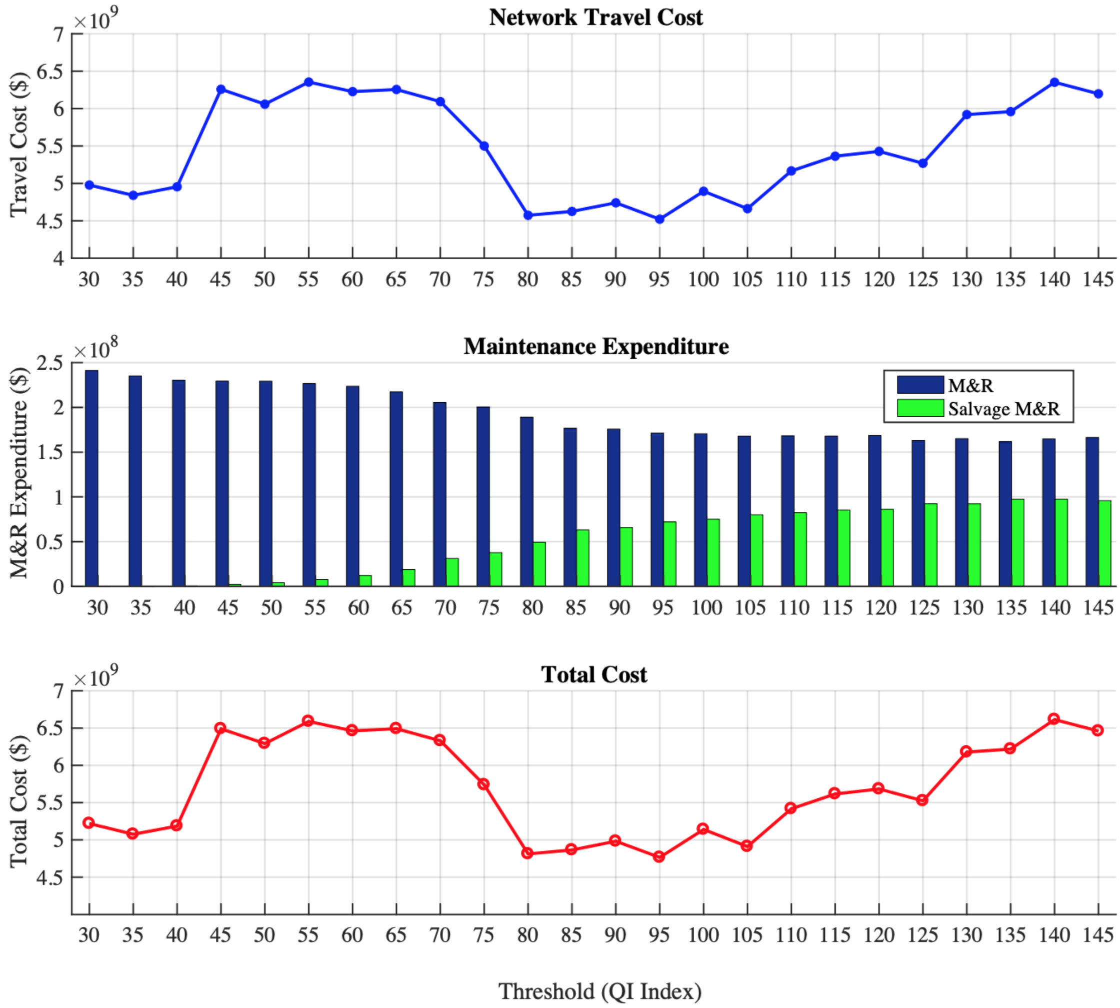


Figure 6.8 Comparison of M&R plans with different threshold values

Next, take threshold=89QI for an example, Figure 6.9 is used to illustrate the impact of information sharing strength, that is n in $G(x) = x^n$ (see Figure 3.4), on the variations of network travel costs under this threshold. The M&R plans of the four cases all result in a series of M&R actions on links between month 36-48, which causes a drastic increase of the network travel costs during the disruption period. It can be seen that $n = 2$ yields higher total network travel costs, which means that focusing information reported by large crowds, tends to create much uncertainties in the decision-making process. It also shows that $n = 0.5$ yields lower total network travel costs, which indicates a phenomenon of network paradox that focus more on limited information reported by small crowds could reduce the overall network travel costs. This could provide a suggestion for the information platforms to pay attention to those less popular travel choices when providing M&R information.

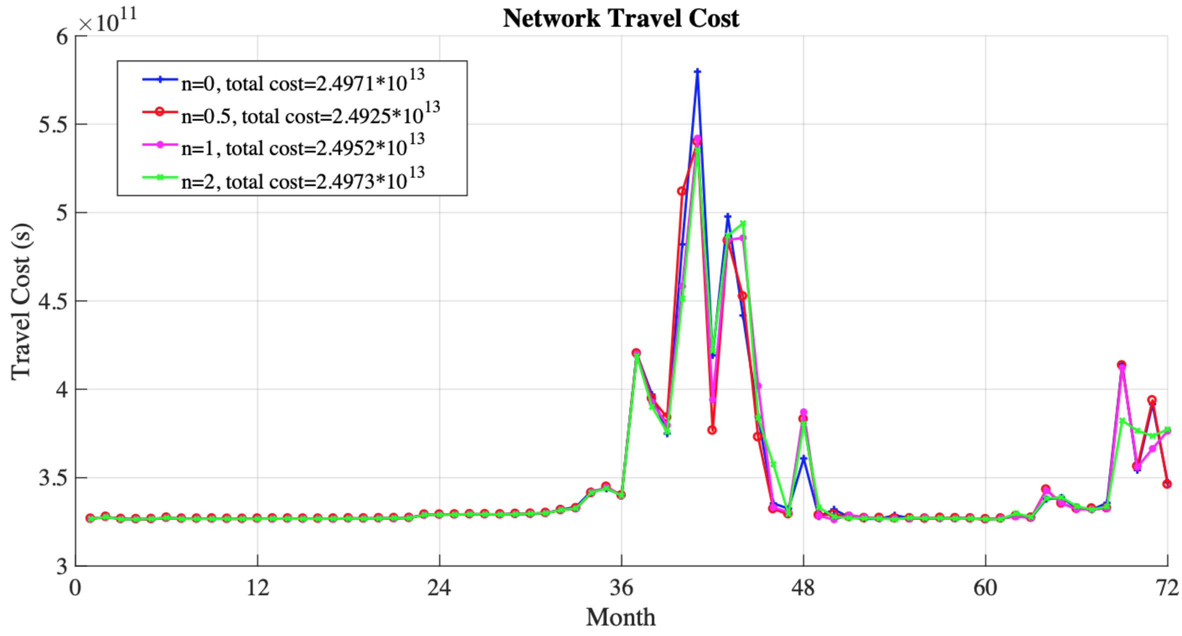


Figure 6.9 Network travel costs corresponding to Base Model II with information sharing (n=0,0.5,1,2)

6.4 Periodic Road M&R Planning at the Network Level

This section illustrates the M&R planning method based on periodic M&R activities; that is, the M&R is conducted at a fixed frequency or cycle (e.g. every several years). Resurfacing actions are assumed to be conducted at the beginning of each M&R cycle. The case studies are again carried out on the Sioux Falls network, and the parameters used for the DDTA model, the DTD road quality model as well as the M&R planning model are given in Section 6.2. In this section, the periodic M&R planning method will be tested firstly on a single road segment and then on a collection of road segments. The periodic M&R solution then will be compared with threshold-based M&R solution. In addition, the need for periodic M&R planning under the proposed doubly DTD DTA model will be demonstrated by comparing with M&R planning under the DUE model. M&R under DUE means that the network traffic is modelled as equilibrium states and not consider M&R derived traffic disequilibrium as well as transient congestion. Moreover, through comparing the M&R solutions with and without modelling day-to-day flow capacity evolution, the necessity of capturing the impact of day-to-day road deterioration on network traffic loading will be examined.

6.4.1 Periodic M&R Planning for a Single Road Segment

As a proof of concept, simulations are performed on n-yearly (n=1, 2, 3, 4, 5) periodic M&R plans for link #68 for a planning horizon of 10 years. This generates five different scenarios (see Table 6.6 scenario 1-5) with different times of M&R within the planning horizon. The M&R activities are conducted at given intensities that different for five scenarios. It is reasonable to assume that lower M&R frequency is related to higher M&R intensity for keeping the road condition at a relative satisfactory level. Therefore, the intensity for each scenario is determined in this way in order to maintain the road within a good and stable roughness level and also satisfies the maximum intensity constraint in Equation (6-7). This case study is to discuss whether is better to conduct M&R more frequently with lower intensity or M&R less with larger intensity.

The periodic M&R results for link #68 of the five scenarios are shown in Table 6.6 and plotted in Figure 6.10. It can be seen that lower frequency could reduce M&R expenditure, while induce more salvage cost due to the less satisfactory road condition, as also suggested in Section 6.3.1. Moreover, travel cost decreases with the decrease of M&R frequency and starts to increase from the frequency of 4-yearly, which indicates that less number of M&R times could reduce the disruptions to the network traffic thus reduce travel costs, however, it could be overpowered by the increased travel costs caused by poor road conditions if the M&R frequency is too low. Indeed, too frequent M&R activities could cause higher maintenance expenditure as well as more disruptions to the network traffic; if the frequency is too low, M&R is incapable of maintaining road conditions and will also generate higher travel costs due to deteriorated roads. As shown in Table 6.6, resurfacing on link #68 every 4 years is the more superior plan in view of M&R expenditure, salvage M&R expenditure and travel cost. Corresponding to this plan, there are 2 resurfacing activities within 10-year planning and a salvage M&R at the end of the planning horizon, which conforms with the optimal threshold-based resurfacing plan for link #68 (see Table 6.4).

Table 6.6 Periodic M&R plans for link #68

Scenario	Cycle (year)	M&R Times	Intensity (mm)	Travel Cost (10^9\$)	M&R Cost (10^6\$)	Salvage Cost (10^6\$)	Total Cost (10^9\$)
1	1	9+1	13	1.4983	9.7152	0.7889	1.5089
2	2	4+1	35	0.7126	5.8008	0.8031	0.7192
3	3	3+1	60	0.5706	5.2525	0.6224	0.5765
4	4	2+1	80	0.4698	4.1170	2.3137	0.4762
5	5	1+1	110	0.5141	2.6947	3.8306	0.5206

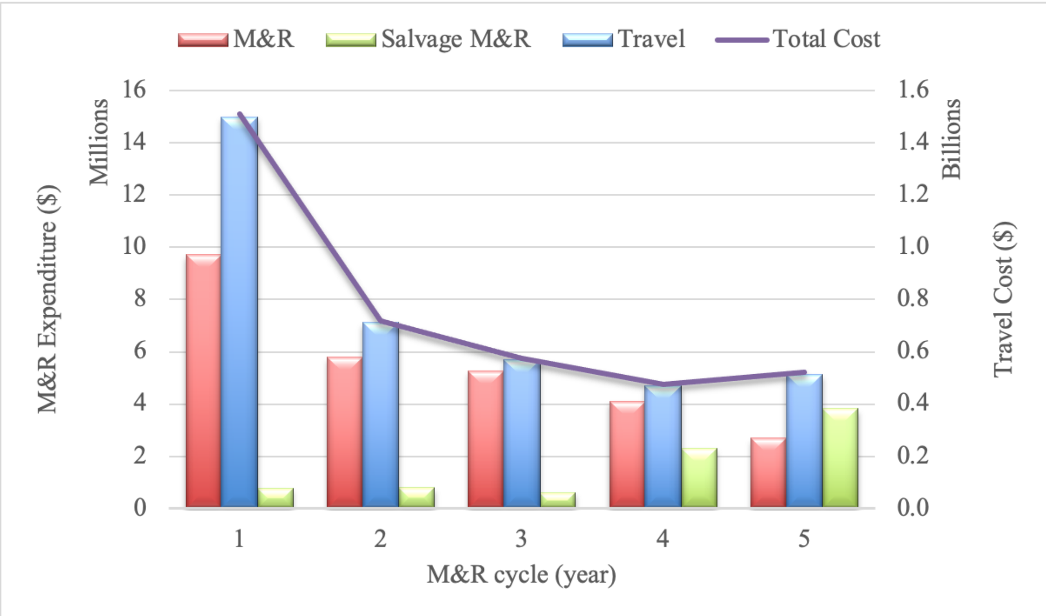


Figure 6.10 Comparison of different periodic M&R plans of link #68

Figure 6.11 further compares the threshold-based M&R solution (threshold=131QI) and the 4-yearly periodic M&R solution of link #68. It is expected that threshold-based approach is capable of scheduling the M&R activities more precisely based on DTD road conditions, thereby keeping road quality under a more stable roughness deterioration process, which is indeed illustrated in the top of Figure 6.11. Furthermore, threshold-based M&R generate lower network travel cost (see the middle of Figure 6.11) as well as lower M&R expenditure (see the bottom of Figure 6.11), which is considered as a more preferable approach compared with periodic M&R. It is more natural to conduct M&R actions when the roads deteriorate to poor conditions based on thresholds, while predetermined schedule-based M&R approach is less intuitive and maybe sub-optimal.

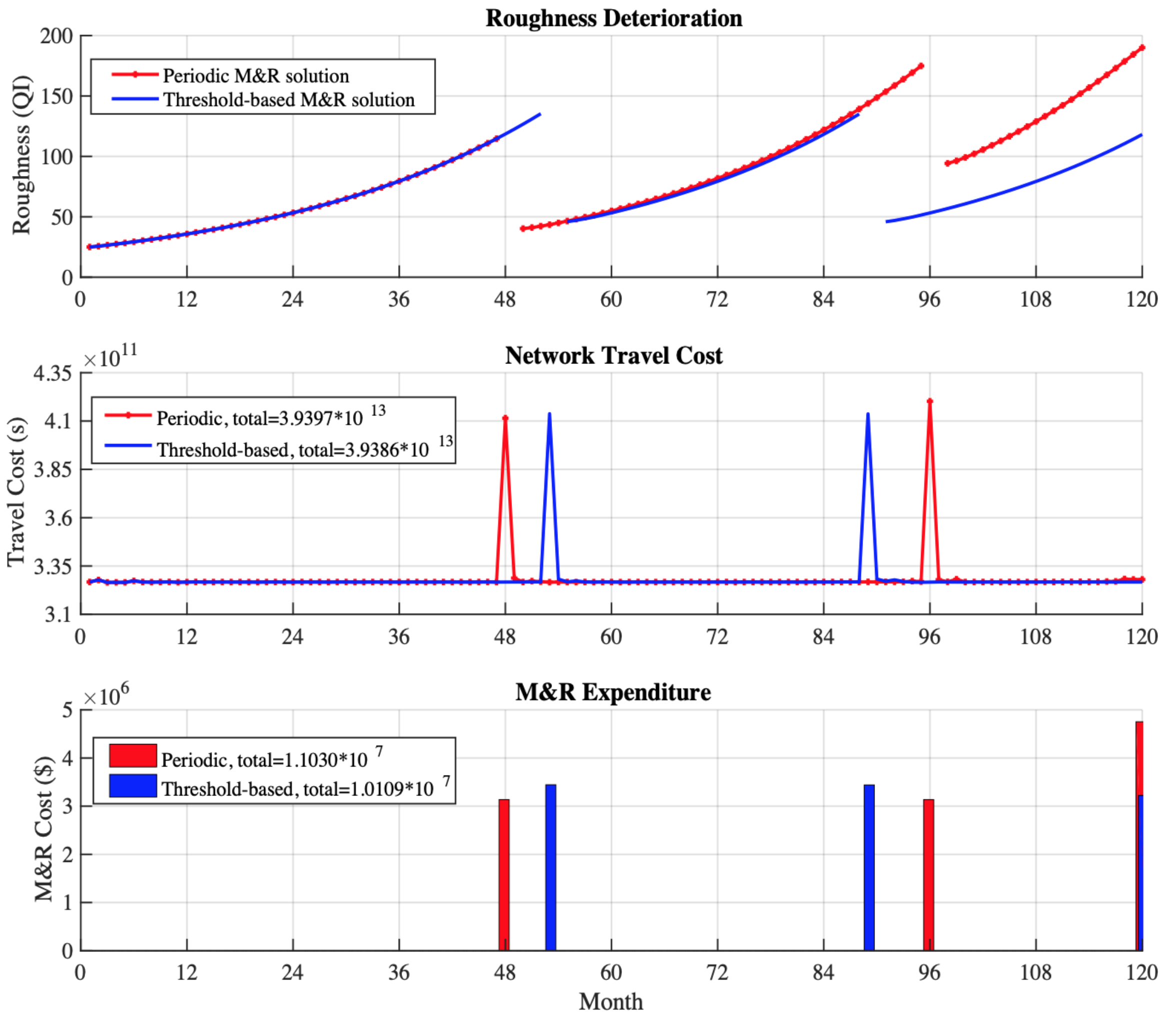


Figure 6.11 Comparison of threshold-based M&R and periodic M&R approaches

Next, this periodic M&R planning solution under the proposed doubly DTD dynamic modelling of network traffic is compared with the dynamic user equilibrium (DUE) scenario on which the same periodic M&R plan is based, and the results are illustrated in Figure 6.12. It can be seen from the lower figure that the periodic M&R plan performs very differently under DTD dynamics and under DUE, which the travel cost estimated by the DUE model is far below the travel cost estimated by the proposed DTD DTA model when the traffic network encountered with M&R actions. This indicates that periodic M&R planning under DUE could obviously underestimate maintenance-derived disruptions to the network traffic, as it ignores M&R-derived transient congestion. Therefore, it is necessary to apply the proposed DTD DTA model in capturing the traffic dynamics when planning periodic M&R, as it is superior in modelling the travel costs induced by traffic disequilibrium states and transient congestion during and after M&R, which is not able to be captured by any DUE models.

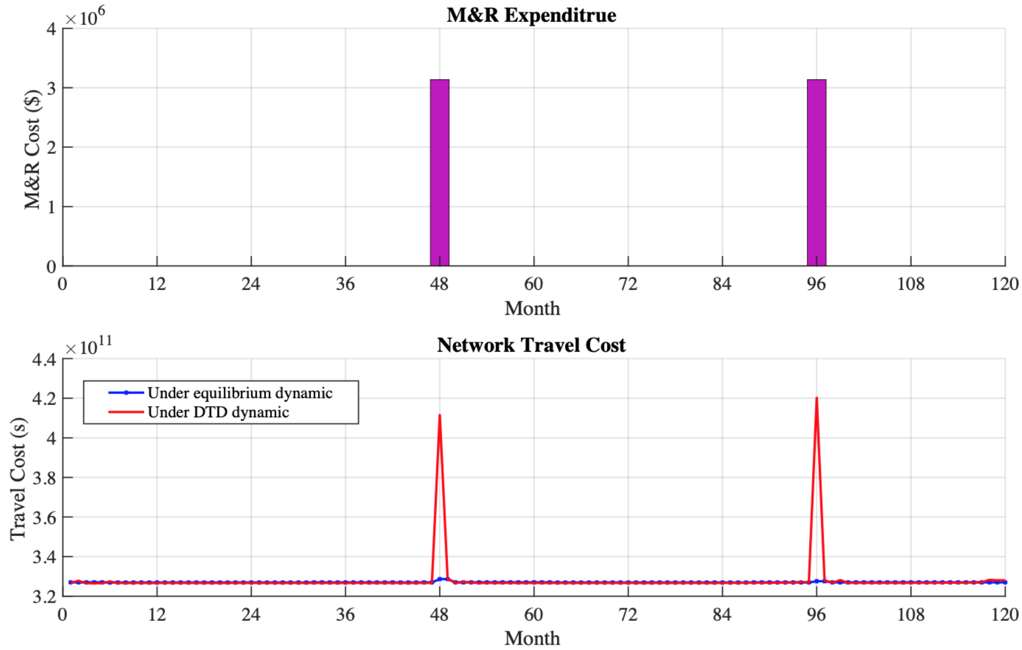


Figure 6.12 Comparison of periodic M&R under DTD DTA and DUE models: DTD DTA solution

Figure 6.13 illustrates the optimal periodic M&R plan derived by DUE, which is to resurface once at year 5 with an intensity of 88 mm; and compares it with the DTD simulation of this plan. Consistent with the results in Figure 6.12, the third picture of Figure 6.13 shows that there is an obvious increase in network travel cost during M&R under DTD simulation, which indicates the M&R derived transient congestion that is ignored by the DUE simulation. Furthermore, it can be seen from the first picture of Figure 6.13 that, under DTD DTA, there is gradually decrease of traffic volume of link #68 after month 48 and after month 72, and the reduction becomes drastic after month 84. This is expected that link #68 suffers DTD flow capacity reduction due to its deterioration, where the road deteriorates to bad conditions (e.g. roughness around 100 QI) after month 48 and month 72 and the road quality becomes very poor (e.g. roughness around 200 QI) after month 84, which causes traffic propagation from link #68 to other links in the network. The third picture of Figure 6.13 also illustrated that there is a significant increase of network travel costs after month 96 under DTD, which means that traffic flow propagation among road network due to poor road condition of link #68 induces traffic disequilibrium states and transient congestion to the network traffic. The irregular fluctuations imply the inherent network complexity resulting from interactions of travellers, infrastructure, and information on a day-to-day time scale. The comparison shows that M&R under the DUE model could result in unrealistic modelling of network dynamics. Therefore, it is necessary to apply the proposed DTD model in capturing traffic disequilibrium states and transient congestion when planning M&R, which is not able to be captured by DUE models.

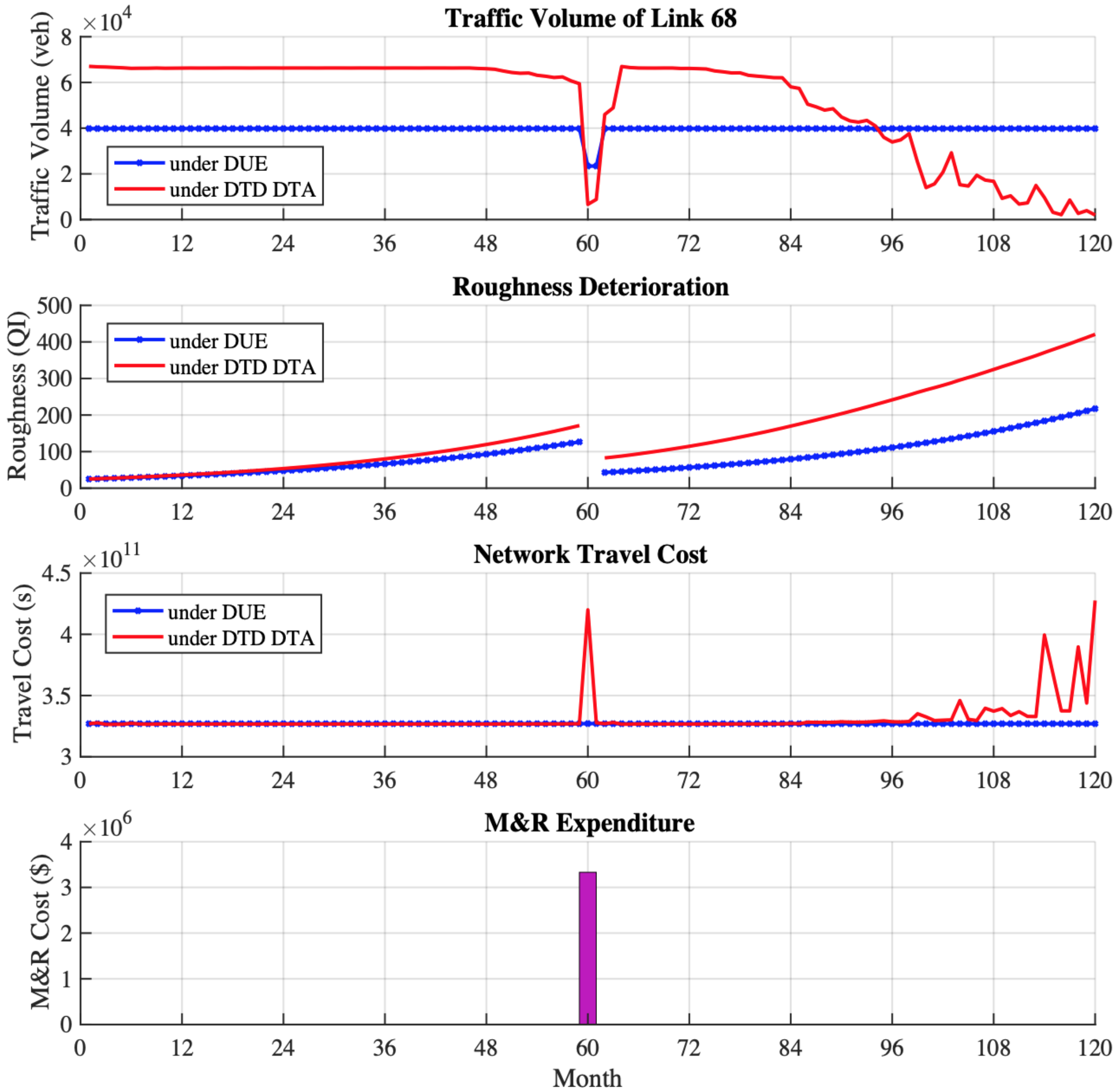


Figure 6.13 Comparison of periodic M&R under DTD DTA and DUE models: DUE solution

6.4.2 Periodic M&R Planning for a Collection of Road Segments

In this section, periodic M&R planning is performed for a system of road segments, where all links in the Sioux Falls network are modelled with DTD road deterioration and DTD flow capacity reduction. Three periodic M&R strategies are considered and will be examined separately in this section. The M&R planning horizon is 6 years for the three cases.

