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ADVANCES ON STOCHASTIC TRAFFIC ASSIGNMENT MODEL FOR DRIVER INFORMATION SYSTEM APPLICATIONS

A Thesis Submitted to the

Department of Civil and Structural Engineering

The Hong Kong Polytechnic University

In Partial Fulfillment of the Requirements

For the Degree of Doctor of Philosophy

By

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Abstract of thesis entitled:

Advances on Stochastic Traffic Assignment Model for Driver Information System Applications

submitted by Chan King Sun

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in October 2001

ABSTRACT

Most metropolitan areas around the world face a variety of problems, including serious traffic congestion and high accident rates during peak hours. Upgrading the existing expressway networks by the application of electronic information and communication technology is one way to curtail these problems. Recently, increased attention has been paid to the provision of the driver information system (DIS) such as the estimated journey times on major routes for drivers. The DIS should help drivers to select better routes and guide them to utilise existing expressway networks efficiently. This can be regarded as one possible strategy for effective traffic management.

For a traffic surveillance and information system using the DIS, the number of speed detectors (or probe vehicles) required is very important because it affects the precision of the measurement of the vehicular travel times. In this study, a bilevel programming model is proposed to determine the number of speed detectors in a network with travel time information provided by the DIS. The lower-level problem is a stochastic probit assignment model to take account of the effects of various measurement on and perceived errors in travel times. The upper-level problem is to determine the optimal speed detector density that minimizes the measured link travel time errors, as well as the social cost of the speed detectors. Numerical examples are used to illustrate the application of the proposed model and a solution algorithm for determining the optimal speed detector density.

Apart from the cost of the DIS (in terms of the social cost of the speed detectors), it is also important to examine the benefits of the DIS for evaluation purposes. In this study, a time-dependent stochastic probit assignment model is proposed for assessing the benefits of providing the DIS. The simulation technique, the shortest path algorithm and the method of successive average (MSA) are adopted for solving the proposed stochastic probit assignment model. By applying the proposed model and solution algorithm to an example network with and without the DIS, the total network travel times can be computed and compared. The total network travel times are used to evaluate the effectiveness of the DIS.

The previous related research work on assessing the DIS show that the accuracy of the provided travel time information affects the benefits arising from the DIS provision. Therefore, a new method is proposed to estimate link travel times based on speed detector data in comparison with the other two existing methods. In order to evaluate the estimated link travel times, a manual license plate survey is conducted for collecting the observed link travel times at the Lantau Link Corridor connecting to the Hong Kong Chek Lap Kok (CLK) international airport. The observed link travel times are then used for the validation of link travel times estimated by different methods.

Although the above various models have been proposed for assessing the effects of the DIS, it is still necessary to validate the drivers' responses to the DIS in practice. Thus, a stated preference (SP) survey is conducted in the Hong Kong CLK international airport for collecting the drivers' route choice responses. This study area is chosen because the DIS (via variable message signs) provided along the Lantau

Link is new to Hong Kong drivers. The collected drivers' route choice responses are used to calibrate the drivers' route choice model (i.e. the SP logit model). A case study is carried out to evaluate the proposed time-dependent stochastic probit assignment model by comparing its results against the SP logit model.

In short, there are three principal findings of the study. The first principal finding is that the proposed time-dependent stochastic probit assignment model can be used to assess the effects of the detector density and location of VMS separately under the DIS environment. The second principal finding is that the numerical results of the bilevel programming model show that detector density required for DIS increases when O-D demands increase. It is because larger O-D demand results in larger link travel time and larger measured travel time error variances. The third principal finding is that the calibrated driver perception errors of the stochastic probit assignment model increase as the volume/capacity ratios increase.

DECLARATION

I hereby declare that the thesis entitled "Advances on Stochastic Traffic Assignment model for Driver Information System Applications" is original and has not been submitted for other degrees or the like in this University or any other institutes. It does not contain any material, partly or wholly, published or written previously by others, except those references quoted in the text.

CHAN King Sun

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LIST OF PUBLICATIONS

Journal Papers:

[1] Lam W.H.K. and Chan K.S. (1998) A link-based alternative to Bell's logit assignment algorithm. *HKIE Transactions*, Vol. 5, pp. 11-18.