6.4.2.1 Periodic M&R Strategy 1

The first strategy is an extension of Section 6.4.1 to a case where 10 links with the highest traffic volumes in the DUE simulation are selected for M&R. In this case, the road segments subject to M&R are predetermined and the question is to decide how often the M&R should be conducted on these roads. Three scenarios (see Table 6.7) are tested respectively: Resurfacing every n (n=1, 2, 3) year on the 10 links simultaneously with predetermined intensity. Scenario 4 is used to be compared with scenario 3. Between each scenario, the M&R intensities are different and are determined based on the same manner with Section 6.4.1; Within each scenario, the M&R intensity is same for the 10 links for each time M&R action.

Table 6.7 Periodic M&R plans of strategy 1

Scenario	Cycle (year)	M&R Times	Intensity (mm)	Travel Cost (10^9\$)	M&R Cost (10^7\$)	Salvage Cost (10^7\$)	Total Cost (10^9\$)
1	1	5+1	15	4.7927	5.2105	1.0576	4.8554
2	2	2+1	40	4.3605	2.8784	1.4115	4.4034
3	3	1+1	65	4.2253	1.8342	2.2371	4.2661
4	4	1+1	65	4.2851	1.7068	3.0816	4.3330

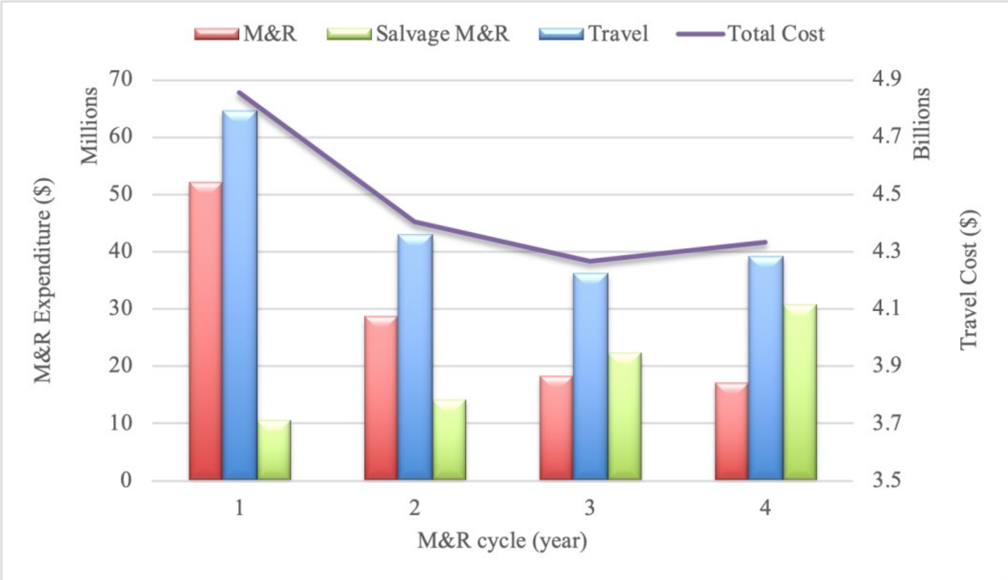


Figure 6.14 Comparison of different M&R plans of strategy 1

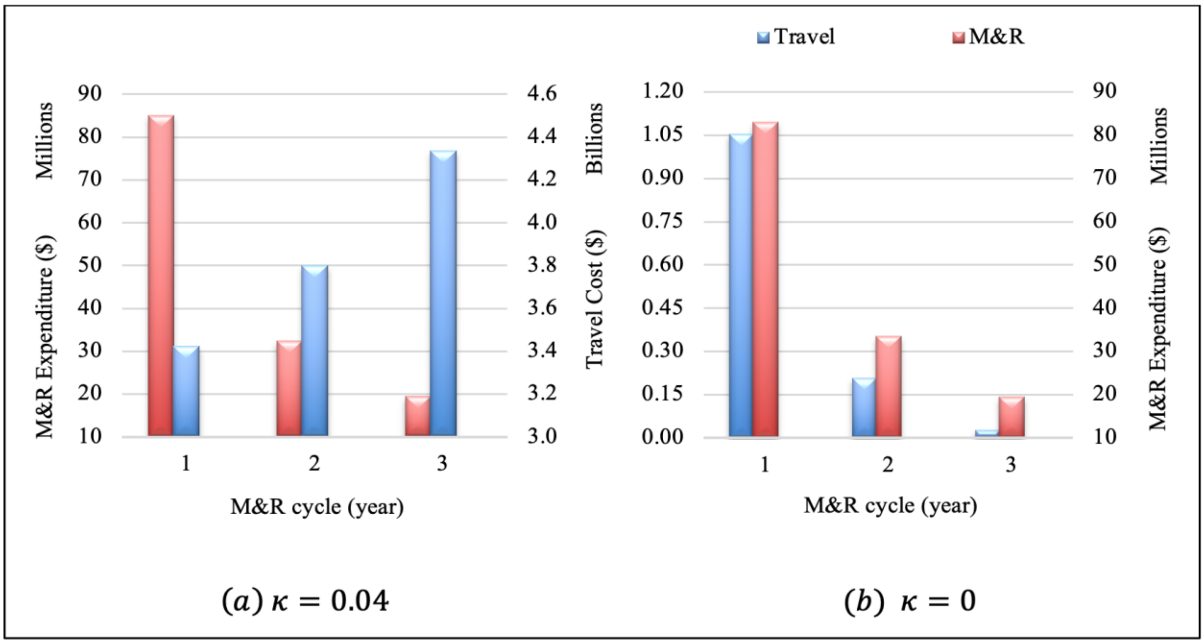
Simulation results of the four scenarios are shown in Table 6.7 and compared in Figure 6.14. The result shows that too frequent M&R activities could cause higher maintenance expenditure as well as higher network travel costs, which is not preferred in this case. As shown in Table 6.7, Scenario 3 is a more superior plan, which induces the lowest network travel cost as well as lowest M&R expenditure (e.g. including both M&R cost and salvage M&R cost). Compared scenario 4 with scenario 3, both have the same number of M&R times, it suggests that deferred resurfacing could cause additional travel costs, owing to traffic delay induced by more deteriorated roads.

6.4.2.2 Periodic M&R Strategy 2

The second strategy is to perform periodic M&R planning also on 10 links, with a distinction that instead of being pre-determined, the 10 links with the highest roughness in the network will be chosen for M&R. Resurfacing activities are conducted at maximum intensity according to the roughness values before resurfacing and the constraint defined in Equation (6-7). This strategy differs from the first one that the total amount of links chosen for resurfacing are unknown in advance depend on the M&R activities as well as network traffic dynamics.

Three periodic resurfacing plans are simulated, and the results of each plan are compared and illustrated in Figure 6.15 (a). It can be seen that, as the M&R activities become more frequent, M&R expenditure increases while network travel costs decrease, which indicates that despite the more frequent disruptions to the network caused by M&R, the long-term benefit of better road quality could generate less travel costs. This case clarifies the importance of road maintenance and suggest more capital investment should be made in road M&R in order to reduce social costs to a greater extent.

The above simulations shown in Figure 6.15 (a) assume DTD flow capacity reduction according to DTD road deterioration with rate $\kappa = 0.04$. The same simulations without modelling DTD flow capacity evolution (e.g. $\kappa = 0$) are further performed for comparison and the M&R solutions are shown in Figure 6.15 (b). Compare (b) with the previous results (a), the travel costs are much lower and the trend of travel cost with M&R frequency is reversed, which means that without modelling DTD capacity evolution could significantly underestimate travel costs induced by deteriorated road conditions and may result in unreasonable M&R decision. Therefore, it is necessary to model the impact of road quality on network traffic loading, which is captured in the proposed M&R planning model in this thesis.



* Different coordinate scales are used for travel cost here due to the travel costs differ much in two cases that could not be managed in the same scale.

Figure 6.15 Comparison of periodic M&R plans with and without DTD capacity reduction

6.4.2.3 Periodic M&R Strategy 3

The third strategy is that there is a predefined number of M&R times for the planning horizon, and the question is how to allocate these M&R actions periodically: whether is better to M&R more frequent with less workload or M&R less with more workload. Two different cases of 50 and 25 times of M&R in total of the 6 year planning horizon are tested respectively, in which M&R actions are evenly allocated according to M&R frequency and forms different periodic M&R plans (see Figure 6.16). Resurfacing activities are conducted on the more deteriorated road segments in the network at each M&R time with maximum intensity.

Simulations are performed on these M&R plans and the results are illustrated and compared in Figure 6.16. Compare Figure 6.16 (b) with (a), it can be seen that: (1) there is a decrease of M&R expenditure in all plans, which is well understood that the total number of M&R times is reduced from 50 to 20; (2) there is a great increase of travel costs in all plans, which implies that less roads being maintained, representing a worse road conditions, could increase daily travel costs significantly and this is consistent with Figure 6.15 (a), which indicates the importance of keeping more roads in good condition could reduce the travel costs generated by deteriorated roads. Both cases see a similar trend of travel costs and maintenance expenditure with M&R frequency, which means that the M&R decisions under this method is robust with the predetermined conditions. Take the left figure (a) for illustration: (1) the M&R expenditure are similar regardless the frequency because the total number of M&R are the same; (2) travel costs decrease as frequency decrease, which is expected that less number of M&R could reduce the disruptions caused to the network traffic thus reduce travel costs. Thus, it seems that maintain the total M&R links at one time is a better plan for this strategy. It should be note that if the network is much more saturated, M&R on a large number of roads at the same time could significantly reduce network flow capacity, which may derive severe congestion among the road network even blocked.

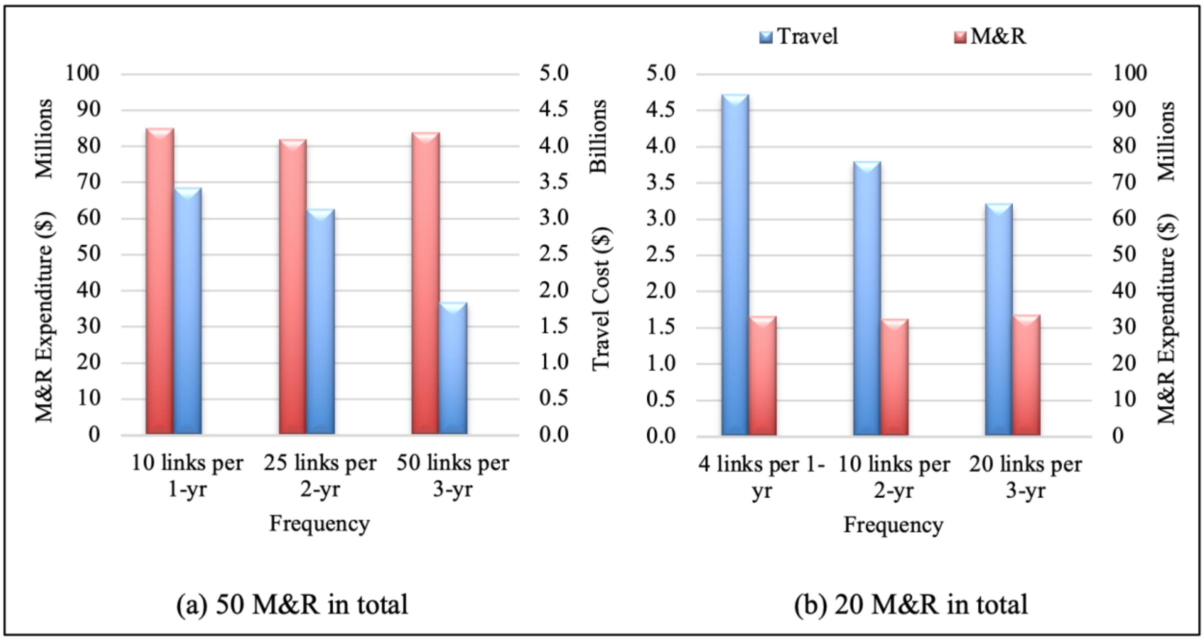


Figure 6.16 Comparison of periodic M&R plans of strategy 3

6.5 Summary

This chapter develop a computable framework of road network M&R with modelling of day-to-day traffic dynamics and transient congestion, which is a bi-level problem that interacting with each other. The lower level problem is the combination of the three sub-models (e.g. the DTD road quality dynamics, the dynamic network loading, the DTD traffic dynamics) that proposed in Chapter 3, 4, 5. This chapter formulates the objective cost functions of network travel cost, M&R expenditure as well as salvage M&R cost supporting

the M&R decision-making of the upper level problem. The proposed M&R planning model is a dynamic Stackelberg game, where the planning agency makes M&R decisions by anticipating the reactions of the road network users who are competitors in a dynamic Nash game. A review of the state-of-the-art M&R planning models shows that this is among the first in the literature to account for day-to-day traffic dynamics as well as capturing M&R derived transient congestion.

The applicability and effectiveness of the proposed M&R planning model has been examined on a large-scale network (e.g. the Sioux Falls network) for both threshold-based M&R method and periodic M&R method. The numerical case studies have demonstrated that:

1) The proposed M&R model is effective in capturing travellers' choice behaviour under different road conditions with or without M&R more realistically and quantify travel costs more accurately.
2) Road networks could experience traffic disequilibrium and transient states during and after M&R, and it may not return to any equilibrium states that DUE model could obtained. By comparing the M&R problems under the proposed DDTA model and under the DUE model (see Figure 7.10 and Figure 6.12), it highlights the need for modelling DTD traffic dynamics and transient congestion derived by M&R activities, as it could generates significant travel costs.
3) It is necessary to model the impact of DTD road deterioration on the DTD road flow capacity reduction then network traffic loading, as the travel costs induced by DTD deteriorated road conditions are significant and could not be ignored in M&R planning (see Figure 6.15). Also, it is necessary to model the influence of traffic loading on road deterioration therefore M&R decisions (see Figure 6.7). This feedback mechanism could be captured by the proposed M&R model.
4) Travellers could act differently during and after the M&R actions when different level of information is provided. In particular, in the Sioux Falls network, the travel cost increase with n under the cases of incomplete information (Figure 6.9), which means that network traffic undergoes larger uncertainty when the travellers only have access to information of a few popular choices.
5) Threshold-based M&R approach could schedule the M&R activities more precisely based on time-varying road conditions, thereby keep road quality under a more stable roughness deterioration process. Threshold-based M&R is a preferable approach compared with periodic M&R, as periodic M&R could generate more travel costs and become sub-optimal (see Figure 6.11). Therefore, Chapter 7 continues with the M&R optimisation problems focusing on threshold-based M&R approach.

7 Threshold-based Long-term Road Network M&R Optimisation Model

Road network maintenance and repair (M&R) is crucial for keeping road infrastructure in satisfactory conditions while ensuring the fluidity of the traffic system. Threshold-based M&R planning, which is to conduct M&R actions when the road deteriorates to a certain threshold level, has been widely adopted by transport agencies due to its intuitive policy and easy-to-implement decision rules. For long-term road M&R, the planning horizon typically spans several years, and the key decision involves M&R scheduling (both temporally and spatially) as well as resource allocation (e.g. resurfacing intensity) of a traffic network, for the purpose of maintaining the road segments above certain service levels. Long-term road M&R problems encompass several aspects of the transport system for decision-making, such as travel cost, M&R expenditure as well as road deterioration process.

M&R derived disruptions to the road network could induce changes in travellers' route and departure time choices, leading to a shift of network traffic flow pattern temporally and spatially. Benefits of a road M&R project are often misinterpreted due to insufficient understanding of road users' travel costs during and after M&R. For road network M&R planning, recognition of maintenance-derived disruptions is especially essential, since these disruptions can produce substantial social and economic costs in the form of transient congestion. The present value of post-maintenance benefits can be offset or even overpowered by the social costs associated with maintenance-derived transient congestion. Explicit traffic models are required to capture travellers' dynamically response to M&R conditions for the purpose of estimating the benefits and costs of M&R strategies accurately.

This chapter develop a modelling framework for optimal road network M&R decision-making that could account for both within-day and day-to-day traffic dynamics as well as transient congestion. The objective is to propose a M&R optimisation model for determining the optimal M&R threshold (and intensity) for threshold-based long-term network-level road M&R planning under the budget constraints. This methodology is tested through the numerical studies on a large-scale network, and a genetic algorithm approach is applied to solve the M&R optimisation problems.

This organisation of this chapter is as follows. Section 7.1 introduces threshold-based M&R approach and the insufficiency of the long-term M&R studies so fr. It also highlights the improvements of the proposed M&R optimisation model through a comparison of literature. Section 7.2 proposes a systematic M&R optimisation methodology framework considering day-to-day dynamics of network traffic and road quality; followed by the formulations of the M&R optimisation model. An introduction of the solution method – Genetic Algorithm (GA) is given in Section 7.3, and the programming of GA applied in the case studies in this chapter is also presented. Section 7.4 conducts case studies on the Sioux Falls network for optimal long-term threshold-based M&R planning. The numerical results of the proposed M&R optimisation model under day-to-day dynamics are compared with under dynamic user equilibrium modelling of traffic in Section 7.5, the purpose of which is to highlights the significant for considering day-to-day traffic dynamics and transient congestion in optimal road M&R planning. Section 7.6 conducts sensitivity analysis on model parameters for management, including the weighting parameter between costs and the budget constraint. The impacts of information sharing is also discussed. Finally, Section 7.7 summarise this chapter.

7.1 Optimal Threshold-based Road Network M&R Planning

Road network maintenance and repair (M&R) planning deals with the decision-making of M&R plans for road segments in the network. Since road pavements are in poor conditions due to long-term usage, it is necessity for conducting road network M&R planning in the purpose of keeping roads within a good serviceability level. Social and economic aspects of a country will benefit much from well-maintained road transportation system. Existing studies on network-level road M&R planning generally composed by a road deterioration model for predicting the quality of road pavements, and the technique to decide M&R plans. In addition to M&R expenditure, M&R constructions on roads could disrupt network traffic flow patterns, which induces significant travel costs that may greater than the M&R expenditure. Therefore, another important part should be accounted for in road M&R planning, which is the modelling of traffic flow dynamics among road network under the conditions with and without M&R.

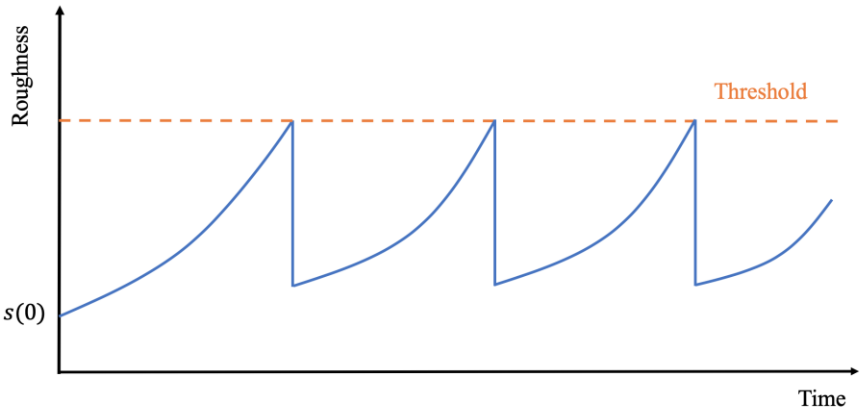


Figure 7.1 Illustration of threshold-based M&R

Threshold-based road M&R planning is to conduct M&R actions when the road segment deterioration reaches a certain threshold, that is a specific roughness value, as illustrated in Figure 7.1. This kind of M&R approach has been widely adopted by transport agencies due to its intuitive policy that is to maintain a road in bad condition, and its easy-to-implement decision rules. However, the current practice of threshold-based road M&R planning is that the thresholds are often determined by historical experience and expert judgements (Chu & Chen, 2012), which do not take into account traffic dynamics and network response on a quantitative level. However, M&R actions on road networks could occupy part of the roads and cause disruptions to the traffic flow, which may change the route and/or departure time choice of travellers for circumventing traffic congestions. Under the previous M&R approaches, the road network condition could not be optimised, and the M&R budgets could not be used cost-effectively. It is desirable to conduct the M&R planning so as to induce less disruptions and traffic congestions to the road network, since M&R derived travel costs usually far exceed the M&R expenditure (Ng et al., 2009). Appropriate M&R planning should reduce the total cost including both M&R expenditure and network travel costs.

Most of the threshold-based road M&R optimisation studies are for a single road segment (e.g. Tsunokawa & Schofer, 1994; Li & Madanat, 2002; Ouyang & Madanat 2006), and only a few consider multiple pavements (e.g. Chu & Chen, 2011, Sathaye & Madanat, 2011). It is a highly complex problem of threshold-based M&R planning for a system of road segments because of the interdependencies between road segments, especially for large-scale networks. The most advanced method of capturing these functional interdependencies between road segments in M&R optimisation problems so far is by traffic assignment models and simulations. Studies of long-term M&R optimisation mostly considering static user equilibrium (UE) include, for example, Uchida and Kagaya (2006) who assumed stochastic user equilibrium model, Ouyang (2007) who applied deterministic user equilibrium model, and Chu and Chen (2012) used a static user equilibrium model. The literature on long-term M&R accounting for dynamic traffic assignment models is rather scarce. Ng et al. (2009) proposed a long-term M&R planning model used dynamic user equilibrium (DUE) based on cell transmission model.

As traffic loading is the most influential factor to road deterioration, traffic propagation among the network and its dynamics should be accurately predicted for the decision-making of M&R plans. However, as also stated in the literature review in Section 2.4, the underlying traffic assignment models of the M&R optimisation models so far are simple and insufficient, since only the equilibrium state is considered. They are unable to capture travellers' learning and adjustment behaviours and the traffic flow variation day by day derived by M&R actions, inducing the transient states disequilibrium which evolves toward equilibrium. It is necessity to consider this transient congestion induced by day-to-day traffic disequilibrium derived by M&R disruptions in optimal M&R planning, since it could produce significant social costs that should not be ignored.

A comparison of the literature on optimal long-term M&R models is presented in Table 7.1.

Table 7.1 Comparison of literature on optimal long-term road M&R planning

Literature	M&R Method	M&R Subject	Network Type	Traffic Model	Road Deterioration Model	'Quality-Usage' Feedback		Solution Method
						Traffic-Quality	Quality-Capacity	
Tsunokawa & Schofer (1994)	Threshold-based	Single	Hypothetical (1 link)	✗	Deterministic	✗	✗	Optimal control
Li & Madanat (2002)	Threshold-based	Single	Hypothetical (1 link)	✗	Deterministic	✗	✗	Proposed method
Durango & Madanat (2002)	Time-based	Single	Hypothetical (1 link)	✗	Deterministic	✗	✗	Adaptive control
Ouyang & Madanat (2004)	Time-based	Multiple	Hypothetical (3 links)	✗	Deterministic	✗	✗	Greedy heuristic
Ouyang & Madanat (2006)	Threshold-based	Single	Hypothetical (1 links)	✗	Deterministic	✗	✗	Branch and bound
Uchida & Kagaya (2006)	Time-based	Multiple	Hypothetical (10 links)	Static UE	Deterministic	✓	✗	Parametric approximation

Ouyang (2007)	Time-based	Multiple	Hypothetical (2 links)	Static UE	Deterministic	✓	✗	Parametric approximation
Maji & Jha (2007)	Time-based	Multiple	Hypothetical (12 facilities)	✗	Deterministic	✗	✗	Genetic Algorithm
Durango-Cohen & Sarutipand (2009)	Time-based	Multiple	Hypothetical (2 links)	Deterministic	Deterministic	✓	✓	KNITRO solver
Ng et al. (2009)	Time-based	Multiple	Hypothetical (24 links)	DUE	Deterministic	✗	✓	Genetic Algorithm
Chu & Chen (2012)	Threshold-based	Multiple	Realistic	Static UE	Stochastic	✓	✓	Tabu Search
Fontaine & Minner (2017)	Time-based	Multiple	Realistic (Sioux Falls)	Static UE	Deterministic	✗	✓	Benders Decomposition
Mao et al. (2019)	Time-based	Multiple	Hypothetical (11 links)	DUE	Deterministic	✓	✗	Heuristic iterative
Liu et al. (2020)	Time-based	Multiple	Realistic (Sioux Falls)	Static UE	Deterministic	✓	✗	Modified active set method
This thesis	Threshold-based	Multiple	Large-scale (Sioux Falls)	DDTA	Deterministic	✓	✓	Genetic Algorithm

As can be seen from Table 7.1, the most realistic M&R optimisation model so far seems to be Ng et al. (2009) or Mao et al. (2019), which considered dynamic traffic assignment into long-term M&R planning. However, they both apply dynamic user equilibrium models, where day-to-day traffic evolutionary dynamics is not accounted for; also, they not modelling the feedback mechanism between DTD road quality and DTD traffic loading in a comprehensive way; and the M&R optimisation models are applied to small-sized hypothetical networks. This thesis, among the first in the literature, considers doubly dynamic traffic assignment (DDTA) (proposed in Chapter 3) in road network M&R optimisation, which could not only capture the long-term traffic evolutionary dynamics towards equilibrium, but also capture the short-term traffic disequilibrium states and transient congestion according to M&R actions through day-to-day traffic assignment model. This could more realistically represent traffic dynamics for richly detailed time-varying flow scenarios and hence more accurately quantify network travel costs in long-term road M&R optimisation. In addition, the interdependency between DTD network traffic flow and road quality is explicitly captured. With the day-to-day traffic assignment is considered, the threshold-based long-term road network M&R optimisation develop in this chapter is essentially a bi-level problem, where the upper level is the threshold-based M&R decision-making problem and the lower level is the traveller response as well as the road quality dynamics under different road conditions. The proposed M&R optimisation model is suitable for long-term M&R planning for multiple pavements of large-scale road networks.

7.2 Long-term Network-level Road M&R Optimisation Model

This section proposes a systematic M&R optimisation methodology that could be applied to threshold-based long-term road network M&R planning, which determines the optimal threshold based on realistic modelling of day-to-day road quality as well as network traffic dynamics, including a ‘quality-usage’ feedback mechanism (see Section 5.2 for details). For example, when the road deteriorates to an unsatisfying condition, traffic has to reduce speed and makes necessary manoeuvres, resulting in a reduction of overall road capacity (in terms of number of vehicles per unit time). This will affect travellers' route choices and hence traffic loads on this and other roads in the network, which could in turn affects the road deterioration. This feedback mechanism between road quality and traffic dynamics is explicitly captured in the proposed M&R optimisation model.

The proposed M&R optimisation model is to determine the optimal threshold-based M&R plan with the objective of minimising a weighted sum of total travel costs and M&R expenditure, under budget constraint as well as applicable road quality constraints. This model is a link-based long-term M&R problem, where the road segments are treated as decision-making units that the M&R actions may conducted. This model is aiming to support the transport agencies for long-term threshold-based M&R planning in a more realistic manner, in order to use the M&R budgets effectively and maintain the roads to the best possible states. The M&R optimisation framework and the model formulations are presented.

7.2.1 M&R Optimisation Model Framework

The proposed M&R optimisation model is a bi-level program, where the upper level is the M&R decision-making problem and the lower level is the responses from roads and travellers, where M&R threshold and intensity are the decision variables of the bi-level problem. As shown in Figure 7.2 the framework for the proposed M&R optimisation model, the upper-level problem is to decide M&R threshold and intensity through the minimisation of network travel cost and M&R expenditure; the lower level problem is the combination and interactions of the three sub-models proposed in the previous chapters: the DTD road quality dynamics, the dynamic network loading, and the DTD traffic dynamics. Therefore, the M&R optimisation model to be developed takes the form of dynamic Stackelberg game, where the planning organization makes decisions by anticipating the reactions of road users who are competitors in a dynamic Nash game. As such, the proposed M&R optimisation model will be complex and computationally demanding.

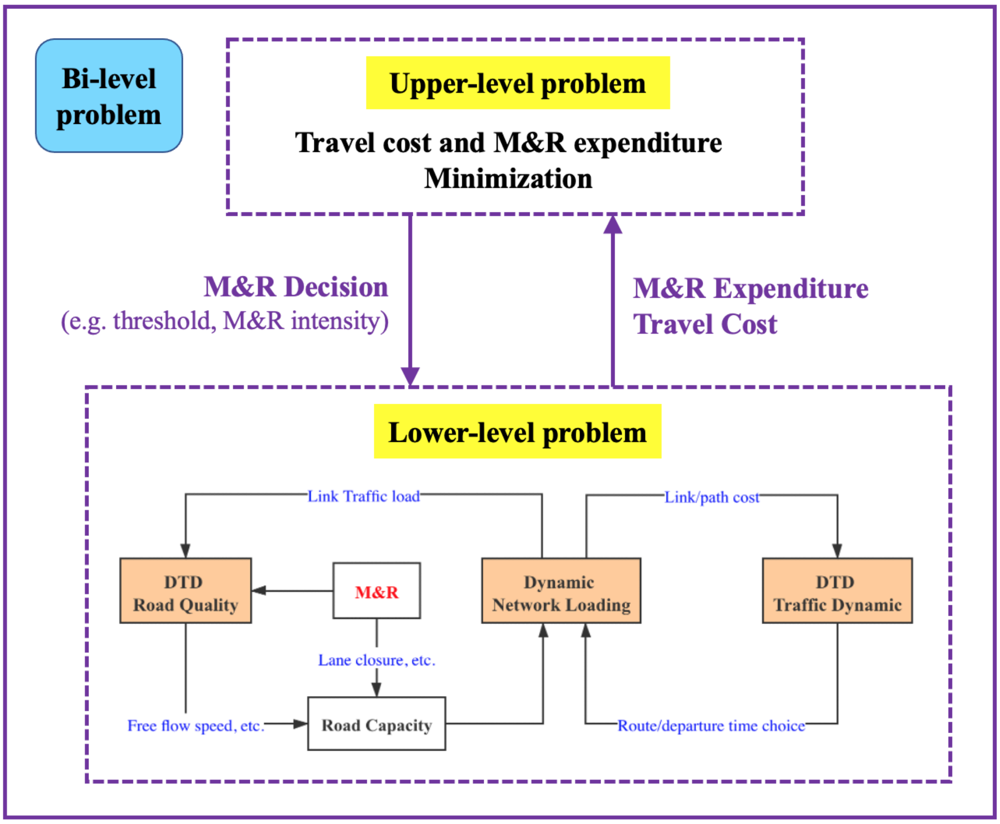


Figure 7.2 M&R optimisation model framework

This is the most realistic assumptions in M&R optimisation so far. The resulted network travel costs together with M&R expenditure from the lower-level are treated as the objective for seeking the long-term optimal M&R plan for road segments in the network. The technique for the upper-level M&R decision-making is through minimising the weighted sum of network travel costs as well as M&R expenditure. A single-objective Genetic Algorithm (GA) is employed in this chapter for solving the nonlinear bi-level optimisation for finding the optimal threshold systematically.

7.2.2 M&R Optimisation Model Formulation: A Bi-level Program

The proposed M&R optimisation model is a network-level problem, where all the links in the network could be treated as the M&R units and they interact with each other. During the M&R planning horizon, travellers in the road network judge their route and departure time choices according to network conditions with and without M&R, based on their memorized travels costs that depends on travel time as well as late/early arrival penalty. Traffic flow dynamics along links are influenced by the road quality, and also road deterioration is affected by traffic loading on the road, assuming that each road segment has approximately homogeneous physical (e.g. deterioration, capacity reduction) properties. The M&R optimisation concerns about the net present value of both network travel costs and M&R expenditure.

The following notations are introduced to facilitate the presentation.

Parameters/variables

τ:	Day-to-day time parameter
s:	Within-day time parameter
r:	Route taken by travellers
a:	Link in the road network
$Q_a(\tau)$:	Road quality (e.g. roughness) of link a on day τ
$w_a(\tau)$:	M&R intensity of link a of M&R action on day τ
$CC_a(\tau)$:	Flow capacity of link a on day τ
$f_{r,s}(\tau)$:	Traffic volume along route r at time step s on day τ
$v_{r,s}(\tau)$:	Departure rate along route r at departure time step s on day τ

Sets

T:	Set of within-day time steps
R:	Set of all routes in the network
A:	Set of links in the road network
A^m:	Set of links in the road network subject to M&R

The M&R optimisation model can be formulated as:

$$\min\left\{ \omega \cdot \sum_{\tau=1}^{n}\sum_{r}\sum_{s} TC_{r,s}\big(f_{r,s}(\tau)\big) \cdot e^{-r\tau} + \sum_{a}\sum_{\tau=1}^{n} M_a\big(w_a(\tau)\big) \cdot e^{-r\tau} + \sum_{a} M_a\big(w_a(n)\big) \cdot e^{-rn} \right\} \tag{7-1}$$

subject to

$$Q_a(\tau) = F[Q_a(\tau-1), f_a(\tau-1)], \qquad \forall a \in A \tag{7-2}$$

$$Q_a(\tau-1) - Q_a(\tau+D_a) = G[Q_a(\tau-1), w_a(\tau)], \qquad \forall a \in A^m \tag{7-3}$$

$$CC_a(\tau-1) - CC_a(\tau) = K[Q_a(\tau), Q_a(\tau-1)], \qquad \forall a \in A \tag{7-4}$$

$$CC_a(\tau) = \cdots = CC_a(\tau+D_a-1) = \phi \cdot CC_a(\tau-1), \qquad \forall a \in A_m \tag{7-5}$$

$$CC_a(\tau+D_a) - CC_a(\tau-1) = P[Q_a(\tau-1) - Q_a(\tau+D_a)], \qquad \forall a \in A_m \tag{7-6}$$

$$f_{r,s}(\tau) = H\big[v_{r,s}(\tau), Q_a(\tau), CC_a(\tau),\big], \qquad \forall r \in R, s \in T, a \in A \tag{7-7}$$

$$0 \leq \ w_a(\tau) \leq S\big(Q_a(\tau-1)\big), \qquad \forall a \in A \tag{7-8}$$

$$LQ \leq \ QT_a \leq UQ, \qquad \forall a \in A_m \tag{7-9}$$

$$\sum_{a}\sum_{\tau=1}^{n} M_a\big(w_a(\tau)\big) \cdot e^{-r\tau} \leq B, \qquad \forall a \in A \tag{7-10}$$

Equation (7-1) denotes the M&R objective function of minimising the network travel costs (first term), the M&R expenditure (second term) and the salvage M&R cost (third term). $TC_{r,s}\big(f_{r,s}(\tau)\big)$ is monetary travel cost for route r and time step s of day τ, which is a function of the corresponding traffic flow of the day; $M_a\big(w_a(\tau)\big)$ is M&R expenditure for a M&R action of intensity w_a on link a conducted on day τ; $M_a\big(w_a(n)\big)$ is salvage M&R cost that occurred on link a at the end of planning period on day n, which is assumed to quantify the roughness level at the end of the planning period. r is the discount rate that discount the costs to the net present values. The detailed derivation of these three costs are already given in Section 6.1.2.1, Section 6.1.2.2, and Section 6.1.2.3 respectively. The weighting parameter ω can be used to indicate the relative importance between travel costs and M&R expenditure by the decision maker. Constraint (7-2) describes the modelling of day-to-day road quality $Q_a(\tau)$ based on the traffic loading on the road segment in the previous day $f_a(\tau-1)$. This DTD road deterioration model is proposed in Section 5.3.1. Constraint (7-3) defines the effectiveness of the M&R action occurred on link a on day τ and lasting for D_a days, which is modeled by the roughness reduction after M&R, depending on the roughness value before M&R $Q_a(\tau-1)$ and the M&R intensity $w_a(\tau)$. This M&R effectiveness model is proposed in Section 5.3.2. Constraint (7-4) describes how flow capacity change day by day according to the day-to-day dynamic of road quality, the model of which is proposed in Section 5.4.2. Constraint (7-5) represents the flow capacity of the M&R link is reduced by ϕ during the M&R time. Constraint (7-6) describes the amount of flow capacity recovered after M&R, depending on how much the road quality increased. This model is proposed in Section 5.4.3. Constraint (7-7) represents the doubly dynamic traffic assignment model that develop in Chapter 3 , where the time-varying traffic flow $f_{r,s}(\tau)$ for each path at each time step on each day can be generated according to the path departure rate, the road quality and the flow capacity dynamics. Constraint (7-8) is the bounds on the M&R intensity that given along with the M&R effectiveness model in Section 5.3.2. M&R intensity is a value equal to or greater than 0, where $w_a(\tau)=0$ means that there is no M&R action conducted on link a on day τ, while $w_a(\tau)>0$ means that M&R is conducted on link a on day τ with an intensity $w_a(\tau)$. Constraint (7-9) set the lower and upper bounds for M&R threshold to ensure the solution is physically feasible. Constraint (7-10) gives the budget constraint on M&R expenditure.

7.3 Solution Procedure: A Genetic Algorithm Approach

Previous section develops a bi-level program for long-term network-level optimal road M&R

planning problem, where the upper-level M&R decision-making should account for lower-level travellers' responses highly dynamically, which causes the problem difficult to solve. The special form of bi-level programming problems makes it cumbersome to solve directly, especially the process could be inefficient for real-world situations (Migdalas, 1995). Heuristic algorithms are widely used to solve such bi-level problems in road M&R planning (Cheu et al., 2004; Maji & Jha, 2007; Ng et al., 2009; Chu & Chen, 2012). This chapter employs a metaheuristic genetic algorithm (GA) approach to solve the M&R optimisation problems on large-scale network, due to its highly nonlinear, nonconvex, and non-differentiable nature. GA was reported as the most applied optimisation method in the M&R literature, which is well suited for complex simulation-based optimisation problems where there is no prior knowledge of the response surface typology (Alrabghi & Tiwari). GAs have been widely applied in solving challenging M&R optimisation problems (Fwa, et al., 1994; Chan et al., 1994; Cheu et al., 2004; Jha, et al., 2005; Morcous & Lounis, 2005; Maji & Jha, 2007; Ng et al., 2009). This section gives a brief introduction of GA and presents the GA procedure that adopted for solving the long-term road network M&R optimisation problem.

A built-in 'ga' toolbox in Matlab is used for solving the optimisation problems in this thesis. Note that there are other heuristic methods (e.g. particle swarm, simulated annealing) to choose from in Matlab optimisation toolbox, a justification of choosing GA is given here.

- *Particle Swarm* is suitable for optimisation problems with no constraint or have only bound constraints. Usually, it is the most efficient solver among these three.
- *Genetic Algorithm* is suitable for optimisation problems with bound, linear, nonlinear and integer constraints. GA is often less efficient than particle swarm but more efficient than simulated annealing.
- *Simulated Annealing* is suitable for optimisation problems with no constraint or have only bound constraints. It is usually the least efficient solver.

The M&R optimisation problems studied in this thesis have bounds and linear constraints of the decision variables, thus GA is a suitable solver that could handle the constraints and remain a relative efficient computation time.

7.3.1 An Introduction to Genetic Algorithm (GA)

Genetic Algorithms (GAs) were proposed by Holland (1975), which is inspired by the principles of natural selection and survival-of-the-fittest. GA is an iterative algorithm that is commonly used to generate high quality solutions for complex optimisation problems. Holland (1975) introduced a binary coding method for mapping a solution of the optimisation problem to a string of chromosomes. In addition to binary coding, real coding and integer coding could also applied in GA (Bandaru et al., 2011; Tao et al., 2003). A population of candidate solutions that encoded as chromosomes, evolves iteratively according to biological rules, including

- *Selection rules*: select parents from the individuals for creation of the population at the next generation.
- *Crossover rules*: combine two parents to generate children for the next generation.
- *Mutation rules*: apply random changes to individual parents to form children.

The algorithm starts from a set of possible solutions to the problem, called the initial population. At each iteration, each individual in the current population is evaluated by its fitness value obtained from the objective function. GA then selects the individuals from the current population based on their fitness values to be parents, and the individuals with better fitness have the greater probability to be selected. According to the genetic rules (e.g. selection, crossover, mutation), the parents produce offspring for the next generation. Over successive generations, the individuals with bad solutions would be eliminated and the more adapted individuals could survive, therefore the population will evolve to an optimal solution. The general framework for GA is illustrated in Figure 7.3.

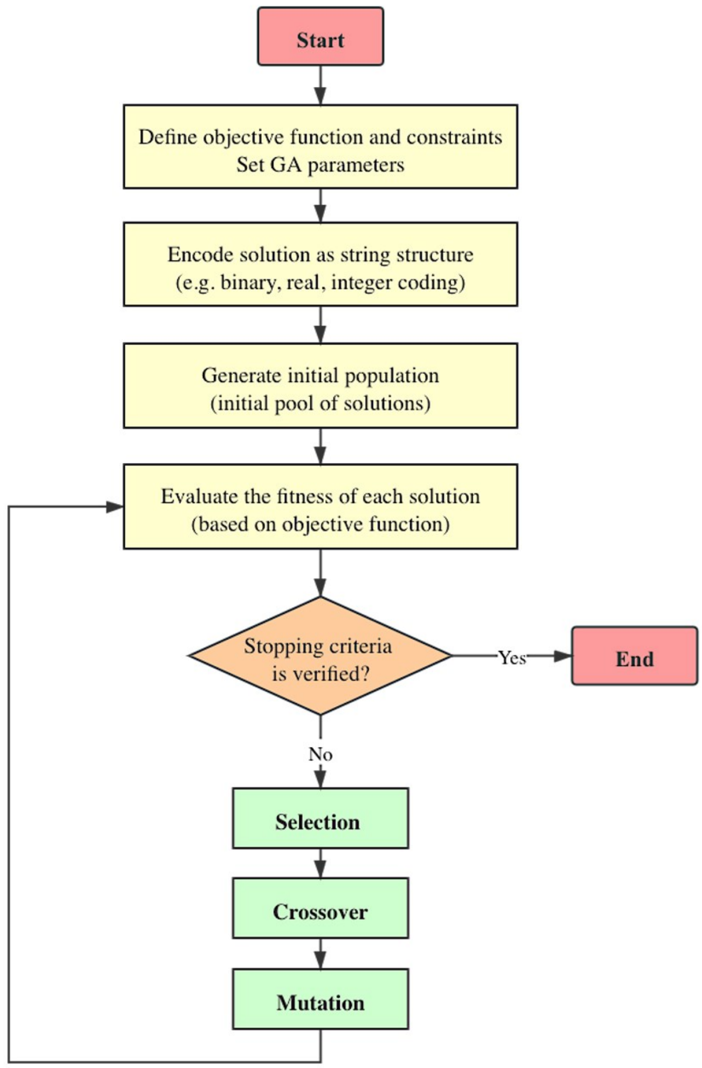


Figure 7.3 General framework for GA

The M&R optimisation model studied in this chapter is a highly nonlinear and typical NP-hard problem. Regards to NP-hard problems even more sophisticated optimisation problems such as the bi-level M&R problem of this thesis, the computation time may increase exponentially according to the dimensions of the problem, which makes exact algorithm infeasible in solving large-scale network M&R problems. GA are capable for this kind of problem due to its search robustness that could overcome the combinational explosion of large-scale optimisation problems. Although metaheuristic GA algorithms could not guarantee the global optima, they usually could find good quality solutions in a reasonable amount of computation time.

7.3.2 GA Programming

The GA program used in this chapter is a Matlab built-in ga-toolbox. At the GA programming stage, the genetic representation, the methods of initial population creation, fitness scaling, selection, crossover, and mutation operations, the constraints handling, and the define of stopping criteria have to be customised for the specific M&R planning problems. This section presents the GA program that adopted for solving the long-term road network M&R optimisation problems in this chapter.

- **Genetic Representation**

In GA, decision variables are represented by genes that form a chromosome. For the threshold-based M&R problem in this chapter, it simply assumes that the road segments to be M&R follow the same M&R threshold. Thus, there is one decision variable in the optimisation, that is M&R threshold, and the chromosome for each solution is encoded as a string of one real value. This chapter also considers the problem of optimizing both M&R threshold and intensity, where the string is encoded as two real values. Note that, for different decision-making manners by the agencies, M&R threshold could be several different levels for various road groups (e.g. road classes), which is not considered in this chapter but could easily incorporated into the proposed M&R optimisation model and achieved by the GA program through setting more decision variables.

- **Creation of Initial Population**

The GA program requires an initial population to start the algorithm. The initial population, that is the initial pool of solutions, are created randomly that satisfy the bounds and constraints of the optimisation. The number of individuals in the population should be defined according to the computational time of the given optimisation problem.

- **Fitness Function**

The objective function for the proposed threshold-based M&R optimisation model is a weighted sum of travel costs and M&R expenditure, named total costs in the following of this chapter. The total costs for each individual solution could be achieved by macroscopic simulation of the lower-level problem of the three sub-models (see Figure 7.2). The fitness function converts the raw values returned by the objective function to values in a range that is suitable for measuring the individuals in the selection operator. The GA program applies a rank scaling method that rank the individuals (scored 1, 2, 3…) based on their fitness values, which could remove the effects of the spread of the values.

- **Constraints Handling**

During the GA process of generating a candidate solution (a possible M&R plan), the constraints for maximum M&R intensity and feasible range of M&R threshold should be satisfied. These constraints are enforced during the GA generation process. When generates the offspring through selection, crossover and mutation, the new chromosome strings are checked against the constraints and the chromosome that violates any of the constraints will be discarded.

- **Selection**

The selection operator selects parents from the current population for creating the offspring for the next generation. In the GA program, the stochastic uniform selection method is employed. Each individual in the current population is assigned to a section of a line, and the length of the section is proportional to its fitness value. The algorithm selects each parent by move along the line for one step of the equal size. The selection process starts from randomly move a length that is smaller than the step size. In this way, the individual with better fitness values, that is lower total costs, are more likely to be selected as parents.

- **Crossover**

The crossover operator combines the selected pairs of parents to form new individuals for the next generation. In the GA program, a scattered method is applied for crossover process, which creates a binary crossover vector that is the same size of the string of chromosome. For a pair of parents, the genes is selected from the first parent where the vector is 1 and from the second parent where the vector is 0, and the genes then combines to form the new individual. For example, consider a pair of parents' chromosomes:

$$p_1 = [1\ \ 2\ \ 3\ \ 4\ \ 5\ \ 6\ \ 7\ \ 8]$$

$$p_2 = [a\ \ b\ \ c\ \ d\ \ e\ \ f\ \ g\ \ h]$$

assume the random crossover vector is:

$$[1\ \ 1\ \ 0\ \ 0\ \ 1\ \ 0\ \ 0\ \ 0]$$

then the new generated individual' chromosome will be:

$$child = [1\ \ 2\ \ c\ \ d\ \ 5\ \ f\ \ g\ \ h]$$

- **Mutation**

The mutation operator makes small changes in the genes of the individuals, which could provide gene diversity and enable the GA program to search a broader space. A selected fraction of points of a chromosome is generated for mutation. Then the gene at the mutation points will be altered by another feasible value randomly. As for the mutation rate, if it too high, the offspring will lose the genetic genes from their parents and cause the optimisation process capricious; if it too low, the problem is easily going into a local basin. It is suggested that the mutation rate would be good in the interval of [0.001, 0.1] (Zalzala & Fleming, 1997).

- **GA Stopping Criteria**

The GA process will terminate when meet the following stopping criteria:

- Reach the specified maximum number of generations.

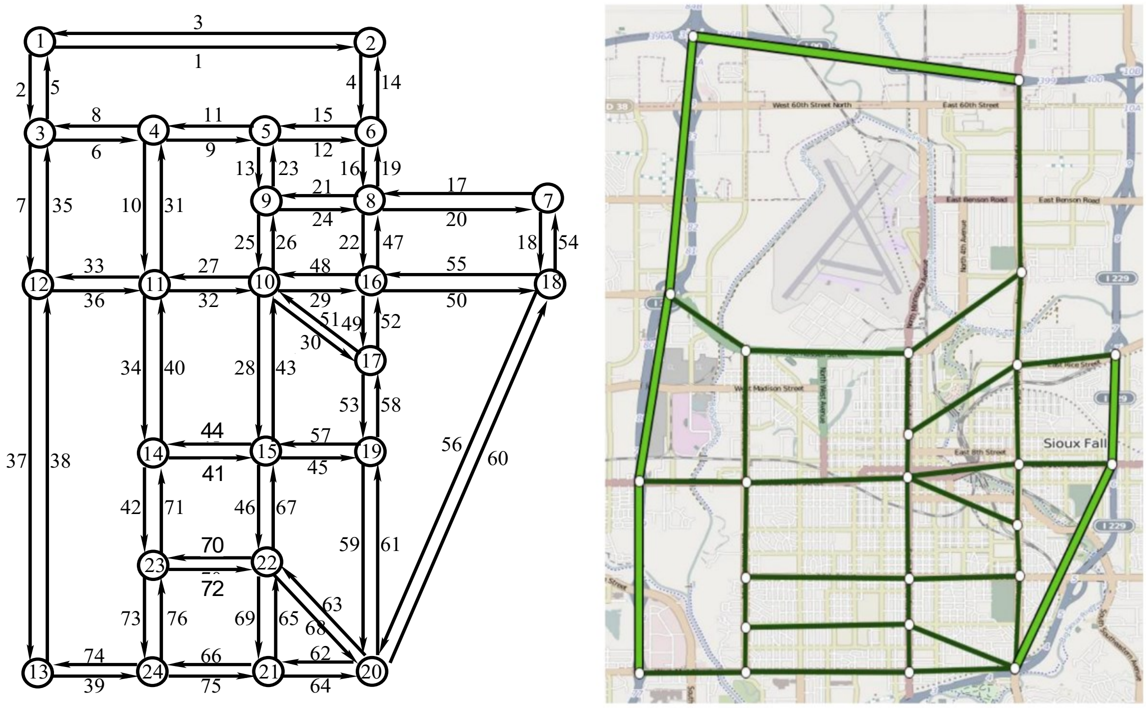
If the average change in the fitness value is less than or equal to a specified tolerance over a specified number of generations, called stall generations. Table 7.2 summarizes the parameter setting for GA that used in the numerical studies in this chapter.