[2] Lam W.H.K. and Chan K.S. (2001) A model for assessing the effects of dynamic travel time information via variable message signs. *Transportation*, Vol. 28, pp. 79-99.

[3] Chan K.S. and Lam W.H.K. (2001) Optimal detector density for the network with travel time information via variable message sign. *Transportation Research A* (forthcoming).

Conference Papers:

[1] Lam W.H.K. and Chan K.S. (1996) The treatment of cycles in the stochastic user equilibrium assignment. Paper presented in the *4th meeting of the EURO Working Group on Transportation*, Newcastle upon Tyne, U.K. 9-11 September.

[2] Lam W.H.K. and Chan K.S. (1996) A stochastic traffic assignment model for road network with travel assignment model for road network with travel time

information via variable message signs. *Proceedings of the 1996 IEEE Intelligent Vehicles Symposium*, Tokyo, Japan 19-20 September, pp. 99-104.

[3] Chan K.S. and Lam W.H.K. (1996) A stochastic traffic assignment model for estimating the variance of the path choice proportion. *Proceedings of the 1st conference of the Hong Kong Society for Transportation Studies*, Hong Kong, 7 December, pp. 31-44.

[4] Chan K.S. and Lam W.H.K. (1997) Estimation of link flow variance by stochastic traffic assignment. Paper presented in *8th IFAC Symposium of Transportation Systems*, Chania, Greece, 16-18 June.

[5] Chan K.S. and Lam W.H.K. (1997) A stochastic simulation assignment model for assessing the effects of perceived and measured link cost errors. *Proceedings of the 2nd conference of the Hong Kong Society for Transportation Studies*, Hong Kong, 6 December, pp. 217-224.

[6] Lam W.H.K. and Chan K.S. (1998) A probit traffic assignment model for estimating the variance of the link flow. Paper presented in *8th World Conference on Transport Research*, Belgium, 12-17 July.

[7] Chan K.S. and Lam W.H.K. (1998) Sensitivity analysis based algorithm for determining the optimal detector density of the network with variable message sign. *Proceedings of the 3rd conference of the Hong Kong Society for Transportation Studies*, Hong Kong, 5 December 1998, pp. 247-256.

[8] Chan K.S. and Lam W.H.K. (1998) Bilevel programming approach for determining the optimal sample size of probe vehicles. *Proceedings of the 4th conference of the Hong Kong Society for Transportation Studies*, Hong Kong, 4 December 1999, pp. 289-298.

[9] W.H.K. Lam, H.P. Lo, K.S. Chan and Amy Y. F. Tang (2000) Link travel time estimates using a series of double-loop detector measurements. *Proceedings of the 6th International Conference on Applications of Advanced Technologies in Transportation Engineering*, Singapore, 28-30 June 2000.

[10] Name : W.H.K. Lam, H.P. Lo, K.S. Chan (2000) Optimal sample size of probe vehicles for advanced traveler information systems. *Proceedings of the 6th International Conference on Applications of Advanced Technologies in Transportation Engineering*, Singapore, 28-30 June 2000.

[11] Chan K.S., Zhu Z. and Lam W.H.K. (2001) Estimation of travel time on expressway with speed detector data. *Proceedings of the 9th World Conference on Transport Research*. Seoul ,South Korea, 22-27 July 2001.

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NOTATIONS

The following notations are used in Chapter 3 unless otherwise specified.

Indicator matrix	a matrix with 2 columns where the elements are the nodes, links or turns
Turn	the connection associated with two successive connecting links
Arc	the connection associated with two successive connecting turns
Route	the connection associated with two successive connecting arcs
Centroid connector	the link that connects the centroid to a node
Centroid turn	the turn that connects the centroid connector to a link
Centroid arc	the arc that connects the centroid turn to a turn
N_l	the number of links and centroid connectors
N_t	the number of turns and centroid turns
N_a	the number of arcs and centroid arcs
M^l	a N_l rows and 2 columns indicator matrix where link r is from node $M^l_{r,1}$ to node $M^L_{r,2}$; so-called the link-node matrix
M^t	a N_t rows and 2 columns indicator matrix where turn e is from link $M^t_{e,1}$ to link $M^t_{e,2}$; so-called the turn-link matrix
M^a	a N_a rows and 2 columns indicator matrix where arc x is from turn $M^a_{x,1}$ to turn $M^a_{x,2}$; so-called the arc-turn matrix
p_{klr}	probability that a trip from node k to node l chooses link r (i.e. link choice proportion)
p'_{rse}	probability that a trip from link r to link s chooses turn e (i.e. turn choice proportion)