Table 7.2 Genetic algorithm parameters

Parameter	Value
Population size	20
Fitness scaling	Rank
Selection	Stochastic uniform
Elite count	1
Crossover fraction	0.8
Crossover	Scattered
Mutation fraction	0.01
Mutation	Uniform
Maximum generation	50

7.4 Model Application to the Sioux Falls Network

This section applies the M&R optimisation model proposed in Section 7.2 to solve the optimal threshold-based M&R plan for both a single road segment and a system of road segments at the network level. Numerical studies are conducted on the Sioux Falls network as shown in Figure 7.4, a large-scale network with 528 O-D pairs, 30,000 trips and 6,180 routes. There are 24 intersections (24 nodes) in the network that separate the network into 38 road sections. Each direction of the road section is treated as an individual road segment, thus there are 76 road segments (76 two-lane links) in the network. The data for the Sioux Falls network, including link length, capacity, free-flow time, link-node connections, origin-destination information and O-D demand are given in Appendix III.



(a) topologic network (b) geographic network (Chakirov & Fourie, 2014)

Figure 7.4 Sioux Falls network

Regarding the modelling parameters, road roughness is measured in QI index and the M&R intensity is in millimetres (mm). The initial road conditions are assumed to be 25QI for all road segments and, as a terminal condition, the roughness level of the maintained links need to be below 40QI at the end of the planning horizon. M&R actions are modelled by reducing 50% of the flow capacity of M&R links with non-empty durations. Base model II with information sharing is applied as the DTD traffic dynamic model, with a simulation 'day' referring to a month. This allows traffic disequilibrium and transient congestion derived by M&R actions to be captured, leading to a more realistic estimation of network travel cost. The parameter setting for the DTD road quality model, the DTD traffic dynamic model and the M&R performance model is consistent with the numerical studies in Section 6.2, and are thus not repeat here. These modelling parameters are applied throughout the numerical studies in this chapter.

In the numerical studies, only one type of M&R activity, resurfacing, is considered. The problems are to solve the optimal M&R threshold and M&R intensity with sufficient budgets. The objective of the optimisation problems in this section is to minimise discounted

M&R-derived total network travel costs and discounted M&R expenditure during the planning horizon with the same weight. The influence of weighting parameter between objective costs as well as M&R budgets on optimal M&R plans will be further analysed in Section 7.6. A genetic algorithm (GA) approach is applied for solving the optimisation problems, where the GA parameters used in the numerical studies are given in Table 7.2. At each GA generation, the individual candidates are evaluated by running the simulation of the day-to-day dynamics. The orders of magnitude of the evaluated objective values is removed for GA optimisation, which could enhance the stability and accuracy of the operation and accelerate the convergence process without changing the nature of the problem. This chapter used the Windows 10 operating system with an Intel Core i7-9700K CPU @3.60 GHz with 16-GB memory. The computer code was implemented in Matlab 2019b.

7.4.1 Optimal M&R Plan for A Single Road Segment

This section solves the optimal threshold-based M&R plan for link #68 in the Sioux Falls network for a planning period of 10 years. The GA optimisation result is illustrated in Figure 7.5, and a CPU time of 3144 minutes (about 2 days and 5 hours) is recorded. The GA process converge after 31 generations as shown in the top left picture of Figure 7.5. The bottom right picture displays the range of fitness values of each generation, which decreases as the amount of mutation decreases. The bottom left picture of the average distance between individuals in each generation indicates a good population diversity of the GA progress. The optimal M&R threshold shown in the top right picture of Figure 7.5 is 130.7076 QI with the optimal M&R intensity of 89.5898 mm. According to the relationship between threshold and maximum intensity in Equation (5-10), this optimisation result indicates that an optimal plan is to conduct the M&R action at maximum intensity. The result is consistent with the simulation in Section 6.3.1.1, which demonstrates the effectiveness of applying the current GA process in solving the proposed M&R optimisation model.

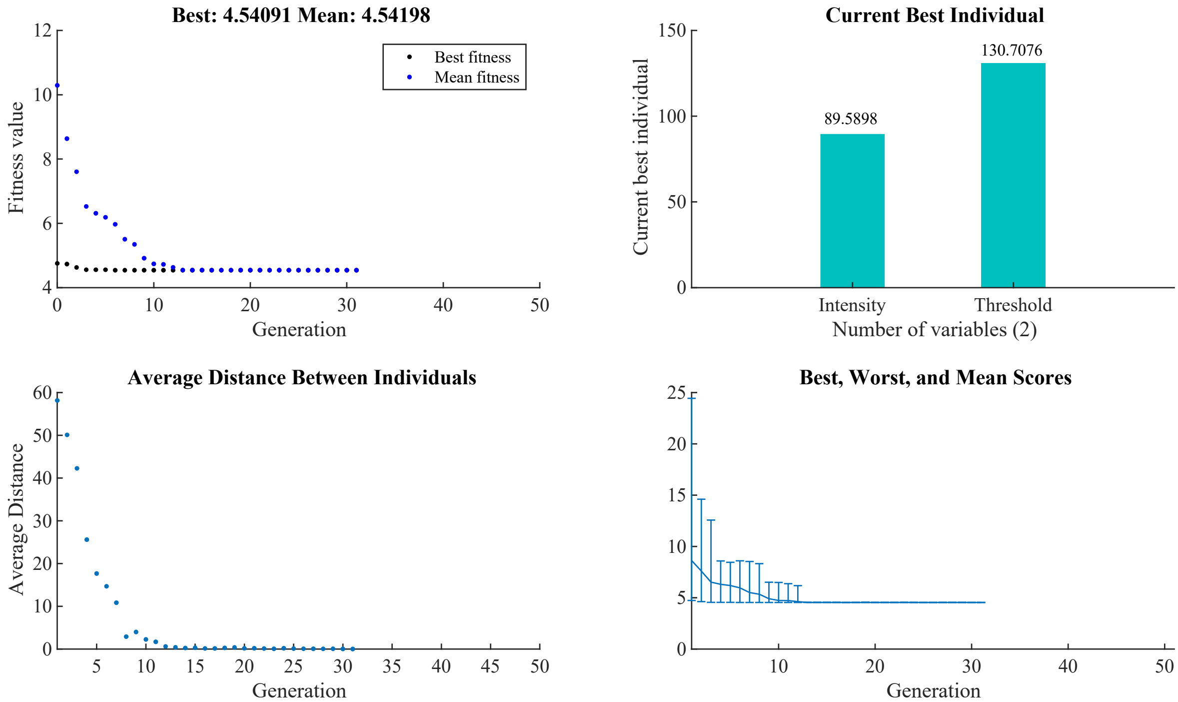


Figure 7.5 GA results for #68

The optimal resurfacing plan is given in Table 7.3 and the corresponding optimal roughness trajectory is plotted in Figure 7.6. According to the result, two M&R actions are conducted on link #68 during the planning horizon and one M&R action is done at the end of planning period to reach the final roughness requirement. The total discounted cost of this optimal plan is $ 454,090,838. During the planning period, the M&R derived network travel costs far exceed the M&R expenditure (see Table 7.3), which highlights the need for quantifying this significant travel costs due to the traffic disequilibrium and transient states induced by M&R actions in road M&R planning problems. This is not achieved by any of the existing M&R methods and could captured by the M&R optimisation model proposed in this thesis.

Table 7.3 Optimal M&R plan for link #68

Action i	Threshold (QI)	t_i (month)	$s_i(t-1)$ (QI)	w_i (mm)	$s_i(t+1)$ (QI)	MC_i (10^6\$)	MC (10^6\$)	MTC (10^8\$)	Total Cost (10^8\$)
1	130.7076	52	130.9107	89.5898	45.1900	2.4666	4.4540	4.4800	4.5409
2		88	132.6445	89.5898	46.6961	1.9874			
Salvage	-	120	124.3221	64.6772	40	1.6342	1.6342		

* the costs shown are discounted values

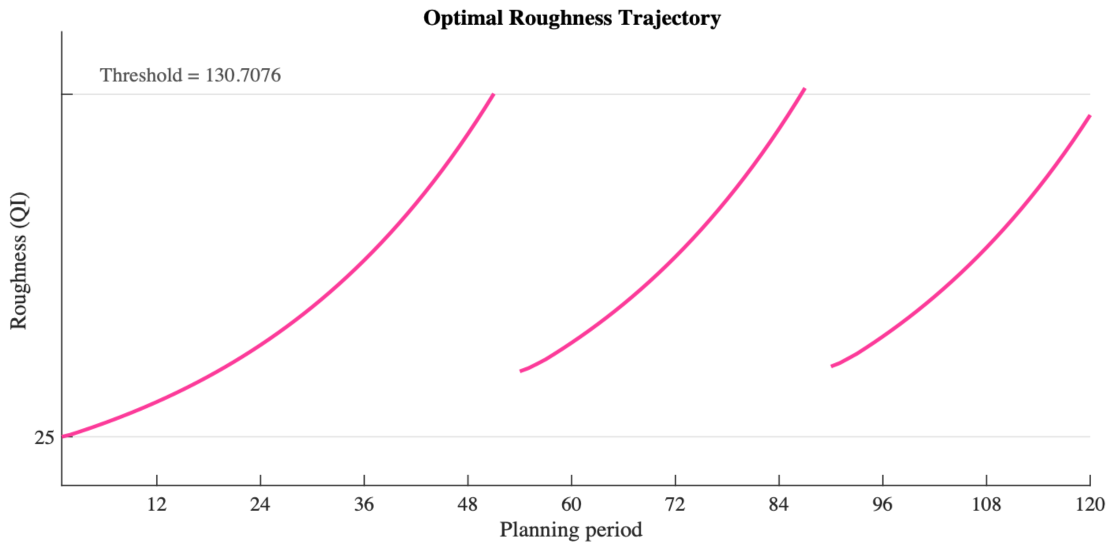


Figure 7.6 Optimal roughness trajectory of link #68

7.4.2 Optimal M&R Plan for A Collection of Road Segments

Next, this section examines the proposed M&R model by solving the optimal threshold-based M&R plan for all links in the Sioux Falls network for a planning period of 6 years. The GA process converged after 33 generations with a recorded CPU time of 1765 minutes (about 1 day and 5 hours). The GA optimisation result is illustrated in Figure 7.7. The optimal M&R threshold for all links is 88.9579 QI with the M&R intensity of 66.8481 mm (see the top right picture), and the minimal discounted total cost in the planning horizon is \$ 4,489,768,284. This optimisation result again indicates that it is optimal to conduct the M&R action at maximum intensity (constrained by Equation (5-10)).

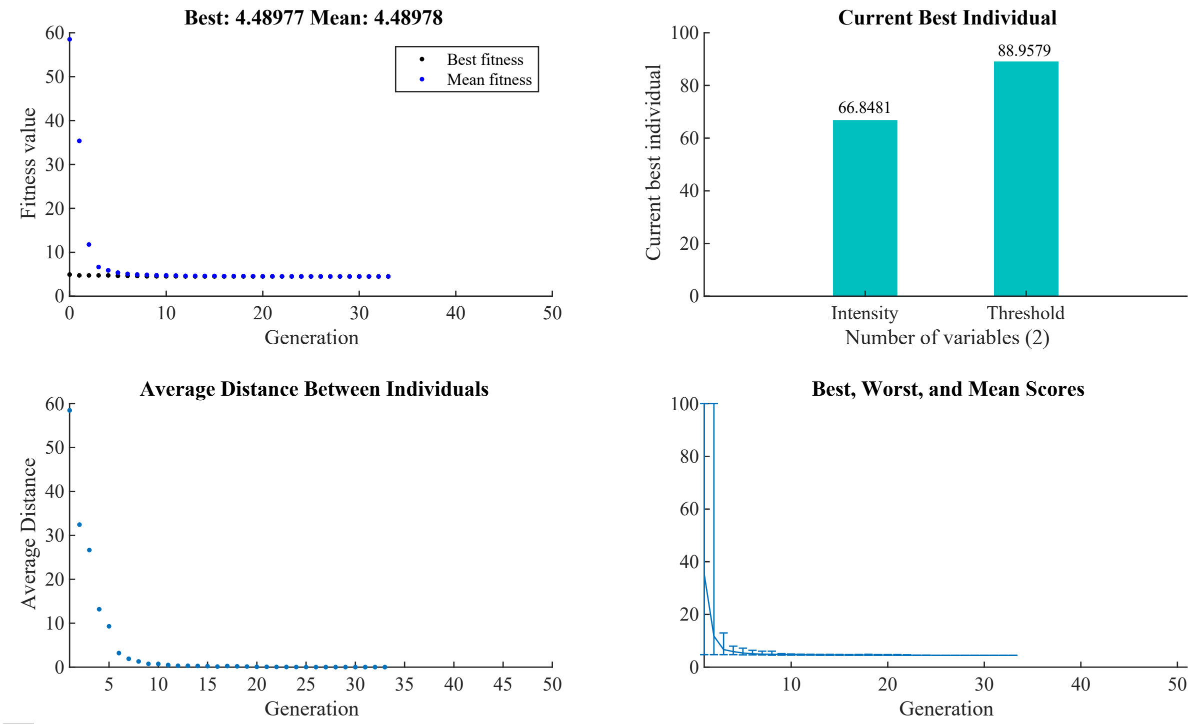


Figure 7.7 GA results for all links

The corresponding M&R plan for all links in the Sioux Falls network is plotted in Figure 7.8. This figure illustrates the evolution of roughness deterioration for all road segments in the top figure and the monthly network travel cost in the bottom figure. It can be observed that, during the planning horizon, a majority of the roads will receive one resurfacing action at the month between 30-50th and a small number of roads will receive another one after 60th month, which cause the obvious increase of network travel cost (see the bottom picture of Figure 7.8) due to M&R-derived transient congestion. Therefore, it is critical to capture these transient congestions by the proposed DTD-based M&R optimisation model, since it could produce substantial travel costs. If ignored, the M&R planning would generate the sub-optimal solutions.

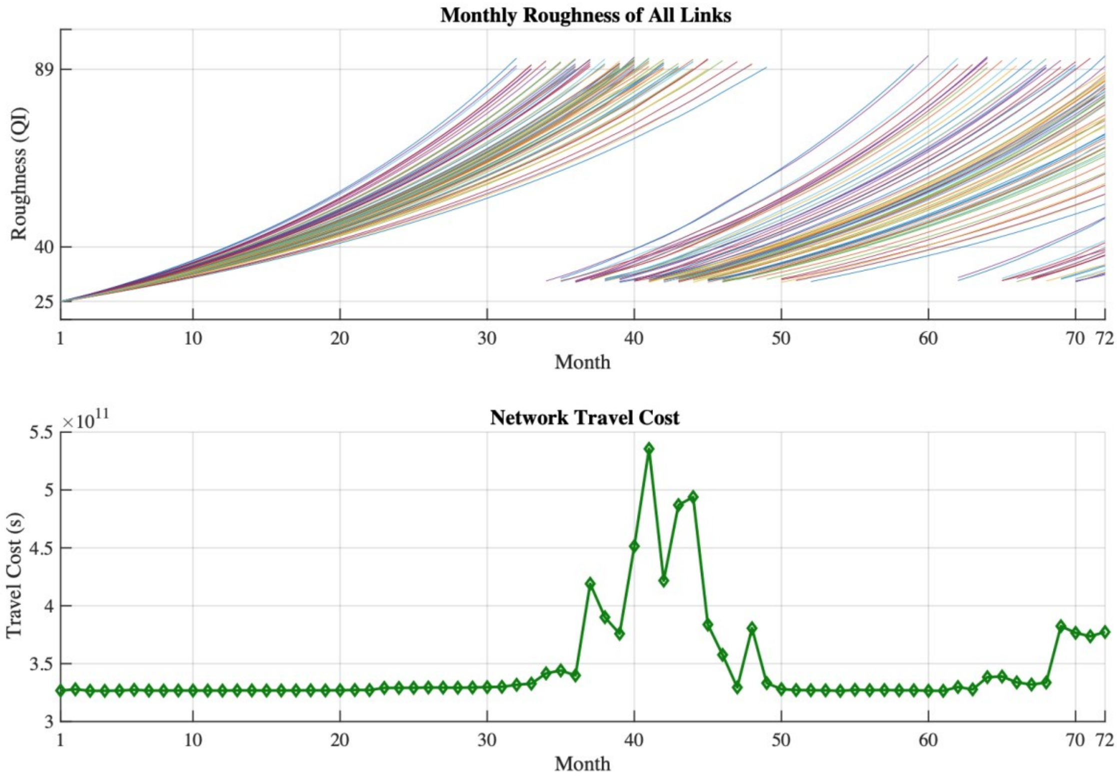
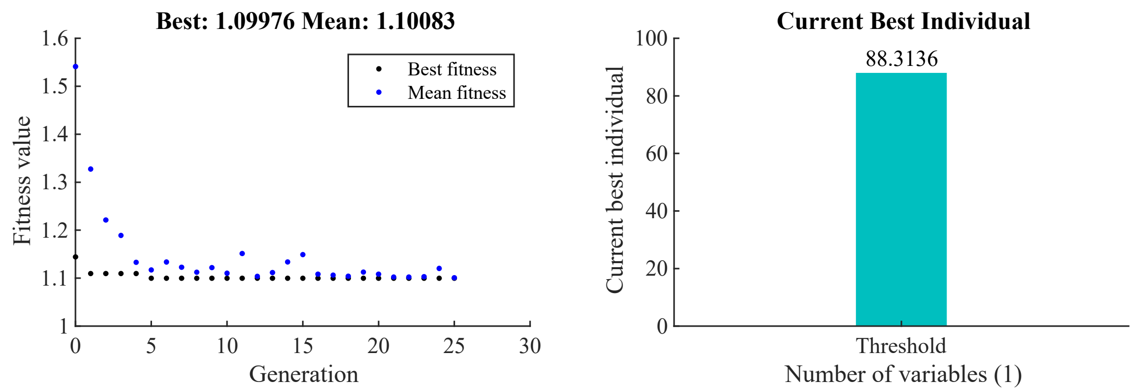


Figure 7.8 Threshold-based M&R plan for all links of the Sioux Falls network

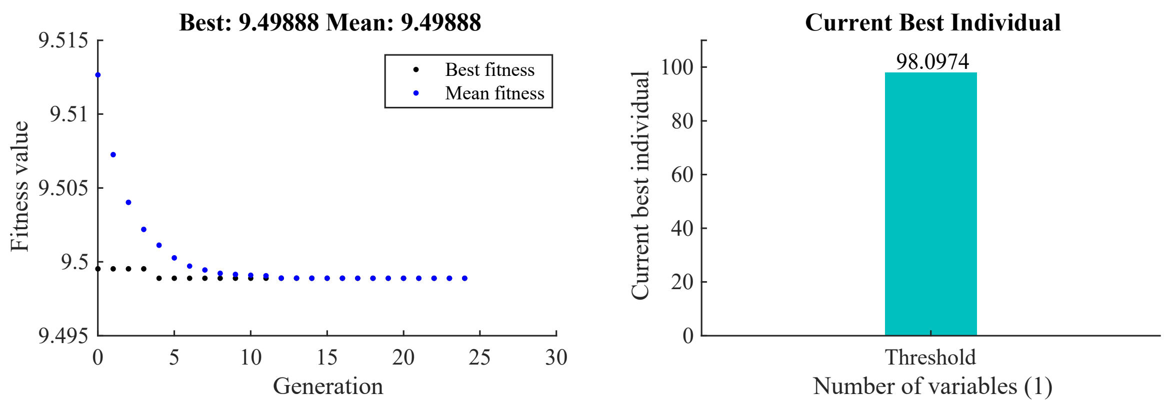
7.5 Comparison with the Equilibrium Modelling of Traffic

In this section, the effectiveness of the proposed M&R optimisation model is tested by comparing the M&R solutions under the dynamic user equilibrium (DUE) condition, and under the proposed day-to-day (DTD) traffic dynamics. M&R under DUE means that the network traffic distribution follows the equilibrium (i.e. without day-to-day traffic evolutionary dynamics as well as transient congestion induced by M&R actions). The purpose of this section is to highlights the need for considering day-to-day traffic dynamics reacting to the network conditions (with and without M&R) and capturing M&R-derived transient congestion when conduct road network M&R planning.

Numerical studies are conducted on the Sioux Falls network for the case that link #49 is subject to M&R planning. The optimisation problem is to solve the optimal threshold of resurfacing on link #49 for a planning horizon of 10 years. Note that each M&R activity is conducted with maximum intensity, which is confirmed as optimal way in Section 7.4. Figure 7.9 gives the optimisation results generated by GA algorithm for both DTD and DUE methods. The resulted optimal M&R threshold for link #49 is 88.3136 QI under the proposed DTD method, compared with the threshold of 98.0974 QI under the DUE method. In the following, the optimal M&R planning generated by the proposed M&R optimisation model under DTD dynamics is compared with the M&R solution derived by the DUE-based M&R planning.



(a) optimal M&R solution under DTD



(b) optimal M&R solution under DUE

Figure 7.9 Optimal M&R solutions for link #49

First, Figure 7.10 compares the optimal M&R planning (threshold=88.3136 QI) for link #49 derived by the proposed threshold-based M&R optimisation model under DTD dynamics and the M&R planning of the same solution under the DUE modelling of traffic. It can be observed that both methods result in three M&R activities and the M&R plan modelled with DUE is delayed in time compared with the M&R plan obtained by the DTD DTA model. This is expected that the traffic volume on link #49 modelled by DUE is much lower than by DTD DTA (see the first of Figure 7.10) resulting in slower deterioration of the road (see the second of Figure 7.10). The first of Figure 7.10 also shows that the DTD DTA model is capable of modelling traffic disequilibrium and transient states with daily traffic variations during and after M&R, and it may not return to any equilibrium states that DUE model obtained. The third of Figure 7.10 shows that, compared with the DUE model: (1) the DTD DTA model could see a much higher peak than the DUE approach during M&R. This highlights the importance of transient congestion induced by M&R activities, which should be accounted for within a quantitative model to realistically capture its network impact; (2) the DTD DTA model could also see the irregular fluctuations that lasted for several periods, which implies the inherent network complexity resulting from interactions of travellers, infrastructure, and information on a day-to-day time scale. This results in higher travel cost estimated by the DTD DTA model than the DUE model when the traffic network encountered with M&R.

In order to fully compare the difference between M&R planning under DTD and DUE modelling of traffic dynamics, Figure 7.11 further illustrates the optimal threshold-based M&R plan (threshold=98.0974 QI) for link #49 obtained by the DUE model and the same M&R solution run by the DTD DTA model. Consistent with the illustration in Figure 7.10, the top and third pictures of Figure 7.11 also shows that M&R under DTD DTA could modelling traffic evolutionary dynamics and disequilibrium states during and after M&R, as well as capture M&R derived transient congestion, which is unachievable by equilibrium-constraint M&R approach. Compared with the DTD plan of a threshold of 88.3136 QI and three M&R actions for 10-year planning (see Figure 7.10), the optimal M&R threshold by the DUE model is 98.0974 QI and two M&R actions are given (see Figure 7.11). DUE approach results in a very different M&R solution compared with the optimal plan under DTD DTA, which is expected since that threshold-based M&R planning under DUE approaches ignore maintenance-derived disruptions in the form of transient congestion that could underestimate travel costs significantly (see the third of Figure 7.11) and render suboptimal M&R plan. Therefore, the proposed DTD DTA model is required to model traffic disequilibrium states as well as transient congestion when planning threshold-based M&R.

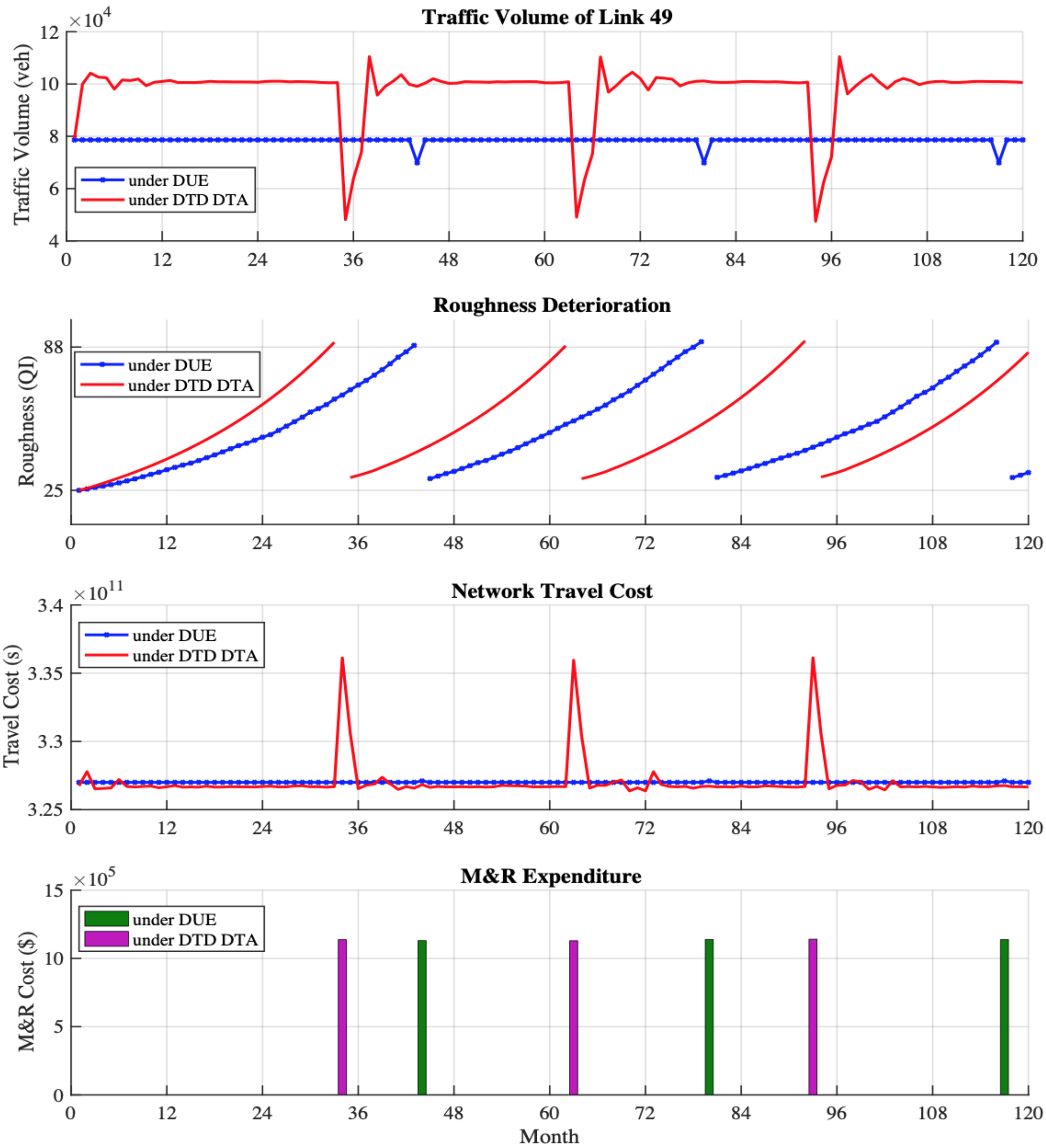


Figure 7.10 Comparison of M&R solutions under DTD DTA and DUE (DTD solution)

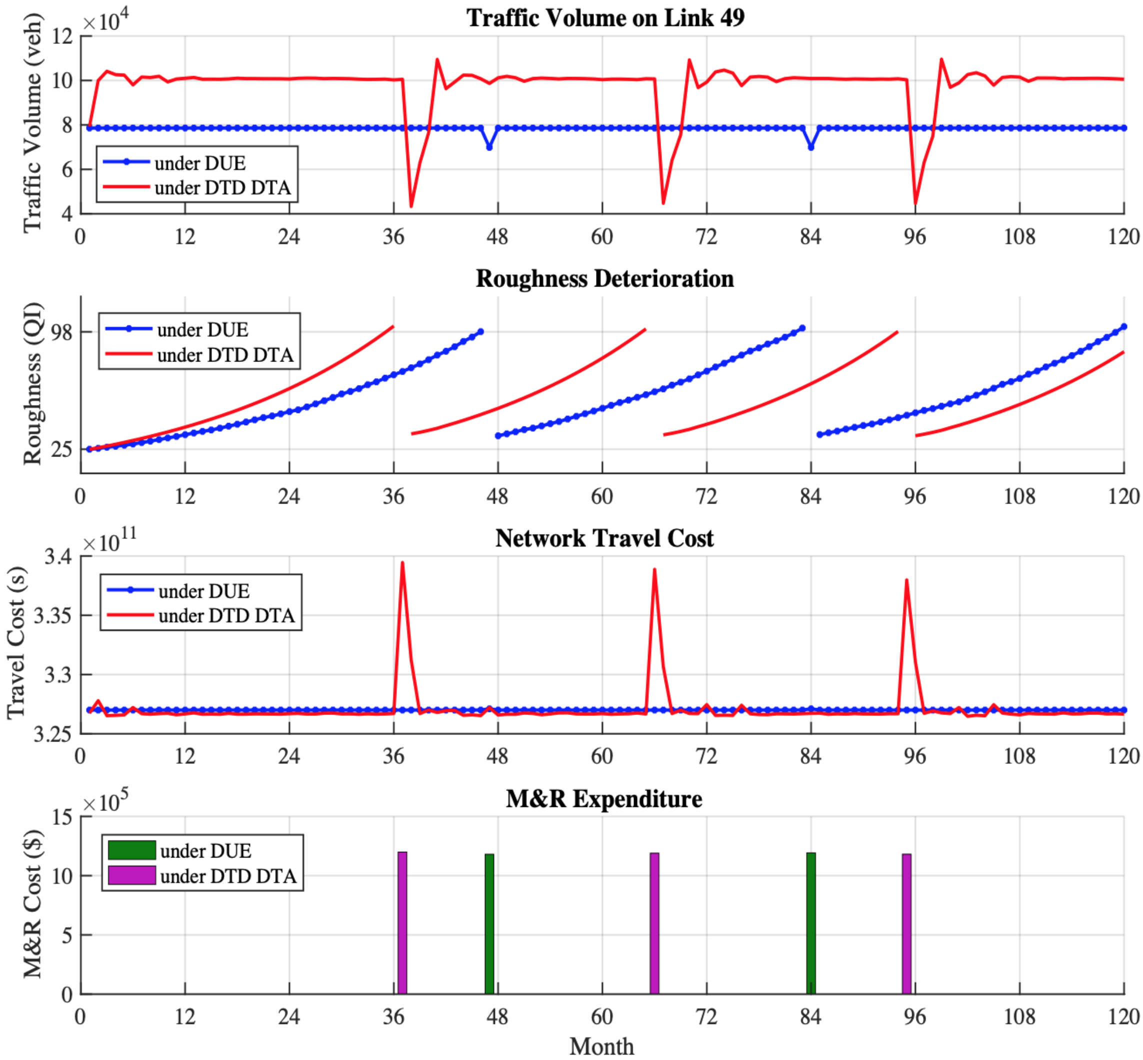


Figure 7.11 Comparison of M&R solutions under DTD DTA and DUE (DUE solution)

Next, the performance of the M&R solutions under DUE and DTD are compared under the simulation of DTD traffic dynamics, which is illustrated in Figure 7.12. The optimal M&R plan for link #49 generated by the DUE method is given in Table 7.4, while the optimal M&R plan for link #49 generated by the proposed DTD method is given in Table 7.5. It can be seen from Figure 7.12 that, by comparison, the proposed M&R model under DTD dynamics yields much lower network travel costs. This is because DUE solution ignores the transient congestion induced by M&R-derived network disruptions, thus rendered sub-optimal solution under the more realistic DTD dynamics. The proposed DTD approach could obviously reduce M&R derived disruptions and traffic congestion to the road network. Compare the results in Table 7.4 with Table 7.5, the M&R plan generated by the proposed DTD method provides lower M&R expenditure as well as lower network travel costs during the planning period, resulted in a significant reduction in the total costs by 20%, that is $24.62 million. This highlights the benefit of using the proposed M&R optimisation model under DTD dynamic in order to capture the network's response to M&R in a more realistic way.

Table 7.4 Optimal M&R plan for link #49 under DUE method

Action i	Threshold (QI)	t_i (month)	$s_i(t-1)$ (QI)	w_i (mm)	$s_i(t+1)$ (QI)	MC_i $(10^5\$)$	M&R Cost $(10^6\$)$	Travel Cost $(10^8\$)$	Total Cost $(10^8\$)$
1	98.0974	37	101.5970	72.20	35.5430	9.6036	2.4289	1.3169	1.3460
2		66	99.8108	72.20	33.9357	8.0060			
3		95	98.2223	72.20	33.3956	6.6797			
Salvage	-	120	85.6310	43.40	40	4.8318	0.4832		

* the costs shown are discounted values

Table 7.5 Optimal M&R plan for link #49 under proposed DTD method

Action i	Threshold (QI)	t_i (month)	$s_i(t-1)$ (QI)	w_i (mm)	$s_i(t+1)$ (QI)	MC_i $(10^5\$)$	M&R Cost $(10^6\$)$	Travel Cost $(10^8\$)$	Total Cost $(10^8\$)$
1	88.3136	34	90.0788	66.70	30.6268	9.2792	2.3553	1.0714	1.0998
2		63	88.5415	66.70	30.1041	7.7413			
3		93	90.7306	66.70	30.8484	6.5326			
Salvage	-	120	85.6544	43.41	40	4.8329	0.4833		

* the costs shown are discounted values

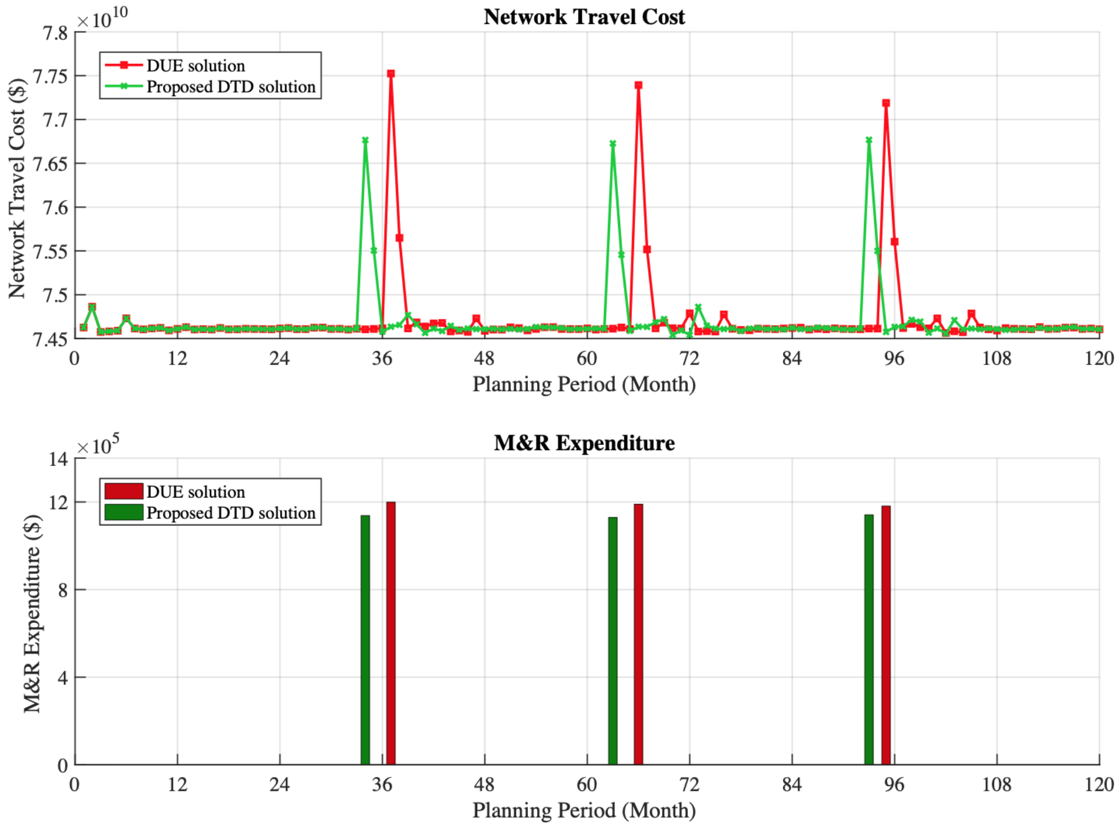


Figure 7.12 Comparison between DUE solution and proposed DTD solution

7.6 Sensitivity Analysis on Model Parameters

This section performs sensitivity analysis on model parameters to obtain approximate relationships between optimal M&R plan and various managerial parameters, including budget constraint and the weighting parameter between network travel cost and M&R expenditure. The influence of travel information sharing strength on M&R solution is also discussed. The numerical studies in this section are conducted on the Sioux Falls network, where 10 links with the highest traffic volumes in the DUE simulation (link #43, #25, #27, #28, #49, #60, #32, #56, #46, #26) are selected for M&R. The planning horizon is 6 years.

7.6.1 Influence of Budget Constraint

This section discuss how budget constraint has an effect on the minimal total cost of M&R plan, by varying the total budget from 35 million to 46 million. Figure 7.13 shows the influence of budget constraint on optimal M&R total costs (both network travel cost and M&R expenditure).

It can be seen that, when the budget decreases from \$38M, the optimal total cost increases drastically, which is due to the fact that the ten road segments cannot be properly maintained during the planning period with a budget below \$38M. The problem becomes infeasible when the budget is below \$36.5M, where no effective M&R action can be conducted. The plot of total cost remains almost flat between the budget of \$38M and \$41M, which allows the ten road segments to be roughly maintained twice during the planning horizon. The total cost gradually decreases from \$41M to \$43M, which corresponds to the higher thresholds that allow some of the ten links to be maintained only once with larger M&R intensity during the planning horizon. This indicates that reducing the total M&R actions may increase M&R expenditure due to the construction work with higher intensity, but could decrease travel cost induced by the M&R disruptions to the road network. The budget constraint above \$4.4M is actually non-binding, where the minimum total cost is reached with the optimal threshold plan.

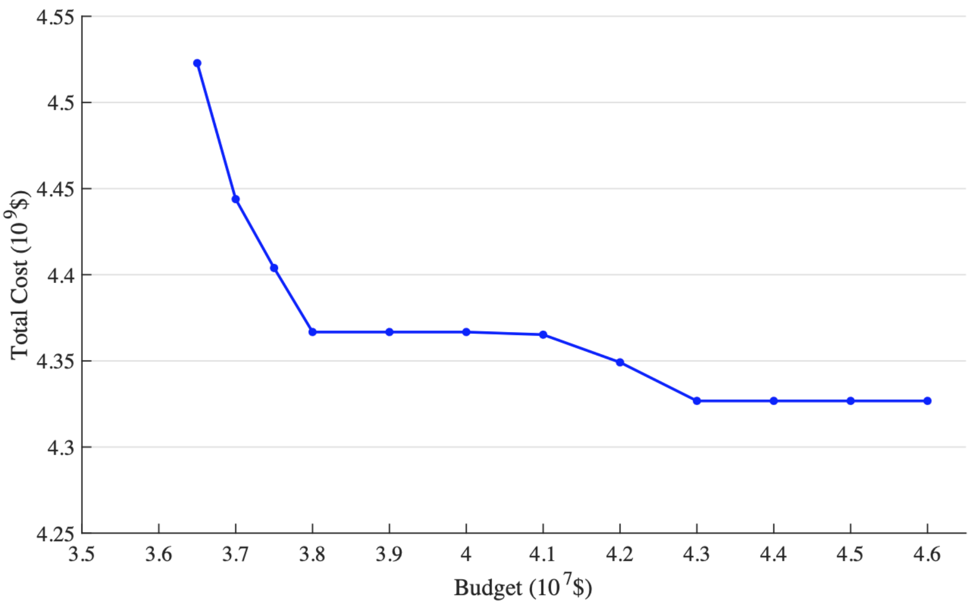


Figure 7.13 Influence of budget constraint on M&R total cost

7.6.2 Influence of Weight of Travel Costs

Another managerial issue of interest is the influence of weighting parameter between total travel costs and M&R expenditure when perform M&R planning, that is parameter ω in

Equation (7-1). This parameter represents the dominance of travel costs over expenditure in M&R decision. By variating this weighting parameter, the results of optimal total costs and M&R threshold are given in Figure 7.14 and Figure 7.15 respectively. Note that the absolute value of travel costs is two orders of magnitude higher than the absolute value of M&R expenditure, thus this numerical study tests the weighting parameter over the range of 0.001-1.0. It can be observed that the optimal total cost increases with the increase of the weight of travel costs with an increasing trend. The optimal M&R threshold also increases with the increase of the dominance of travel cost in M&R decision-making. This indicates that when the weight of travel costs increases, it is better to conduct M&R actions on the ten links less frequently to reduce the transient congestion derived by M&R-induced disruptions to the road network.

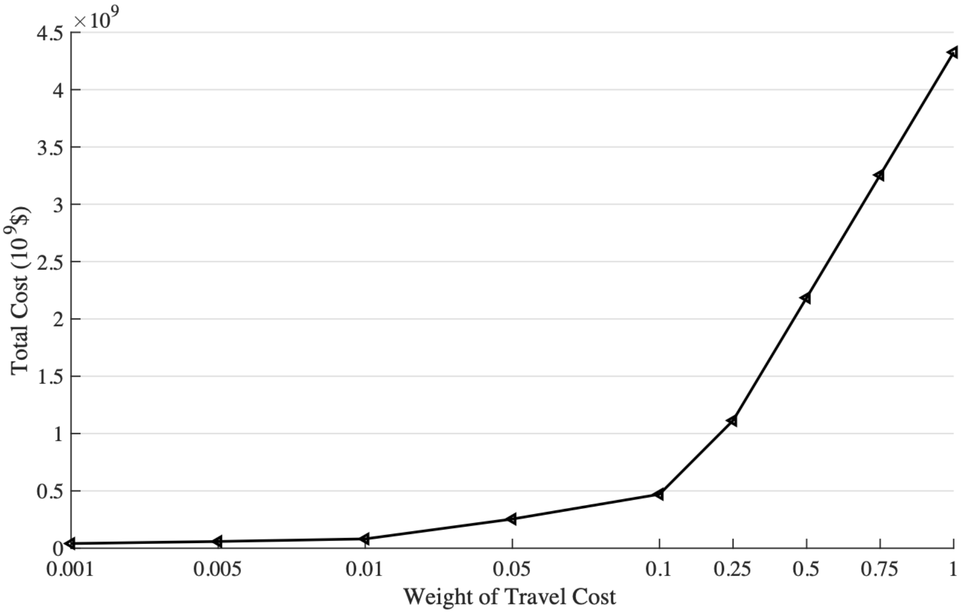


Figure 7.14 Influence of weight of travel cost on M&R total cost

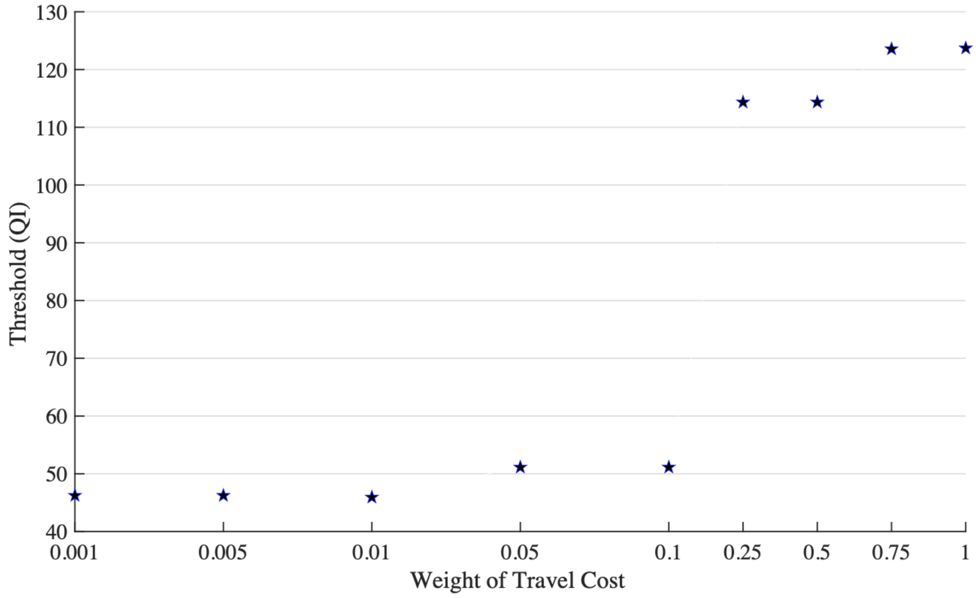


Figure 7.15 Influence of weight of travel cost on M&R threshold

7.6.3 Influence of Information Sharing

Information sharing behaviour between travellers may have an impact on the optimal M&R decision. Figure 7.16 shows the influence of the information sharing strength, that is parameter n in $G(x) = x^n$, on the optimal M&R total cost. It can be seen that the case of completer information (n=0) yields higher optimal total cost than the incomplete information cases (n=0.5, 1, 1.5, 2). This can be viewed as a generalized Braess paradox where information transparency is working against the network performance. The figure also shows that n=0.5 result in less total costs than other cases, which means that give importance to the information reported by small crowds tends to achieve better M&R plan. This suggests the transport management agencies to pay attention to the information provided by travellers with those less popular choices when providing M&R construction information to road users.

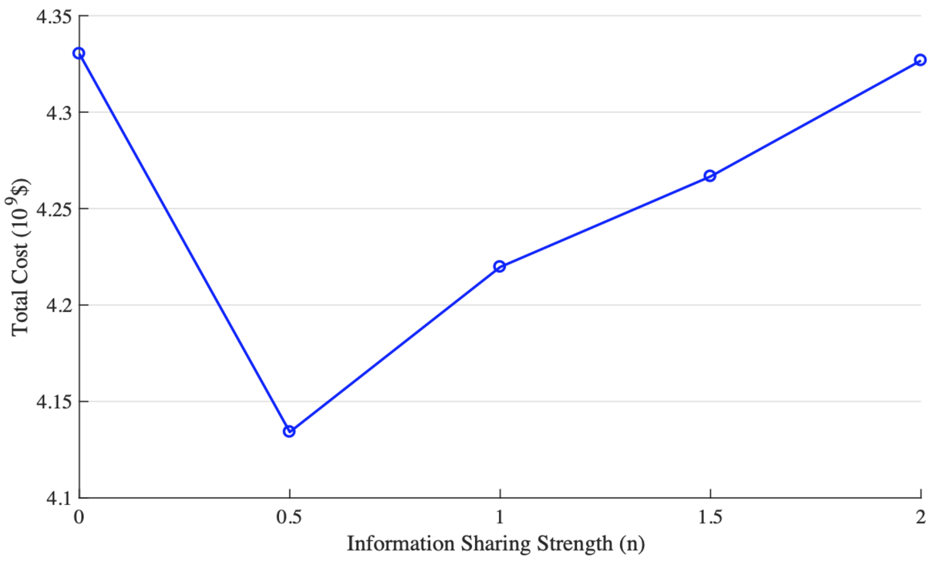


Figure 7.16 Influence of information sharing strength on M&R total cost

7.7 Summary

This chapter proposes an optimal long-term road network M&R planning model that considers day-to-day traffic dynamics and transient congestion. This model is a bi-level problem where the upper level is to minimise the discounted total cost, including network travel cost and M&R expenditure; and the lower level is a modelling of day-to-day traffic dynamics and road quality dynamics. A feedback mechanism between traffic usage and road quality is captured.

The performance of proposed M&R optimization model is tested through conducting numerical studied on the Sioux Falls network for threshold-based M&R planning for a system of road segments. The numerical studies show the necessity to capture traffic equilibrium and transient congestion by the proposed DTD based M&R planning model. A metaheuristic genetic algorithm approach is used to solve this M&R optimization problem due to its highly non-linear non-differentiable nature. Sensitivity analysis is performed on some modelling parameters, including budget constraint, weighting parameter between travel costs and M&R expenditure, and information sharing strength. All these parameters have an impact on the optimal M&R solution and minimal total costs. This results could provide managical insights for M&R management and planning agencies.

A comparison of the M&R solutions of the proposed M&R optimization model and of the user equilibrium approach is conducted. The result shows that the proposed day-to-day method could significantly reduce the M&R total cost, which highlights the benefit of using the proposed M&R optimisation model under DTD dynamics. The resulting solutions, unlike those pursued in the existing literature, account for short-term as well as long-term benefits/impacts of the M&R activities in a realistic way.

8 Conclusions and Future Work

With the increasing road traffic, road networks are currently facing the issues of frequent road deterioration. Transport agencies have shifted their attention to maintain existing roads from construction of new ones. A systematic method for efficient optimal road M&R planning is therefore demanding. A hallmark of current M&R studies is the use of traffic equilibrium models to capture the response of travellers to road conditions with and without M&R. However, this approach does not account for the day-to-day traffic evolutionary dynamics and traffic disequilibrium states induced by M&R actions, which could derive significant social costs in the form of transient congestion that should not be ignored in planning road M&R.

This thesis has developed an optimal road M&R planning methodology considering day-to-day traffic dynamics and transient congestion. This chapter concludes this thesis by revisiting the research objectives and presenting the contributions achieved by this research in Section 8.1. A note on the implementation of the proposed M&R framework is given in Section 8.2. Subsequently, the sources of model uncertainty and its propagation though modelling process are presented in Section 8.3. Section 8.4 discusses some directions for future work, while Section 8.5 lists the publications that resulted from this research.

8.1 Revisiting Research Objectives - Research Contributions

This section revisits the aim and objectives of this thesis given in Section 1.2, and to conclude the research contributions achieved by this thesis.