P_{rsu}	probability that a trip from link r to link s uses link u
P'_{efg}	probability that a trip from turn e to turn f uses turn g
P''_{xyz}	probability that a trip from arc x to arc y uses arc z
d_{rs}	is 0 if no turn from link r to link s; is 1 if there exist turn from link r to link s
q_e	turning movement on turn e
V_u	traffic flow on link u
t_{ij}	trip rate from centroid connector i to centroid connector j
M^w	matrix of weights
w_{kl}	kth row and lth column entry of matrix M^w of weights
h_p	traffic flow on path p
α	dispersion parameter of the perceived travel time error
ξ_u	perceived travel time error on each link u
c_u	travel time on link u
a_{upij}	the number of times link u is included on path p between i and j
c_{pij}	the travel time of path p from i to j

The following notations are used in Chapter 4 unless otherwise specified.

C_k^{rs}	the perceived travel time on path k between origin r and destination s
c_k^{rs}	the measured travel time on path k between origin r and destination s
A	the link-path incidence matrix with element a_{lk}

a_{lk} $= \begin{cases} 1, & \text{if link } l \text{ belongs to path } k \\ 0, & \text{otherwise.} \end{cases}$

ε_k^{rs} the measured path travel time errors

ξ_k^{rs} the perceived path travel time errors

V_l the flow on link l

c_l the travel time of link l

P_k^{rs} the path choice proportion of path k between origin r and destination s, i.e. proportion of flow from r to s that use path k

p_l^{rs} the link choice proportion of link l between origin r and destination s, i.e. proportion of flow from r to s via link l

Σ the covariance matrix of the link flow with element σ_{km}

σ_{ll} the variance of the flow on link l

σ_{lm} the covariance of the flows on the links l and m

σ_{ll}^{rs} the variance of the link choice proportion for link l

σ_{lm}^{rs} the covariance of the link choice proportion for links l and m

The following notations are used in Chapter 5 unless otherwise specified.

L_k set of link belongs to path k

A link-path incidence matrix

C_l travel time of link l

C_{ml} measured travel time of link l

C_{pl} perceived travel time of link l

ε_{ml} measured travel time error of link l

ε_{pl}	perceived travel time error of link l with travel time information
ε_{fl}	perceived travel time error of link l without travel time information
v_l	flow on link l
C_k	perceived time of travel on path k
L_{VMS}	set of links on which travel time information is provided via VMS
L'_{VMS}	set of links on which no travel time information is provided via VMS
d_{sl}	detector density of link l
v_{it}	flow on link i in time interval t
D_{it}	traffic arrival on link i at time interval t
q_{it}	traffic queue on link i at time interval t
d_i	traffic delay on link i
s_i	capacity of link i per hour

The following notations are used in Chapters 6–9 unless otherwise specified.

Sets

A_n	the set of links in the network
A_d	the set of links with speed detectors
W	the set of origin-destination(O-D) pairs
P_w	the set of paths between O-D pair $w \in W$

Constants

T_w	demand between O-D pair $w \in W$
$\mathbf{T}$	a vector of all O-D demands
B	budget of the social cost for the RGS and speed detector system
D_a	distance of link a
θ_{da}	scaling factor of the social cost for the speed detectors on link a