The aim of this research was "*to develop a generic optimisation framework and systematic methodology for optimal long-term road network M&R planning considering day-to-day* *traffic dynamics and transient congestion*". This has been achieved in this thesis with the development of a road maintenance and repair (M&R) optimisation model in Chapter 7 , and the development of its three sub-models: the day-to-day dynamic traffic assignment (DTD DTA) model (Chapter 3), the within-day dynamic network loading (DNL) model (Chapter 3), and the day-to-day road quality model (Chapter 5). To fulfil this aim, the following objectives were elaborated:

- The objectives, constraints and requirements for long-term road network M&R planning considering day-to-day traffic dynamics were identified through the comprehensive review of the literature in Chapter 2 and were specified in Chapter 7 .
- A macroscopic dynamic network loading (DNL) model was employed for predicting the within-day traffic flow dynamics on large-scale road networks and capturing traffic phenomena such as shockwaves and vehicle spillback, which was achieved in Chapter 3 ;
- Day-to-day (DTD) dynamic traffic assignment (DTA) models with simultaneous route and departure time (SRDT) choices were developed in Chapter 3 , where the within-day traffic dynamics follow the DNL model. These models are capable of realistically capturing travel choice evolution and network flow dynamics day by day under different road conditions (e.g. with and without M&R), which was demonstrated in Chapter 4 ;
- A road deterioration model was achieved in Chapter 5 , which allows a realistic representation of day-to-day road quality evolution according to the day-to-day traffic loading on the roads;
- Modelling of day-to-day road flow capacity reduction due to road deterioration was achieved in Chapter 5 , which was incorporated into the DNL model to capture the impact of road deterioration on day-to-day traffic dynamics;
- Modelling of M&R effectiveness on road quality improvement as well as flow capacity reduction and restoration during and after M&R were achieved in Chapter 5 .
- The road M&R planning framework considering day-to-day traffic dynamics and transient

congestion was proposed in Chapter 6 , where the M&R performance models of network travel costs and M&R expenditure were formulated. This framework was demonstrated on the Sioux Falls network for both threshold-based and time-based M&R methods.

- The development of an optimal long-term road network M&R planning model considering day-to-day traffic dynamics was achieved in Chapter 7 , and a metaheuristic Genetic Algorithm (GA) was applied to solve the threshold-based M&R optimisation problems on the Sioux Falls network. Sensitivity analysis on M&R management parameters was tested for the illustration of the model performance.

The following is a list of contributions achieved by this thesis:

(1) This thesis among the first in the literature proposed a macroscopic day-to-day dynamic traffic assignment (DTD DTA) model with simultaneous route and departure time (SRDT) choices, where the within-day dynamics follow the Lighthill-Whitham-Richards (LWR) fluid dynamic network loading (DNL) model. The proposed model allows a realistic representation of travellers' choices in response to network conditions and changes, which is suitable to understand and quantify the impacts of M&R activities on traffic networks. Travel information sharing behaviour was further incorporated into the macroscopic dynamic network model to account for the effect of incomplete information on travellers' SRDT choices.

(2) This thesis proposed a realistic 'quality-usage' feedback mechanism, on one hand by modelling day-to-day road deterioration with evolving traffic loads on the road, on another hand by modelling day-to-day flow distribution influenced by road quality dynamics.

(3) This thesis formulated a computable theory of road network M&R planning, in which both with-in day and day-to-day time scales are integrated into a dual-time scale network traffic and road quality dynamic system. This model is superior to existing ones by realistically modeling traffic disequilibrium states and maintenance-induced transient

congestion derived by M&R actions, and revealing the complexity of reaction of the network as a whole to M&R activities, in terms of user behavior, flow distribution, and infrastructure dynamics.

(4) Based on this dual-time scale M&R model, this thesis employed metaheuristics in search of optimal M&R plans, which is a joint location-scheduling problem and can be studied under the Stackelberg game paradigm. Optimisation method - Genetic Algorithm (GA) is selected to solve a variety of M&R optimisation problems on a large-scale network. The resulting solutions, unlike those pursued in the existing literature, account for short-term as well as long-term benefits/impacts of the M&R activities in a realistic way, and could reduce the M&R total cost by 20%. Traffic disequilibrium states, transient congestion, and complex phenomena such as network paradoxes arising from M&R activities were illustrated, which could provide valuable managerial insights for infrastructure planning and management.

8.2 A Note on Framework Implementation

This thesis develops a dual-time-scale M&R optimisation framework for optimal M&R planning, which could simultaneously capture the long-term effects of M&R activities under traffic equilibrium, and the M&R-derived transient congestion under day-to-day traffic evolutionary dynamics. This modelling framework is potentially to be applied by traffic engineering and management agencies in practice for assisting long-term M&R planning for large-scale road networks. Figure 8.1 shows the general flow chart of the implementation of the M&R optimisation model.

The data required for the practical implementation of this model are: 1) road network data, including network topology, node coordinates, path lists, link length, capacity and free flow time; 2) traffic demands data; 3) initial and target road quality data; 4) M&R planning data, including planning period, road segments to be M&R, and M&R budgets; 5) M&R planning parameters, especially the weighting parameter between travel costs and M&R expenditure, that need to be specified by the M&R agencies. These inputs will be processed into the simulation of the M&R optimisation model, which will output the optimal M&R threshold and intensity and a detailed M&R scheduling plan.

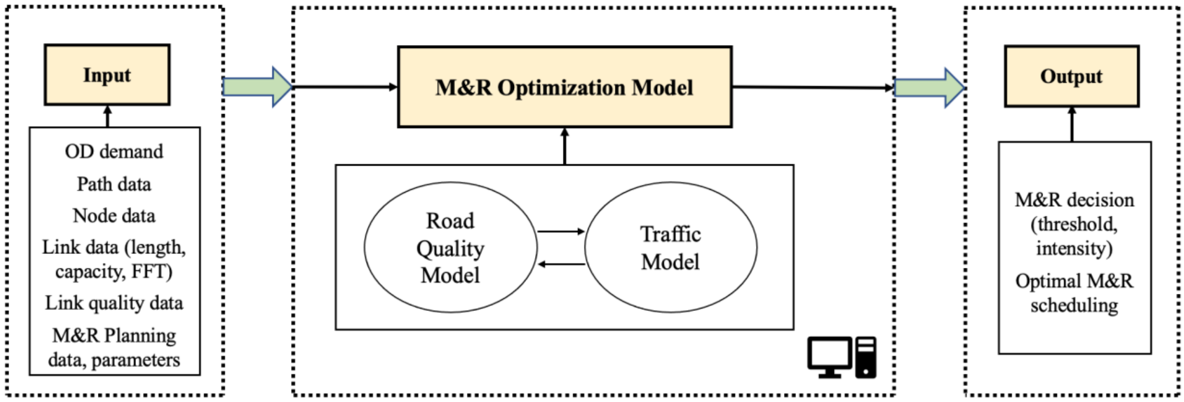


Figure 8.1 Potential implementation of the M&R optimisation framework

The proposed doubly dynamic traffic assignment (DDTA) models with simultaneous route and departure time (SRDT) choice that incorporated bounded rationality (BR) and/or information sharing (IS) behaviour are also potentially to be applied in other traffic management and control applications (such as traffic signal control, variable message signs, ITS-related strategies, and network recovery from disruptions), serving as the modelling of network traffic evolutionary dynamics reacting to different network conditions and controls. The practical implementation of the proposed DDTA models is within the scope of many transport authorities.

Note that there are simulation software that provide various traffic simulation approaches. A comparison of the DDTA models developed in this thesis with other simulation tools (e.g. Vissim, SUMO, MATSim) is given here. (1) Vissim, SUMO and MATSim process traffic flow simulation at a microscopic level by applying different versions of car-following models or queue-based models. They focus on each road user as an individual and model their trips to destinations based on discrete choice models. These agent-based simulation models allow detailed information setting for the attributes of each vehicle or traveller's activity for reflecting demand-level heterogeneity. However, for long-term traffic planning and management problems such as the M&R planning in this thesis, the very detailed information at a microscopic level (such as, which lane to travel on by each individual, what is the speed or location of each vehicle, etc.) or travel demand details (such as, travellers' personal information, trip purposes, etc.) are not that important and could be computational demanding. Rather, the problems focus on traffic phenomena and dynamics at an aggregated traffic flow level and traffic supply-level modelling. This thesis uses the macroscopic-level dynamic network loading (DNL) model for within-day traffic flow modelling, which is more computational efficient for large-scale simulations with generalizable insights not easily accessible from agent-based simulations, such as shock waves and vehicle spillback. (2) Vissim, SUMO and MATSim consider only route assignment for each individual with the departure-time predetermined, and the routes used could be updated by each iteration of simulation to reach a convergence condition after a number of iterations. This could be treated as the problem of within-day dynamic traffic assignment (DTA), but the day-to-day traffic evolutionary dynamics is not captured by these three simulation tools. The DDTA models proposed in this thesis could modelling travellers' route and departure time choice dynamics, while capturing traffic disequilibrium states and transient congestion induced by network disruptions using day-to-day DTA. This is crucial for analysing real-world networks with constant supply shortage due to recurrent or incidental disruptions.

8.3 Model Uncertainty

This section discusses the sources of uncertainty and their propagation through the modelling process of this thesis. There are ten categories of uncertainty realised in the proposed modelling procedure and Figure 8.2 shows the model counterparts where these uncertainties sourced from and how the uncertainties propagate through the modelling process, illustrated by a flowchart. Table 8.1 summaries these ten categories of model uncertainty, listed their sources and discussed whether these uncertainties are accommodated in the proposed models. If considered, then provides how the uncertainty is managed in this thesis; if not, then gives the reasonable reasons for not considering at present.

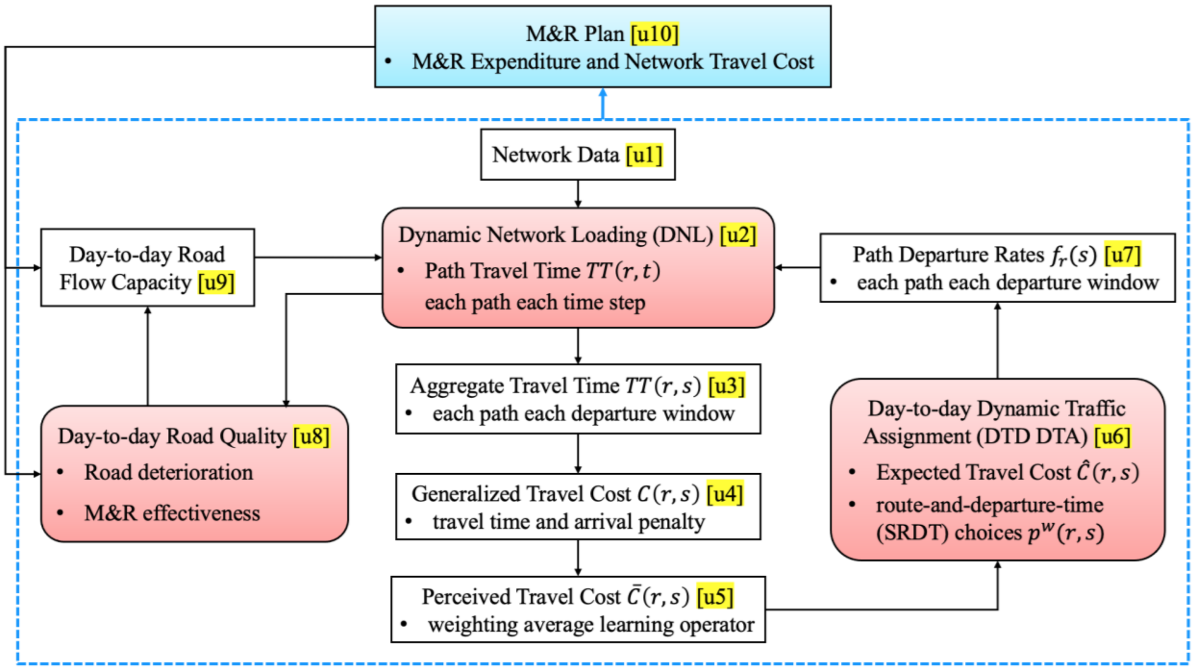


Figure 8.2 Sources of uncertainty and the propagation through modelling process

The most important uncertainty that should be considered in this research is the uncertainties in the DDTA model, especially the travel choice modelling. This thesis developed day-to-day stochastic travel choice models based on random utility theory, which could accommodate some of the uncertainty in travellers' route and departure time choice behaviour. Information sharing behaviour and bounded rationality are considered in the travel choice models to further capture travel choice uncertainty. As for the within-day DNL model, it is a macroscopic traffic flow model for aggregated traffic quantities such as traffic flow, density and average speed. While it is a deterministic model, its inherent traffic variations are encapsulated in the fundamental diagram, which describes the aggregate relationship between traffic density and flow. The proposed M&R optimisation models take the form of dynamic Stackelberg games, the behavioural uncertainty of which is explicitly captured by the stochastic travel choice models. It is noted that there exist other uncertainties that are not managed or cannot be managed within the modelling process of this thesis. However, they are reasonably acceptable or the impacts of these uncertainties are minimal in the final M&R optimisation problem, are therefore ignored in this thesis. The details are given in Table 8.1.

Table 8.1 Summary of model uncertainties

Sources of Uncertainty	**Uncertainty Management**
Input Data Uncertainty [u1]	
Network Data Traffic Demand Data Initial Road Quality Data	X (Data uncertainty is important to be considered in the demand-level modelling, while the proposed mode is a supply-level model, where the data inputs uncertainty has minimal influence on the model behaviour.)
Dynamic Network Loading Model Uncertainty [u2]	
DNL Model • Macroscopic traffic flow model • Deterministic model • Fundamental diagram that predict special-temporal density, flow and speed dynamics	✓ (This is a deterministic model, however inherent traffic variations are encapsulated in the fundamental diagram, describing the aggregate relationship between traffic flow and density.)
uncertainty from [u1] [u7] [u9]	---
Aggregate Travel Time Uncertainty [u3]	
Calculation Method • Exactly average formulation	X (The standard deviation is not considered in the average calculation, since it has a minimal impact on the resulting network travel costs.)
uncertainty from [u2]	---
Generalized Travel Cost Uncertainty [u4]	
Weighting parameters between travel time and early/late arrival penalty α, β, γ	X (The proposed DDTA model is a macroscopic model, where a consistent assumption is made on the three parameters for traffic flow. It is noted that these parameters could be differently assumed for heterogenous traveling purposes in microscopic modelling, which is outside the scope of this thesis.)
uncertainty from [u3]	---
Perceived Travel Cost Uncertainty [u5]	

Weighting Average Learning Operator	✓ (Sensitivity analysis is conducted on the parameter of memory weight λ.)
uncertainty from [u4]	---
Day-to-day Dynamic Traffic Assignment Model Uncertainty [u6]	
Travel Choice Model • Stochastic choice model (Multinomial Logit, Nested Logit) • Bounded rationality (BR) • Information sharing (IS)	✓ (This thesis introduces expected travel costs by adding error terms into the perceived travel costs, where the opposite of error terms follows Gumble distribution, and forms stochastic travel choice models. The models incorporate BR/IS to further accommodate behavioural uncertainty in traffic modelling.) * *This is the most important uncertainty*
Model Parameters • Logit model dispersion parameter θ • Information sharing strength n • Bounded rationality indifference band δ	✓ (Sensitivity analysis are conducted on parameter θ, δ, n.)
uncertainty from [u5]	---
Path Departure Rates Uncertainty [u7]	
Path Flow Calculation • Deterministic formulation	✗ (According to Cantarella and Watling (2016), deterministic process DTD models are more inherently to be related with traditional equilibrium traffic assignment models, and are also capable to capture transitions, such as when some disruptions occur (e.g. M&R). The stochastic process DTD model is discussed in the future research in Section 8.4.)
uncertainty from [u6]	---
Day-to-day Road Quality Model Uncertainty [u8]	
Road Deterioration Model • Deterministic Model • Model parameters	✗ (Recent research shows that the impact of road deterioration uncertainty on the costs of optimal M&R policies is minimal (Sathaye & Madanat, 2011). and is therefore ignored in this thesis. The stochastic road quality model is discussed in the future research in Section 8.4. Sensitivity analysis on deterioration rate is conducted to accommodate part of the uncertainty)

uncertainty from [u2]	---
Day-to-day Road Flow Capacity Uncertainty [u9]	
Capacity Reduction Rate	✓ (This rate is based on the empirical data estimated by Chandra (2004), in which the data uncertainty was considered in regression.)
uncertainty from [u8]	---
M&R Optimisation Model Uncertainty [u10]	
M&R Objective • Network travel costs • M&R expenditure	uncertainty from the lower-level problem [u1-u9]
Weighting parameter between network travel costs and M&R expenditure	✓ (Sensitivity analysis is conducted on this parameter.)
M&R Budget Constraint	✓ (Sensitivity analysis is conducted on M&R budget.)
Optimisation Solution Method • Genetic Algorithm	✓ (Heuristic approach GA is adopted for solving the M&R optimisation problem, which is a stochastic method.)

8.4 Future Research

This thesis is among the first to propose an optimal long-term M&R planning model that considers both the long-term effects of M&R actions under traffic equilibria and the short-term maintenance-derived transient congestion under day-to-day traffic disequilibrium dynamics. From the work presented, the following are proposed for future research to extend the work presented in thesis (points 1-3) and improve of this thesis (points 4-8).

1. **Consider Vehicular Emission into Road M&R Optimisation Objective**

The M&R optimisation model developed in this thesis make M&R decisions in accordance with network travel costs and M&R expenditure, since they are two essential decision goals of long-term M&R planning. However, other factors could be considered into the objective of the M&R optimisation problems according to the requirements of the M&R projects. Environmental consideration is another important aspect that attracted more attentions in sustainable M&R planning, which is not accounted for in this thesis. Increased vehicular emission as well as road dust due to deteriorated road surfaces are important causes of air pollution. Thus, it is also necessary to recognize the vehicular emission into the future research, and quantify the day-to-day vehicular emission generated from the transport network due to M&R disruptions. The following introduces the feasible method to accommodate vehicular emission into the M&R model in the future work.

Several studies have been conducted on the relationship between vehicular emission and road roughness (Kalemno et al. 2012, Li et al. 2016). Khan (2018) evaluate the relationship between IRI and vehicular emissions through multilevel wavelet analysis using the data collected by Portable Emission Measurement System (PEMS). This research concludes that the road roughness has a correlation with emissions according to the Pearson correlation of r = 0.2904~0.6337, which indicates a positive linear or quasilinear relationship between IRI and emission gases. Therefore, since this thesis have quantified DTD road roughness values, then it is easy to further quantify DTD vehicular emissions according to the relationship between roughness and emission gases.

In the study by Khan (2018), the emission data collected by PEMS are in the unit of gram/veh/second. In order to quantify the emission exhausted for each link among the road network each day, it is needed to calculate the amount of vehicles accumulated on each link for each day. The cumulative vehicles on links during the simulation period with nt time steps can be calculated by the shaded area shown in Figure 8.3, and the formulation is given in Equation (8-1).

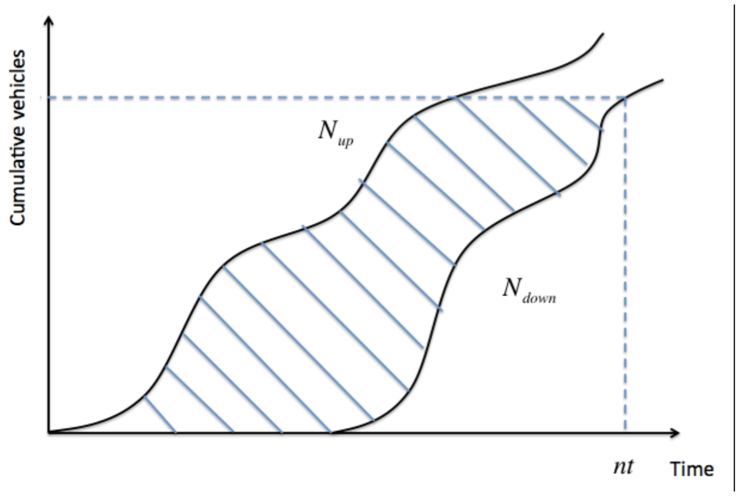


Figure 8.3 Calculation of cumulative vehicles on links

$$\int_0^{nt} \left(N_{up}(t) - N_{down}(t)\right) dt \tag{8-1}$$

Cumulative vehicles at the upstream N_{up} and downstream N_{down} of each link for each time step can be generated by the DNL model. Therefore, for each simulation day, the emission exhausted on each link of the simulation period can be calculated by the formulation below as a discretised version, assuming that there is a positive linear relationship between roughness and emission.

$$Emission = \chi \cdot Q \cdot \sum_{i=1}^{n} \left(N_{up}(i) - N_{down}(i)\right) dt \tag{8-2}$$

where, Q is the roughness value of the day, χ is the linear coefficient reflecting the correlation between roughness and emission, which varies according to different emission species. The total amount of simulation time steps is n and the duration of each time step is dt.

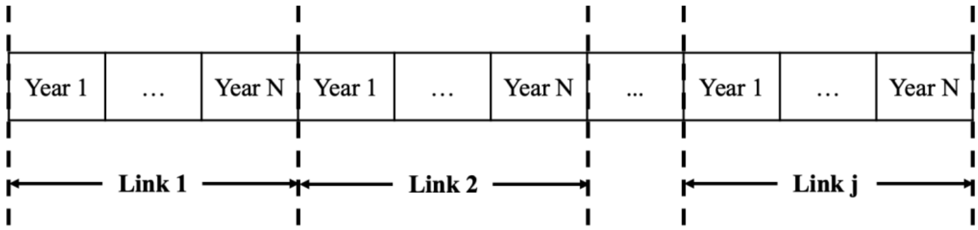
2. Road M&R Optimisation Model of Multiple M&R Types

The proposed road M&R optimisation model only considered one type of M&R (e.g. resurfacing). However, the proposed road M&R planning model can be extended to accommodate multiple M&R types with heterogeneous effects by defining different thresholds and M&R expenditure for different types of M&R. The M&R actions will be automatically chosen according to the road conditions and different M&R thresholds, and the M&R intensity values will be selected based on the type of M&R actions.

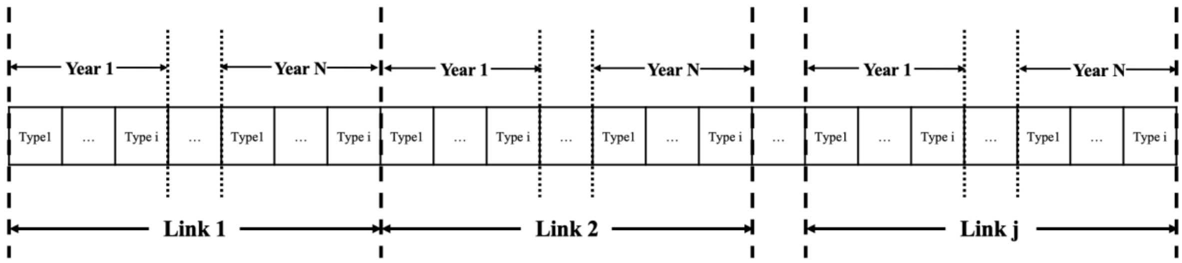
3. Time-based Road M&R Optimisation Model

This thesis studied threshold-based M&R optimisation problems, since threshold-based approach is widely adopted by transport agencies due to its intuitive policy to conduct M&R actions when the roads deteriorate to poor conditions; also, the decision rules of this M&R approach is easy for implementation. The proposed M&R model framework (see Figure 7.2) in this thesis is also suitable for time-based M&R planning. Time-based M&R is to determine whether to perform M&R actions at a certain point in time (e.g. beginning of each year) within the planning horizon. The difference lies in the representation of chromosome, i.e. the string of decision variable, of the GA algorithm. The technical method is introduced here for future work in this direction.

Assuming a number of j links are considered for M&R in a road network for a planning horizon of N years, and the M&R actions are conducted at the beginning of years. If only one type of M&R is considered, Figure 8.4 (a) shows the representation of the chromosome of the M&R schedules for all M&R links, where the first N entries represents the M&R schedule for link 1 over the planning horizon, and the next N entries represents link 2, and so on. A binary variable can be used for each entry to indicate whether to perform M&R, where a value of 1 indicates M&R is conducted and a value of 0 otherwise. Also, a real-value variable can be used to indicate the M&R intensity for each entry if required. As mentioned in the second point, the proposed M&R model is easy to extend to incorporate for multiple M&R types. In this case, the chromosome of GA can be represented in Figure 8.4 (b). For each year of each M&R link, the entry is further divided into i entries to represent i types of M&R to be chosen. A value of 1 or a real number could be used to indicate the specific M&R type or the M&R intensity, and a value of 0 otherwise.



(a) one M&R type



(b) multiple M&R types

Figure 8.4 GA chromosome representation of M&R schedules

4. Stochastic Process Day-to-day Dynamic Traffic Assignment Model

The proposed DTD DTA models in this thesis are deterministic process models with stochastic travel choice models. The departure volumes for each SRDT choice of a day is calculated by a deterministic formulation of the OD demand multiplied by the choice probability, such as in Equation (3-15) :

$$f_{(r,t)}(\tau) = d^w \cdot P^w_{(r,t)}(\tau) \qquad \forall r \in R^w, t \in T \tag{8-3}$$

Stochastic process DTD models are more naturally associated with modelling the variability that is seen to occur in real-life systems, which will be considered for the future research as extension of the proposed DTD DTA models. It can be achieved by a Monte Carlo method through implying a probability distribution (e.g. multinomial distribution) in the space of OD demand when calculate the departure volumes. Then, for each OD pair w, the departure volumes for travel choice (r, t) on day τ is conditional on its choice probability:

$$f_{(r,t)}(\tau) \sim multinomial \left(d^w, P^w_{(r,t)}(\tau)\right) \qquad \forall r \in R^w, t \in T \tag{8-4}$$

Therefore, the stochasticity among the travellers in the same OD pair is accounted for by random residuals around the population-mean of the perceived travel costs calculated by Equation (3-13).

5. Stochastic Road Deterioration Model

The road deterioration model applied in this thesis is a deterministic roughness model, which requires less data and computational burden. Stochastic road deterioration models are capable of capturing the stochastic nature of road deterioration and quantify the uncertainty in the road performance predictions. The deterministic deterioration model proposed in this thesis can be transformed to a stochastic one by introducing a transition probability distribution, such as normal distribution, and formulated as a Markov decision processes (MDPs). Since the deterministic method is capable of providing critical insights of road deterioration in this thesis, the stochastic modelling of road deterioration will be left as future work.

6. Computational Time of the M&R Optimisation for Large-scale Network

It is confirmed by this research that the day-to-day traffic evolutionary dynamics and disequilibrium states derived by M&R disruptions to the road networks could generate significant social costs in the form of transient congestion. However, there is an inevitable problem of computational burden due to the huge gap between two timescales, that is the upper-level long-term (e.g. 5-20 years) M&R optimization and the lower-level day-to-day simulations (e.g. simulate every month/week/day). Furthermore, the proposed M&R model is a link-based network-level model, where each road segment is treated as the decision-making unit, and is employed to solve large-scale network problems, which requires even more computational efforts when the number of links in question is large.

It takes about 4 seconds for the proposed DDTA model to simulate the traffic dynamics on the Sioux Falls network (24 nodes, 76 links) for a simulation day. If the simulation epoch in the

M&R model refers to a calendar day, then the simulation of a M&R plan with a period of 10 years will take about 4-5 hours. The computational time will drastically increase if the M&R model is conducted on larger networks (e.g. the Anaheim network with 416 nodes and 914 links). In order to reduce the computational time, one may extend the simulation epoch to refer to a longer time period (e.g. week/month). For example, the computational time of a M&R planning of 10 years on the Sioux Falls network will reduce to about 40min and 10min if the simulation day represents a week and a month, respectively. However, this will come at a cost of accuracy and granularity in traffic modelling, which should be balanced by transport agencies according to their requirements.

The computational burden further aggravates in solving the M&R optimization problems using GA. To solve a M&R optimization problem, the GA progress need to run a number of generations, with a population of many individual chromosomes of each generation. Thus, hundreds to thousands of simulation runs are anticipated. It takes about 2-3 days to finish the optimization process on the Sioux Falls network with a GA population of 20 and the maximum generation defined as 50, where the underlying day-to-day simulation epoch refers to a month and the M&R planning horizon is 5 years. Due to the heuristic nature of the GA algorithm, the computational time will increase exponentially with the increase of the GA population size or the M&R planning horizon. The optimization time will increase to 10-15 days when the GA population reaches 100, or the M&R planning horizon is set to 20 years, or the simulation epoch is set to a week. For an ideal practical implementation of a 20-year M&R planning on the Sioux Falls network with the simulation of daily evolution of traffic dynamics and the GA population of 100, it would take a couple of months for the optimization. Although the increase of GA population size could ensure a more thorough searching of the optimal solution and the more detailed day-to-day traffic modelling could achieve more accurately estimation of network costs, these would increase the computational burden. Therefore, A trade-off needs to be made between the model performance and computational time. Future work should try to improve the computational efficiency of the optimization by using more high-performance computing CPU/GPU or through implementing more advanced solution algorithm (e.g.

parallel genetic algorithms).

7. Model Validation

The validation for the path-based DTD DTA models is practically difficult, since it requires very detailed and time-varying information on path flows. Access to such data as well as data accuracy makes the validation process difficult. In the real world, tracking the paths of all travellers in the road networks is very costly and technologically challenging. Also, the dynamic system is highly sensitive to the inputs and parameters, which makes the validation not that attractive. Rather, this thesis validates the DTD DTA models from the performance aspect by analysing the parameters within the models with the expectation that the proposed DTD models could be consistent with some real-life traffic phenomena and reflect travellers' decision behaviours.

8. Travel Demand Evolution

This research is conceived in a dynamic traffic assignment framework where the network O-D demand matrix is fixed over the course of the M&R planning period (several years to several decades). However, traffic demand may have evolved or shifted during this period. Hence, the proposed framework should be incorporated with a demand modelling and prediction module that accounts for the systematic change of network demand.

8.5 Publications

Yu, Y., Han, K., Ochieng, W.Y. 2020. Day-to-Day Dynamic Traffic Assignment with Imperfect Information, Bounded Rationality and Information Sharing. *Transportation Research Part C,* 114, 59-83.

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Appendix I – Dynamic Network Loading Model Supplement

The dynamic network loading (DNL) model in this thesis is implemented by a macroscopic simulation procedure, which algorithm is based on the network-level LWR-based kinematic wave model proposed in Han et al. (2019). The DNL model is composed of link model, source model, junction model as well as a delay operator. The formulations for each component are presented separately in this appendix.

In this DNL section, s represents the discrete time steps for the DNL simulation. The following notations are introduced to facilitate the presentation.

S:	Set of origins in the network
R:	Set of routes employed by all travelers
R^o:	Set of routes originating from $o \in S$
I^J:	Set of incoming links of a junction J
O^J:	Set of outgoing links of a junction J
$A^J(s)$:	Flow distribution matrix of junction J, which is time-dependent
$f_r(s)$:	Route departure rate along $r \in R^w$ at time s
$\mathrm{TT}_r(s)$:	Travel time along route r with departure time s
$f_i^{\mathrm{in}}(s)$:	Inflow of link i
$f_i^{\mathrm{out}}(s)$:	Outflow of link i
$N_i^{\mathrm{up}}(s)$:	Link i's cumulative entering count
$N_i^{\mathrm{dn}}(s)$:	Link i's cumulative exiting count
$D_i(s)$:	Demand of link i

$S_i(s)$:	Supply of link i
$\mu_i^r(s)$:	Percentage of flow at the entrance of link i associated with route r
$q_o(s)$:	Point queue at the origin node $o \in S$
$\xi_i(s)$:	Entry time of link i corresponding to exit time s
$\zeta_i(s)$:	Exit time of link i corresponding to entry time s
ds:	Time step size for the dynamic network loading
$L_i, C_i, v_i, u_i, \rho_i^{\text{jam}}$	Length, capacity, forward wave speed, backward wave speed, and jam density of link i (assuming triangular fundamental diagram)

I.1 Link Model

This sub-section presents the formulations for modelling link dynamics among the road network. A link-based kinematic wave model (LKWM) is employed for modelling link flow dynamics. The LKWM is formulated as a differential algebraic equations (DAEs) system, which are able to capture queue spillback as well as shock formation and propagation on transportation networks. This model is based on the LWR model (Lighthill and Whitham, 1955; Richards, 1956), which temporally and spatially describes the evolution of traffic density on a link as a first order scalar conservation law formulation:

$$\frac{\partial}{\partial t}\rho(t,x)+\frac{\partial}{\partial x}f(\rho(t,x))=0$$

where $\rho(t,x)$ denotes density and $f(\rho)$ denotes flow. The function $f(\cdot):\left[0,\rho^{jam}\right]\to\left[0,C\right]$ refers to the fundamental diagram as a description of the flow-density relationship, where C denotes the link flow capacity and ρ^{jam} denotes the link jam density.

A triangular fundamental diagram is applied and is formed as below. Traffic flow on the link is divided by the separating shock into two states: the uncongested (free flow) state and the congested state (see Figure I.1). Flow under uncongested state increase with density at forward propagating wave speed υ (equal to free flow speed) until flow reach capacity C at critical density ρ^c. After this point, flow under congested state decrease with density at backward propagating wave speed u and flow become zero when density reach jam density ρ^{jam}.

$$
\begin{aligned}
f(\rho) &= \upsilon\rho && \rho \in \left[0, \rho^c\right] \\
f(\rho) &= -u\left(\rho - \rho^{jam}\right) && \rho \in \left(\rho^c, \rho^{jam}\right]
\end{aligned}
$$

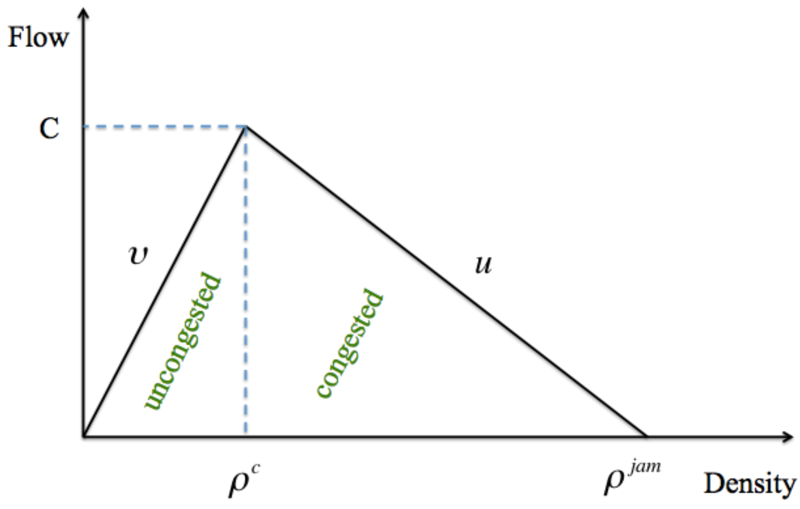


Figure I.1 Triangular Fundamental Diagram

The LKWM model assumes that the initial condition of the link is empty, and there is no more than one separating shock in the link. As implemented into the DNL model, the initial network needs to be empty. This model is formed by the notions of demand and supply. Variational principle is applied in the LKWM to detect the circumstances when the separating shock reaches the entrance or exit of the link (named latent shock), where the link demand or supply needs to be revised.

Three cases are studied in the LKWM model: when the shock is within the link, when the shock reaches the downstream boundary of the link, and when the shock reaches the upstream boundary of the link.

1) For the shock within the link, no matter what interior position it is, supply is equal to

capacity because the entrance of the link is at free flow state, and demand is also equal to capacity because the exit is congested.

$$D(s) = S(s) = C$$

2) For the shock reaches the downstream boundary, the entire link is in uncongested state and a constant forward propagating wave speed υ is applied to the entire link.

$$f_{out}(s) = f_{in}(s - \frac{L}{\upsilon})$$

where, L is link length.

3) For the shock reaches the upstream boundary, the link is in congested state and a backward propagating wave speed u is applied to the entire link.

$$f_{in}(s) = f_{out}(s - \frac{L}{u})$$

The network-based LKWM is then formulated as a differential algebraic equation (DAE). The demand and supply for each link can be calculated by the formulations below.

$$\frac{d}{dt} N_i^{up}(s) = f_i^{in}(s) \quad , \quad \frac{d}{dt} N_i^{dn}(s) = f_i^{out}(s)$$

$$D_i(s+1) = \begin{cases} f_i^{\mathrm{in}}(s - L_i/v_i) & \text{if} \quad N_i^{\mathrm{up}}(s - L_i/v_i) \leq N_i^{\mathrm{dn}}(s) \\ C_i & \text{if} \quad N_i^{\mathrm{up}}(s - L_i/v_i) > N_i^{\mathrm{dn}}(s) \end{cases}$$

$$S_j(s+1) = \begin{cases} f_j^{\mathrm{out}}\left(s - L_j/u_j\right) & \text{if} \quad N_j^{\mathrm{up}}(s) \geq N_j^{\mathrm{dn}}\left(s - L_j/u_j\right) + \rho_j^{\mathrm{jam}} L_j \\ C_j & \text{if} \quad N_j^{\mathrm{up}}(s) < N_j^{\mathrm{dn}}\left(s - L_j/u_j\right) + \rho_j^{\mathrm{jam}} L_j \end{cases}$$

The DNL link model is based on the discretized DAE system above. The continuous time are discretized into several time intervals with time step ds. This link model will output the demand and supply for all links in the simulated network, which will be used in the junction model.

I.2 Source Model

Source nodes are the origin nodes of the traffic network. A source model is needed for the purpose of accommodating the flows that exceeds the supply of the links downstream the origin nodes. A point-queue model is implemented as the source model for the DNL process. This model forms a virtual point-queue $q_o(s)$ at each source node to store the excessive departure demand. Assume a link j is connected to the source node,

$$q_o(s+1) - q_o(s) = ds \sum_{r \in R^o} f_r(s) - \min\{D_o(s), S_j(s)\}$$

where, R^o is the set of paths origin from source node $o \in S$. $f_r(s)$ denotes the departure rate from source o at time s. On the right hand of the formulation, the first and second terms are the flow into and leaving the point queue. The demand at source nodes can be calculated as:

$$D_o(s+1) = \begin{cases} M & \text{if } q_o(s) > 0 \\ \sum_{r \in R^0} f_r(s) & \text{if } q_o(s) = 0 \end{cases} \qquad o \in S$$

where, M is a sufficient large number that greater than the link flow capacity.

I.3 Junction Model

Given the demand and supply from the link and source models, the modelling of traffic dynamics at road network junctions are proposed in this sub-section. Links set is modified by adding visual links (with infinite capacity and no length) at sources as well as sinks for using in the junction model and first-in-first-out (FIFO) principle is followed.

Take a junction as below for example, at the junction, there are m inflow links i, and n outflow links j. The turning ratio for each link i turn to each link j at the junction will be calculated according to paths component of flow. Outflows for each in-coming links i and inflows for each out-going links j at each time step will be outputted by the junction model. Inflows for each out-going links j will also be split into flow for each path r.

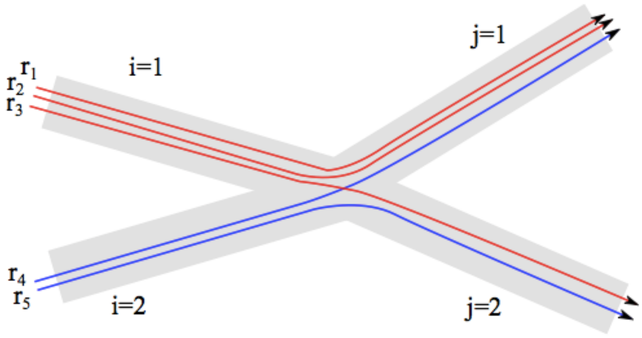


Figure I.2 Example junction

1) Turning Ratio

Calculation for the turning ratios for every link i to every link j at the junction is the curtail part of the junction model. The turning ratios at junctions are calculated according to the recorded inflow $f_{i(r)}^{in}(s)$ of each path on each passing link at every time steps. The ratio of flow of path r entering link i to total flow into link i at time s that go to outflow links j is denoted by:

$$\mu_i^r(s) = \frac{f_{i(r)}^{in}(s)}{f_i^{in}(s)}, \qquad \forall i, j \in \mathrm{A} \quad r \in R_{i,j}$$

Turning ration for inflow link i to outflow link j at the junction then can be calculated by the sum of path flow that passing link i and flow into link j.

$$\alpha_{i,j}(s) = \sum_r \mu_i^r(s)$$

2) Outflow on in-coming links

Effective link supply for the inflow link i is denoted as:

$$S_i^e = \min\left\{C_i, \frac{S_j}{\alpha_{i,j}}\right\}$$

where C_i is the capacity of link i and S_j is the supply of link j

Then the outflow on incoming link i can be calculated as:

$$f_i^{out}(s) = \min\left\{D_i(s), S_i^e(s)\right\}$$

3) Inflow on out-going links

The inflow on out-going link j is calculated by the sum of outflow from in-coming links i multiplied by the corresponding turning ratio:

$$f_j^{in}(s) = \sum_i \alpha_{i,j}(s) \cdot f_i^{out}(s)$$

The above inflow on out-going links can be split for each out-going path inflow, formed as:

$$f_{j(r)}^{in}(s) = \mu_i^r(s) \cdot f_i^{out}(s)$$

The junction model can be conceptually formed as the following mapping:

$$\left([f_i^{\text{out}}(s)]_{i=1}^m \;, \left[f_j^{\text{in}}(s)\right]_{j=1}^n\right) = \Theta\left([D_i(s)]_{i=1}^m \;, \left[S_j(s)\right]_{j=1}^n \;; A^J(s)\right)$$

where, $A^J(s) = \left\{\alpha_{ij}(s)\right\}$ is the flow distribution matrix. The outputs of the junction model, shown as the left-hand side, are the outflows of the incoming links and inflows of the outgoing links; and the inputs that shown in right hand side are demands, supplies and turning ratios. The mapping Θ in the conservation law studies is sometimes referred to as the Riemann Solver.

Outputs $f_i^{out}(s)$ and $f_j^{in}(s)$ from the junction model can be used to generate the amount of travellers at upstream (enter) and downstream (exit) of links.

$$N_i^{\text{up}}(s+1) = N_i^{\text{up}}(s) + ds \cdot f_i^{\text{in}}(s), \quad N_i^{\text{dn}}(s+1) = N_i^{\text{dn}}(s) + ds \cdot f_i^{\text{out}}(s)$$

I.4 Calculating Path Travel Time

A delay operator is introduced to generate path travel time in the DNL model. For calculating link travel time, denote $\zeta(s)$ as the exit time of a link when the entry time for the same link is s. Exit time for each link can be produced by the process (see Figure I.3) that find the

N^{up} at entry time s and then find the exit time $\zeta(s)$ at which:

$$N^{up}(s) = N^{dn}(\zeta(s))$$

Link travel time can be generated as $\zeta(s) - s$ and path travel time is the sum of link travel times for the links on corresponding path lists.

$$\mathrm{TT}_r(s) = \zeta_o \circ \zeta_1 \circ \dots \circ \zeta_K(s), \quad \forall r = \{o, 1, \dots, K\}$$

where, the composition function $y_1 \circ y_2(s) \doteq y_2\big(y_1(s)\big)$.

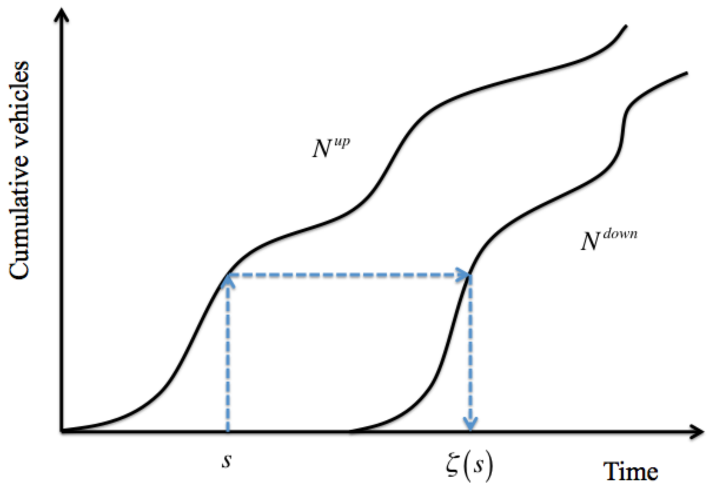


Figure I.3 Find the exit time

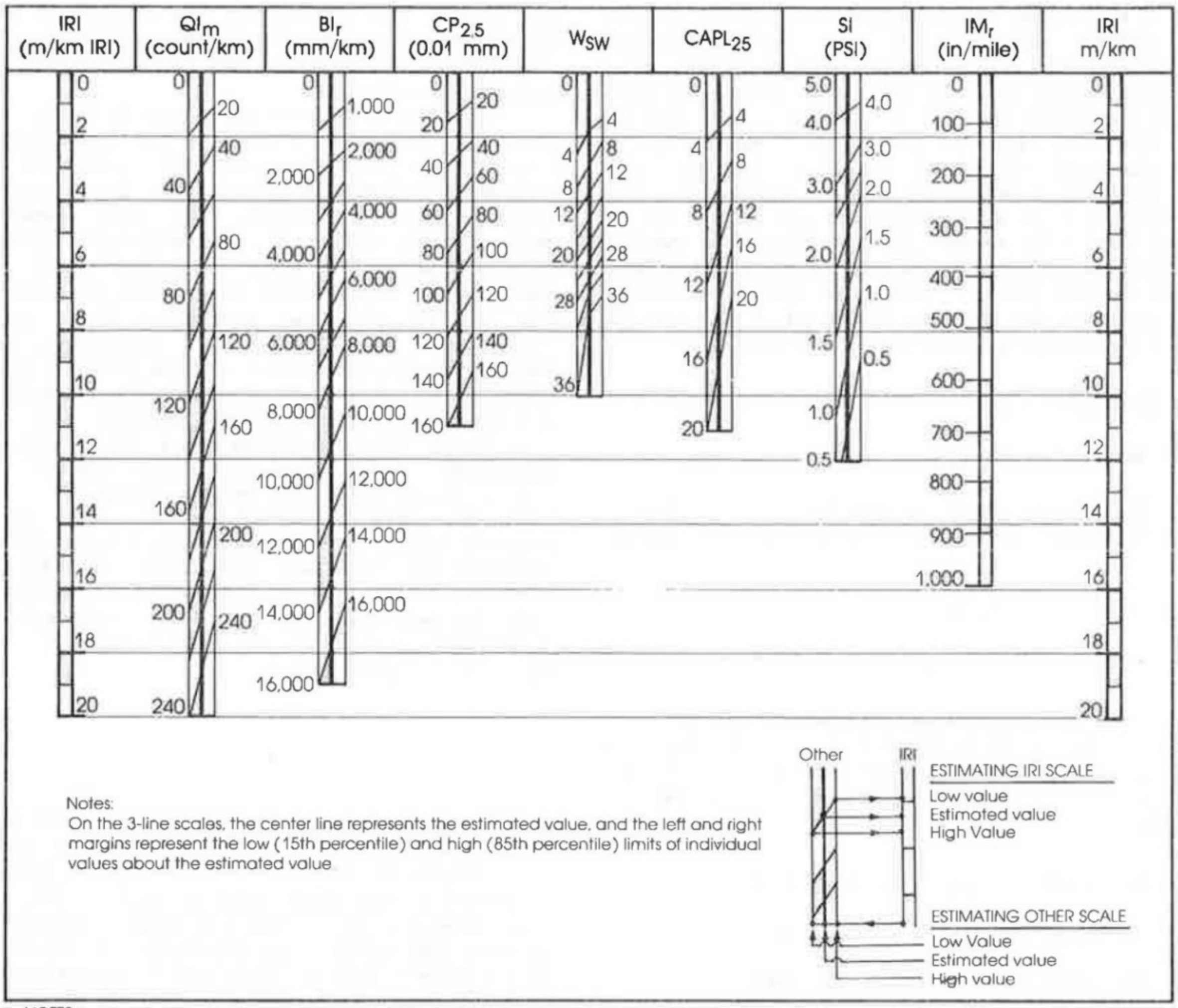
Appendix II – Relationships between Roughness Scales

Road roughness has been measured by various scales in the world. Paterson (1990) proposed the relationships and conversions between major roughness scales by analysing the data from the International Road Roughness Experiment (IRRE), the result of which is presented in this appendix for the purpose of facilitate the comparison and conversions between this thesis and other previous and current research findings in the road quality modelling.