Variables

$TT(\tau)$	the average link travel time of the traffic entering a link during interval τ
d_{da}	speed detector density of link $a \in A_d$ t
$\mathbf{d}$	a vector of speed detectors (upper-level decision variables)
P_k^w	choice proportion on path $k \in P_w$ for O-D pair $w \in W$
$\mathbf{P}^w$	path choice probability vector for O-D pair $w \in W$
v_a	flow on link $a \in A_n$
$\mathbf{v}$	a vector of all link flows (lower-level decision variables)
$C_a(v_a)$	travel time on link $a \in A_n$
C_{ma}	measured travel time on link a
C_{pa}	perceived travel time on link a
$\mathbf{C(v)}$	a vector of link time functions
ε_{ma}	measured travel time error on link a
ε_{pa}	perceived travel time error on link a
Δ^w	link/path incidence matrix for the O-D pair w

The following acronyms are used throughout this thesis:

ARE	Average relative error
ATIS	Advanced traveler information system
ATT	Advanced transport telematics
BPR	Bureau of Public Roads
CCTV	Closed Circuit Television
CLK	Chek Lap Kok
CTS-3	Third Comprehensive Transport Study
DIS	Driver information system
IIA	Independence of Irrelevant Alternatives
ITS	Intelligent Transportation System
LOS	Level of service
LUTO	Land Use Transport Optimization
MSA	Method of successive averages
NDP	Network design problem
NTT	Network time time
O-D	Origin-Destination
pcu	Passenger car units
RGS	Route guidance system
RMS	Root mean square
RMSE	Square root of the mean square error
RP	Revealed preference
RTNTT	Ratio of the total network travel time
SP	Stated preference

SPTT	Sum of the present travel time
SUE	Stochastic user equilibrium
TCSD	Traffic Control and Surveillance Division
TMCA	Tsing Ma Control Area
TNTT	Total network travel time
UE	User equilibrium
v/c	Volume/capacity
VMS	Variable message sign

1 INTRODUCTION

1.1 BACKGROUND

The expressway network in Hong Kong carries a disproportionately high amount of total traffic. Growing demand for network use cannot be accommodated by further extension. This causes an increasing incidence rates due to the heavy congestion. Therefore, delay and accidents are also increased.

It is noteworthy that Hong Kong has been at the forefront of practical applications of information technology in transport. The pilot area pricing scheme in Hong Kong has excited interest throughout the transport planning community and the real time traffic information has been used to adjust signal timings at major road intersections so as to improve the efficiency of road networks.

Even though Hong Kong has made use of information technologies in transport, heavy pressures on the transport system have still grown. Therefore, it is necessary to consider additional or alternative information technologies for transport. It is suggested that providing the driver information system (DIS) can be an alternative for reducing the traffic congestion problem in Hong Kong.

In the event of heavy congestion, or a major incident on the expressway network, a pre-planned information strategy can be implemented utilizing the DIS. This DIS would be linked via the existing cable network to a control center. The potential benefits of providing the DIS to drivers are in terms of reduced drivers' travel times and delay. However, the exact value of these benefits depends on the design of the system to accommodate variations in driver behaviour in response to the DIS and the accuracy of the travel time estimation. These facts have to be studied in detail. Attention is paid in this research to incorporating the accuracy of the travel time in the modelling approach and the investigation of the drivers' reaction to the DIS and the benefits of providing the DIS.

1.2 THE NEED FOR THE STUDY

In view of the serious traffic congestion on most of the Hong Kong expressways and recent improvements in information technology, there is a growing aspiration to relieve traffic congestion by the application of electronic information and communication technology. Providing drivers with travel time information such as estimated journey times on major routes should help drivers to select better routes and guide them to utilise existing expressway networks. Therefore, the investigation of the drivers' responses to the DIS and the evaluation of effects of providing the proposed DIS become significant research topics in the field of transport planning.

Most of the conventional traffic assignment models (Sheffi, 1985) have only considered the perceived link travel time errors (and/or variances) when estimating drivers' route choices under the DIS environment. This study introduces a new approach of time-dependent stochastic probit assignment models for investigating the benefits of the provision of the DIS. The proposed time-dependent stochastic probit assignment model takes account of both the measured link travel time error variances and the perceived link travel time error variances.

The measured travel time error variances which relate to the quality of information are not considered in previous related work. However, the route choice behaviour and the acceptance rate of the advice are closely correlated with the prediction precision and quality of travel time information (Yang et al., 1993), also the un-informative and inaccurate information causes overreaction (Emmerink et al., 1995a). This study seeks to overcome such limitations. This research brings a new concept of considering measured link travel time error variances.