Conversion Relationship		Standard Error	Coefficient of Variation	Bias Slope	Units
$E[\hat{IRI}]$	$= QI_m/13$	0.919	15.4	0.989	m/km
	$= (QI_r + 10)/14$	0.442	7.34	0.975	m/km
	$= 0.0032\ BI^{0.89}$	0.764	12.7	1.008	m/km
	$= CP_{2.5}/16$	0.654	12.4	0.993	m/km
	$\cong 5.5 \log_e (5.0/PSI)$	–	–	–	m/km
	$= 0.80\ RARS_{50}$	0.478	–	1.002	m/km
	$= 0.78\ W_{sw}^{0.63}$	0.693		0.994	m/km
	$= CAPL_{25}/3.0$ if asphalt				
	$= CAPL_{25}/2.2$ if not asphalt	1.050		1.030	m/km
$E[\hat{QI}_m]$	$= 13\ IRI$	12.0	15.3	0.993	Counts/km
	$= 9.5 + 0.90\ QI_r$	14.5	18.7	0.985	Counts/km
	$= \begin{cases} BI/55 \text{ if not earth} \\ BI/73 \text{ if earth} \end{cases}$	11.7	15.0	1.002	Counts/km
	$= 0.81\ CP_{2.5}$	11.7	17.2	0.986	Counts/km
	$\cong 72 \log_e (5.0/PSI)$	–	–	–	Counts/km
	$= 7.9\ W_{sw}^{0.70}$	8.78		0.996	Counts/km
	$= 6.2\ CAPL_{25}$	18.29		1.13	Counts/km
$E[\hat{QI}_r]$	$= -10 + 14\ IRI$	6.32	8.35	1.024	Counts/km
	$\cong BI/62$	14.0	18.3	1.006	Counts/km
	$= -10 + 0.89\ CP_{2.5}$	13.1	20.3	0.980	Counts/km
$E[\hat{BI}]$	$= 630\ IRI^{1.12}$	694	14.7	0.998	mm/km
	$= 36\ QI_m^{1.12}$	1100	22.8	0.985	mm/km
	$= \begin{cases} 55\ QI_m \text{ if not earth} \\ 73\ QI_m \text{ if earth} \end{cases}$	673	14.2	0.976	mm/km
	$= 62\ QI_r$	850	18.1	0.971	mm/km
$E[\hat{CP}_{2.5}]$	$= 16\ IRI$	10.5	12.4	0.994	0.01 mm
	$= 11 + 1.12\ QI_r$	14.8	17.6	0.995	0.01 mm
	$= 1.23\ QI_m$	14.4	17.2	0.986	0.01 mm
	$= 11.7\ W_{sw}^{0.65}$ (if $CP_{2.5} < 150$)	8.87		1.018	0.01 mm

Note: Roughness scale codes:
BI = TRRL Bump Integrator trailer at 32 km/h (mm/km).
$CAPL_{25}$ = APL profilometer coefficient for 21.6 km/h operation.
$CP_{2.5}$ = APL profilometer coefficient of planarity (.01 mm).
IRI = International Roughness Index (m/km)
QI_m = RTRRMS-estimate of QI roughness in Brazil study (counts/km).
QI_r = Profile RMSVA-function of QI roughness (counts/km).
$RARS_{50}$ = ARS response of reference roughness simulation at 50 km/h
W_{sw} = Short wavelength (1 to 3.3 m) energy index W of APL72 profilometer as defined by French LCPC

Figure II.1 Relationships and statistics for conversions between roughness scales (Paterson, 1990)



NOTES:
Conversions estimated on data from the International Road Roughness Experiment, (Sayers, Gillespie and Queiroz, 1986) as follows

1. IRI — International Roughness Index (Sayers, Gillespie and Paterson, World Bank Technical Paper 46, 1986)
2. QI_m — Quarter-car Index of calibrated Maysmeter, Brazil-UNDP Road Costs Study
   $\hat{IRI} = QI_m/13 \pm 0.37\sqrt{IRI}$ $\quad IRI<17$
3. BI_r — Bump Integrator trailer at 32 km/h, Transport and Road Research Laboratory, UK
   $\hat{IRI} = 0.0032\, BI_r^{0.89} \pm 0.31\sqrt{IRI}$; $\quad IRI<17$
4. $CP_{2.5}$ — Coefficient of planarity over 2.5m baselength for APL72 Profilometer, Centre de Recherches Routiers, Belgium:
   $\hat{IRI} = CP_{2.5}/16 \pm 0.27\sqrt{IRI}$, $\quad IRI<11$
5. W_{sw} — Short Wavelength Energy for APL72 Profilometer, Laboratoire Central des Ponts et Chaussées, France
   $\hat{IRI} = 0.78\, W_{sw}^{0.63} \pm 0.69$ IRI, $\quad IRI<9$
6. $CAPL_{25}$ — Coefficient of APL25 Profilometer, Laboratoire Central des Ponts et Chaussées, France
   $\hat{IRI} = 0.45\, k\, CAPL_{25} \pm 16\%$; $\quad IRI<11$
   where k = 1 for general use, k = 0.74 for asphalt concrete surfaces, k = 1.11 for surface treatment, earth or gravel.
7. SI — Serviceability Index, American Association of State Highway and Transportation Officials:
   $\hat{IRI} = 5.5 \ln(5.0/SI) \pm 25\%$; $\quad IRI<12$
8. IM_r — Inches/mile equivalent of IRI from Reference Quarter-Car Simulation at 50 mile/hr (see 'HSRI-reference' in Gillespie, Sayers and Segel NCHRP report 228, 1980; and '$RARS_{80}$' in Sayers, Gillespie and Queiroz, World Bank Technical Paper 45, 1986):
   $IRI = IM_r/63.36$

Figure II.2 Approximate conversions between the International Roughness index and major roughness scales (Paterson, 1990)

Appendix III – Sioux Falls Network Data

Table III.1 Link data of the Sioux Falls network

Link No.	Tail Node	Head Node	Capacity (veh/s)	Length (m)	Free Flow Time (s)
1	1	2	7.1945	9656.064	360
2	1	3	6.5010	6437.376	240
3	2	1	7.1945	9656.064	360
4	2	6	1.3773	8046.720	300
5	3	1	6.5010	6437.376	240
6	3	4	4.7529	6437.376	240
7	3	12	6.5010	6437.376	240
8	4	3	4.7529	6437.376	240
9	4	5	4.9397	3218.688	120
10	4	11	1.3636	9656.064	360
11	5	4	4.9397	3218.688	120
12	5	6	1.3744	6437.376	240
13	5	9	2.7778	8046.720	300
14	6	2	1.3773	8046.720	300
15	6	5	1.3744	6437.376	240
16	6	8	1.3607	3218.688	120
17	7	8	2.1783	4828.032	180
18	7	18	6.5010	3218.688	120
19	8	6	1.3607	3218.688	120
20	8	7	2.1783	4828.032	180

21	8	9	1.4028	16093.440	600
22	8	16	1.4016	8046.720	300
23	9	5	2.7778	8046.720	300
24	9	8	1.4028	16093.440	600
25	9	10	3.8655	4828.032	180
26	10	9	3.8655	4828.032	180
27	10	11	2.7778	8046.720	300
28	10	15	3.7533	9656.064	360
29	10	16	1.3486	6437.376	240
30	10	17	1.3871	12874.752	480
31	11	4	1.3636	9656.064	360
32	11	10	2.7778	8046.720	300
33	11	12	1.3636	9656.064	360
34	11	14	1.3546	6437.376	240
35	12	3	6.5010	6437.376	240
36	12	11	1.3636	9656.064	360
37	12	13	7.1945	4828.032	180
38	13	12	7.1945	4828.032	180
39	13	24	1.4142	6437.376	240
40	14	11	1.3546	6437.376	240
41	14	15	1.4243	8046.720	300
42	14	23	1.3680	6437.376	240
43	15	10	3.7533	9656.064	360
44	15	14	1.4243	8046.720	300

45	15	19	4.0458	4828.032	180
46	15	22	2.6664	4828.032	180
47	16	8	1.4016	8046.720	300
48	16	10	1.3486	6437.376	240
49	16	17	1.4528	3218.688	120
50	16	18	5.4666	4828.032	180
51	17	10	1.3871	12874.752	480
52	17	16	1.4528	3218.688	120
53	17	19	1.3400	3218.688	120
54	18	7	6.5010	3218.688	120
55	18	16	5.4666	4828.032	180
56	18	20	6.5010	6437.376	240
57	19	15	4.0458	4828.032	180
58	19	17	1.3400	3218.688	120
59	19	20	1.3896	6437.376	240
60	20	18	6.5010	6437.376	240
61	20	19	1.3896	6437.376	240
62	20	21	1.4055	9656.064	360
63	20	22	1.4099	8046.720	300
64	21	20	1.4055	9656.064	360
65	21	22	1.4528	3218.688	120
66	21	24	1.3570	4828.032	180
67	22	15	2.6664	4828.032	180
68	22	20	1.4099	8046.720	300

69	22	21	1.4528	3218.688	120
70	22	23	1.3889	6437.376	240
71	23	14	1.3680	6437.376	240
72	23	22	1.3889	6437.376	240
73	23	24	1.4107	3218.688	120
74	24	13	1.4142	6437.376	240
75	24	21	1.3570	4828.032	180
76	24	23	1.4107	3218.688	120

Table III.2 OD information of the Sioux Falls network

No.	O	D	Demand	No.	O	D	Demand	No.	O	D	Demand
1	2	2	100	177	4	6	700	353	20	4	1600
2	3	2	100	178	5	5	800	354	21	8	600
3	4	3	500	179	6	6	400	355	22	8	1200
4	5	3	200	180	7	13	600	356	23	13	500
5	6	2	300	181	8	7	800	357	24	16	300
6	7	16	500	182	10	4	2800	358	1	20	400
7	8	8	800	183	11	6	1400	359	2	19	200
8	9	5	500	184	12	10	600	360	3	20	100
9	10	7	1300	185	13	11	600	361	4	18	500
10	11	5	500	186	14	10	600	362	5	16	200
11	12	3	200	187	15	7	900	363	6	16	500
12	13	3	500	188	16	13	1400	364	7	6	1000
13	14	14	300	189	17	10	900	365	8	12	1400

14	15	11	500	190	18	13	200	366	9	10	900
15	16	17	500	191	19	13	400	367	10	7	3900
16	17	12	400	192	20	14	600	368	11	12	1000
17	18	17	100	193	21	15	300	369	12	22	600
18	19	17	300	194	22	11	700	370	13	20	500
19	20	22	300	195	23	18	500	371	14	14	700
20	21	19	100	196	24	14	200	372	15	7	1500
21	22	18	400	197	1	9	1300	373	16	5	2800
22	23	17	300	198	2	10	600	374	18	6	600
23	24	9	100	199	3	8	300	375	19	6	1700
24	1	2	100	200	4	8	1200	376	20	5	1700
25	3	3	100	201	5	6	1000	377	21	11	600
26	4	3	200	202	6	9	800	378	22	6	1700
27	5	3	100	203	7	14	1900	379	23	12	600
28	6	2	400	204	8	11	1600	380	24	20	300
29	7	17	200	205	9	4	2800	381	1	20	100
30	8	8	400	206	11	4	4000	382	4	21	100
31	9	5	200	207	12	11	2000	383	6	18	100
32	10	7	600	208	13	11	1900	384	7	1	200
33	11	6	200	209	14	10	2100	385	8	8	300
34	12	5	100	210	15	6	4000	386	9	14	200
35	13	6	300	211	16	12	4400	387	10	13	700
36	14	15	100	212	17	7	3900	388	11	19	200
37	15	11	100	213	18	13	700	389	12	22	200

38	16	19	400	214	19	10	1800	390	13	18	100
39	17	13	200	215	20	12	2500	391	14	17	100
40	19	17	100	216	21	17	1200	392	15	11	200
41	20	25	100	217	22	11	2600	393	16	3	500
42	22	18	100	218	23	15	1800	394	17	8	600
43	1	2	100	219	24	15	800	395	19	10	300
44	2	2	100	220	1	9	500	396	20	2	400
45	4	1	200	221	2	9	200	397	21	7	100
46	5	2	100	222	3	9	300	398	22	7	300
47	6	2	300	223	4	8	1500	399	23	12	100
48	7	16	100	224	5	6	500	400	1	21	300
49	8	8	200	225	6	10	400	401	2	20	100
50	9	5	100	226	7	19	500	402	4	22	200
51	10	6	300	227	8	13	800	403	5	20	100
52	11	4	300	228	9	6	1400	404	6	20	200
53	12	2	200	229	10	5	3900	405	7	9	400
54	13	2	100	230	12	9	1400	406	8	12	700
55	14	12	100	231	13	8	1000	407	9	9	400
56	15	10	100	232	14	9	1600	408	10	7	1800
57	16	17	200	233	15	8	1400	409	11	13	400
58	17	13	100	234	16	15	1400	410	12	23	300
59	22	16	100	235	17	9	1000	411	13	21	300
60	23	15	100	236	18	18	100	412	14	11	300
61	1	3	500	237	19	11	400	413	15	5	800

62	2	3	200	238	20	18	600	414	16	8	1300
63	3	3	200	239	21	21	400	415	17	4	1700
64	5	1	500	240	22	14	1100	416	18	8	300
65	6	2	400	241	23	12	1300	417	20	7	1200
66	7	15	400	242	24	12	600	418	21	11	400
67	8	7	700	243	1	8	200	419	22	7	1200
68	9	4	700	244	2	9	100	420	23	10	300
69	10	5	1200	245	3	7	200	421	24	19	100
70	11	4	1400	246	4	7	600	422	1	24	300
71	12	3	600	247	5	7	200	423	2	25	100
72	13	3	600	248	6	9	200	424	4	23	300
73	14	12	500	249	7	19	700	425	5	21	100
74	15	10	500	250	8	11	600	426	6	21	300
75	16	15	800	251	9	11	600	427	7	2	500
76	17	11	500	252	10	11	2000	428	8	10	900
77	18	15	100	253	11	8	1400	429	9	15	600
78	19	13	200	254	13	1	1300	430	10	12	2500
79	20	20	300	255	14	13	700	431	11	22	600
80	21	18	200	256	15	13	700	432	12	22	500
81	22	16	400	257	16	19	700	433	13	20	600
82	23	14	500	258	17	15	600	434	14	14	500
83	24	10	200	259	18	19	200	435	15	11	1100
84	1	4	200	260	19	18	300	436	16	5	1600
85	2	4	100	261	20	19	400	437	17	9	1700

86	3	4	100	262	21	15	300	438	18	2	400
87	4	4	500	263	22	15	700	439	19	8	1200
88	6	3	200	264	23	14	700	440	21	6	1200
89	7	16	200	265	24	6	500	441	22	4	2400
90	8	8	500	266	1	16	500	442	23	10	700
91	9	5	800	267	2	17	300	443	24	15	400
92	10	6	1000	268	3	15	100	444	1	24	100
93	11	5	500	269	4	16	600	445	4	26	200
94	12	7	200	270	5	18	200	446	5	26	100
95	13	7	200	271	6	19	200	447	6	24	100
96	14	13	100	272	7	21	400	448	7	5	200
97	15	10	200	273	8	18	600	449	8	13	400
98	16	16	500	274	9	17	600	450	9	15	300
99	17	12	200	275	10	16	1900	451	10	17	1200
100	19	13	100	276	11	18	1000	452	11	21	400
101	20	18	100	277	12	12	1300	453	12	21	300
102	21	15	100	278	14	11	600	454	13	13	600
103	22	14	200	279	15	16	700	455	14	10	400
104	23	16	100	280	16	19	600	456	15	12	800
105	1	5	300	281	17	19	500	457	16	10	600
106	2	5	400	282	18	20	100	458	17	12	600
107	3	5	300	283	19	19	300	459	18	5	100
108	4	5	400	284	20	18	600	460	19	9	400
109	5	3	200	285	21	10	600	461	20	4	1200

110	7	12	400	286	22	9	1300	462	22	3	1800
111	8	5	800	287	23	10	800	463	23	6	700
112	9	6	400	288	24	2	800	464	24	10	500
113	10	8	800	289	1	16	300	465	1	18	400
114	11	7	400	290	2	17	100	466	2	20	100
115	12	8	200	291	3	16	100	467	3	17	100
116	13	9	200	292	4	16	500	468	4	17	400
117	14	17	100	293	5	15	100	469	5	17	200
118	15	12	200	294	6	20	100	470	6	20	200
119	16	15	900	295	7	15	200	471	7	6	500
120	17	14	500	296	8	20	400	472	8	13	500
121	18	12	100	297	9	11	600	473	9	11	700
122	19	14	200	298	10	9	2100	474	10	13	2600
123	20	15	300	299	11	6	1600	475	11	15	1100
124	21	15	100	300	12	14	700	476	12	17	700
125	22	15	200	301	13	13	600	477	13	13	1300
126	23	19	100	302	15	4	1300	478	14	7	1200
127	24	15	100	303	16	17	700	479	15	9	2600
128	1	19	500	304	17	14	700	480	16	10	1200
129	2	20	200	305	18	15	100	481	17	12	1700
130	3	21	100	306	19	10	300	482	18	6	300
131	4	20	400	307	20	14	500	483	19	10	1200
132	5	18	200	308	21	11	400	484	20	6	2400
133	6	18	400	309	22	5	1200	485	21	5	1800

134	8	8	1000	310	23	4	1100	486	23	5	2100
135	9	13	600	311	24	13	400	487	24	12	1100
136	10	13	1900	312	1	18	500	488	1	17	300
137	11	19	500	313	2	19	100	489	3	16	100
138	12	22	700	314	3	17	100	490	4	16	500
139	13	18	400	315	4	17	500	491	5	16	100
140	14	17	200	316	5	15	200	492	6	19	100
141	15	11	500	317	6	18	200	493	7	11	200
142	16	4	1400	318	7	10	500	494	8	14	300
143	17	9	1000	319	8	14	600	495	9	12	500
144	18	2	200	320	9	10	1000	496	10	13	1800
145	19	10	400	321	10	7	4000	497	11	10	1300
146	20	2	500	322	11	9	1400	498	12	15	700
147	21	7	200	323	12	18	700	499	13	14	800
148	22	7	500	324	13	17	700	500	14	5	1100
149	23	12	200	325	14	5	1300	501	15	8	1000
150	24	14	100	326	16	8	1200	502	16	13	500
151	1	10	800	327	17	7	1500	503	17	15	600
152	2	10	400	328	18	8	200	504	18	11	100
153	3	10	200	329	19	3	800	505	19	11	300
154	4	10	700	330	20	7	1100	506	20	11	700
155	5	6	500	331	21	12	800	507	21	6	700
156	6	6	800	332	22	5	2600	508	22	4	2100
157	7	4	1000	333	23	6	1000	509	24	12	700

158	9	9	800	334	24	18	400	510	1	20	100
159	10	12	1600	335	1	19	500	511	4	21	200
160	11	15	800	336	2	20	400	512	6	23	100
161	12	13	600	337	3	19	200	513	7	15	100
162	13	17	600	338	4	18	800	514	8	20	200
163	14	18	400	339	5	17	500	515	9	17	200
164	15	14	600	340	6	17	900	516	10	19	800
165	16	5	2200	341	7	2	1400	517	11	18	600
166	17	13	1400	342	8	7	2200	518	12	17	500
167	18	4	300	343	9	11	1400	519	13	3	700
168	19	13	700	344	10	10	4400	520	14	10	400
169	20	5	900	345	11	15	1400	521	15	15	400
170	21	10	400	346	12	20	700	522	16	17	300
171	22	10	500	347	13	19	600	523	17	18	300
172	23	19	300	348	14	19	700	524	19	15	100
173	24	14	200	349	15	10	1200	525	20	12	400
174	1	7	500	350	17	7	2800	526	21	9	500
175	2	7	200	351	18	2	500	527	22	8	1100
176	3	6	100	352	19	9	1300	528	23	9	700

Appendix IV – DTD DTA Source Code

This appendix presents the implements of the day-to-day dynamic traffic assignment model developed in the thesis. Base Model II that further considers information sharing (IS) behaviour is coded in Matlab and provided as below. It simulates the daily evolution of dynamic traffic flow on networks, in which a scenario of link disruption followed by a full recovery is simulated.

```
****************************************************************

clear
clc

load 'Path_flow_data.mat'; % simulation time step (180s) and initial path departure rates
load 'OD_info.mat'; % origin-destination structure
load 'Network_planning_parameters'; % O-D demand and target arrival times (for departure time
choices)
load('SiouxFalls6180_pp.mat','pathList','link'); % path and link information

NumOD=size(OD_set,1);
time_horizon=[0, 5*3600]; % time horizon of the within-day dynamics, in seconds
T_A=T_A*3600;    % target arrival times (in second)
n_paths=size(pathDepartures,1); % number of paths

%% User-defined parameters
factor=1; % Total demand scaling factor
N=3; % memory days
lambda=0.7; % memory weight
theta=0.002;    % Logit model dispersion parameter
theta_T=0.002;
Num_days=150; % total number of days for the DTD simulation
DT=900; % departure time window in seconds
TSPW=DT/dt; % Time Steps Per Window
NT=range(time_horizon)/DT; % number of departure time windows
nt=range(time_horizon)/dt; %number of time step in DNL
beta_PS=400; % coefficient of the Path Size nexted logit model
```

```
%% Path Size correction
PS=zeros(n_paths,1);    % the path size attribute
plength=zeros(n_paths,1); % the path length attribute
for j=1:NumOD
    ODpath=ODpath_set{j};
    for i=ODpath
        dummy=pathList(i); dummy(dummy==0)=[];
        plength(i)=sum(link.length(dummy));
        Paths_through_link=zeros(size(dummy));
        for k=1:length(dummy)
            Paths_through_link(k)=sum(sum(pathList(ODpath,:)==dummy(k)));
        end
        PS(i)=sum(link.length(dummy)/plength(i)./Paths_through_link);
    end
end

%% Initialize variables
pathDepartures=factor*pathDepartures; OD_demand=OD_demand*factor;
aggPath_flow=zeros(n_paths,NT,Num_days); % aggregated path departure rates
for i=1:NT
   aggPath_flow(:,i,1)=sum(pathDepartures(:,(i-1)*TSPW+1:i*TSPW,1),2)/TSPW;
end
aggE=zeros(n_paths, NT, Num_days); % aggregated travel costs for each path, departure window,
and day
PC=zeros(n_paths,NT,Num_days);    % perceived travel cost for each path, departure window, and
day
Flow_split=zeros(n_paths,NT,Num_days);


%% loop for T simulation days

 for T=1:Num_days
    fprintf('Day no. %4.0f \n\n', T);

    %% Dynamic Network Loading

    if T>50 && T<=100
delay=DYNAMIC_NETWORK_LOADING(pathDepartures,nt,dt,'SiouxFalls6180_pp_68.mat');
    else
        delay=DYNAMIC_NETWORK_LOADING(pathDepartures,nt,dt,'SiouxFalls6180_pp.mat');
    end

    %% Arrival penalty and travel cost
```

```
time_grid=linspace(time_horizon(1),time_horizon(end),nt);
gamma_early=0.8; gamma_late=1.8; % coefficients of early and late arrival penalties
AP=zeros(size(delay));   % initialize arrival penalty
Arrival_Time=ones(n_paths,1)*time_grid+delay;
for k=1:NumOD
    for i=1:length(ODpath_set{k,1})
        dummy=Arrival_Time(ODpath_set{k,1}(i),:)-T_A(k);
        dummy(dummy>0)=dummy(dummy>0)*gamma_late;
        dummy(dummy<=0)=-dummy(dummy<=0)*gamma_early;

        AP(ODpath_set{k,1}(i),:)=dummy;
    end
end
E=delay+AP;    % travel cost, 'E' stands for effective delay, meaning generalized cost

for i=1:NT
    aggE(:,i,T)=sum(E(:,(i-1)*TSPW+1: i*TSPW),2)/TSPW;
end

%% Perceived cost and multinomial logit model
ave_cost=zeros(1,NumOD);
for i=1:NumOD
    index=ODpath_set{i};
    Flow_split(index,:,T)=aggPath_flow(index,:,T)/sum(sum(aggPath_flow(index,:,T)));
    ave_cost(i)=sum(sum(aggPath_flow(index,:,T).*aggE(index,:,T)*DT))/OD_demand(i);
end
alpha=2; % the weighting function for information sharing is g(x)=x^alpha
if T>=N   % N: number of memory days, T: day index
    weight=Flow_split(:,:,T).^(alpha)*1;
    dummy=weight.*aggE(:,:,T);
    Sumweight=weight;
    for i=T-1:-1:T-N+1
        weight=Flow_split(:,:,i).^(alpha) *lambda^(T-i);
        dummy=dummy + weight.*aggE(:,:,i);
        Sumweight=Sumweight+weight;
    end
else
    weight=Flow_split(:,:,T).^(alpha)*1;
    dummy=weight.*aggE(:,:,T);
    Sumweight=weight;
    for i=T-1:-1:1
        weight=Flow_split(:,:,i).^(alpha)*lambda^(T-1);
        dummy=dummy + weight.*aggE(:,:,i);
```

```
                Sumweight=Sumweight+weight;
            end
        end
        if T==1
            PC(:,:,T)=aggE(:,:,T);
        else
            PC(:,:,T)=1./Sumweight.*dummy;
        end

        % choice model
        for i=1:NumOD
            % matrix of perceived costs of all alternatives in OD pair i
            PC_alt=PC(ODpath_set{i},:,T);
            % the probability of choosing a departure window (multinomial logit)
            % change 'mean' to 'harmmean' for harmonic mean (see reference)
            Prob_T=exp(-theta_T*mean(PC_alt,1))/sum(exp(-theta_T*mean(PC_alt,1)));

            for k=1:NT
                Den=sum(exp(theta*(-PC_alt(:,k) + beta_PS*log(PS(ODpath_set{i})))));
                for j=1:length(ODpath_set{i})
                    aggPath_flow(ODpath_set{i}(j),k,T+1)=OD_demand(i)/DT ...
                                                        * Prob_T(k) ...
                                                        * exp(theta*(-PC_alt(j,k) +
beta_PS*log(PS(ODpath_set{i}(j)))))/Den;
                end
            end
        end

        %% Disaggregate path flows into smaller time steps for DNL on the next day
        for i=1:n_paths
            for j=1:NT
                pathDepartures(i , (j-1)*TSPW+1 : j*TSPW)=aggPath_flow(i,j,T+1);
            end
        end
end


% OUTPUTS:
%   aggE -
%           effective path delay aggregated (averaged) by the departure time
%           window. aggE is a 3-d matrix where the 1st dimension indicates
%           paths, the 2nd dimension indicates time window, and the 3rd
%           dimension indicates day.
%
```

```
%   aggPath_flow -
%             path flow within a departure window. aggPath_flow is a 3-d
%             matrix with the same format as aggE.
%
%   PC -
%             perceived cost for each path (1st dimension) and time window
%             (2nd dimension) on a given day (3rd dimension)
```

****