In fact, the measured link travel time error variances can be a function of speed detector density. The choice of the speed detector density is related to the investment cost (in terms of the social cost of the speed detectors) and the link travel time measurement error. In this study, a bilevel programming model is proposed for determining the optimal detector density which can minimize both the investment cost and the link travel time measurement error. The lower-level problem is a stochastic user equilibrium (SUE) assignment model to take account of the effects of various measurement on and perceived errors in travel times. The upper-level problem is to determine the optimal speed detector density that minimizes the measured link travel time errors, as well as the social cost of the speed detectors. In the past, very little has been done on the effects of the speed detector density. However, speed detector density will have significant impacts on the measured link travel error variances under DIS environment. Filling that gap is one of the main objectives of this research.

In order to do so, there is a need to review the advances on SUE model development. Basically, there are two types of SUE model; namely, logit and probit assignment models. Their new development will be investigated in this research.

1.3 OBJECTIVES OF THE RESEARCH

The objectives of the research are to develop the stochastic traffic assignment models for DIS applications by:

(i.) proposing a new alternative logit assignment approach;

(ii.) proposing a probit assignment approach for taking account both of the measured link travel time error variances and the perceived link travel time error variances;

(iii.) investigating the effects of the DIS by the time-dependent stochastic probit assignment model;

(iv.) estimating the link travel times by using the speed detector data;

(v.) conducting a stated preference (SP) survey and calibrating the drivers' route choice model by using the SP data;

(vi.) determining the optimal detector density under the DIS environment; and

(vii.) validating the proposed time-dependent stochastic probit assignment model by a case study in Hong Kong.

1.4 STRUCTURE OF THE THESIS

The thesis contains ten chapters. The first chapter presents the background of the research. A literature review of existing stochastic user equilibrium (SUE) models, the applications and evaluations of the DIS and the link travel time estimation methods is given in Chapter 2.

Chapter 3 proposes a link-based alternative to Bell's node-based logit assignment method (Bell, 1995) to progressively eliminate cycles which exist in Bell's method. The absence of any efficiency constraint on the set of feasible paths makes the link-based logit assignment method attractive for use in the SUE method or in the approximation of user equilibrium (UE) through SUE.

In Chapter 4, a probit assignment model is presented for estimating the link flows and their variances. The effectiveness of the probit assignment model and the simulation method are illustrated in the numerical example.

A time-dependent probit assignment model is proposed in Chapter 5 for investigating the effects and benefits of providing the DIS. The measured link travel time error variances and the perceived link travel time error variances are taken into account in the proposed model. The simulation technique, shortest path algorithm and method of successive average (MSA) are adopted in the proposed model.

In Chapter 6, link travel times are estimated by a new method, plus two existing methods by using speed detector data. The link travel time estimation results are evaluated by the observed data collected at the selected site on Tsing Ma Control Area (TMCA) in Hong Kong. The link travel time and link speed distributions have been investigated using data collected from the manual license plate number survey.

In Chapter 7, a stated preference (SP) survey is conducted to gauge driver reaction to road traffic information. The relationship between the provided travel times and the drivers' perceived travel times are investigated. In the SP survey, drivers are asked to choose the expressway and urban road for travel from the Hong Kong Chek Lap Kok (CLK) international airport to the urban area. The SP logit model for route choice is calibrated by using the SP data.

Chapter 8 presents a bilevel programming model for determining the optimal speed detector density. The lower-level problem is a probit assignment model, while the upper-level problem is to determine the speed detector density that minimizes the measured travel time error variances as well as the social costs of the speed detectors. A sensitivity based solution algorithm for solving the proposed bilevel programming model is derived in Chapter 8.

A Hong Kong case study in is presented in Chapter 9. The case study is used to validate the time-dependent stochastic probit assignment model in Chapter 5 and to compare its results against the calibrated SP logit model in Chapter 7. Finally, the contributions of this thesis are summarized in Chapter 10 and recommendations for further research are given.

Figure 1.1 shows a flowchart which highlights the interrelations between the core subject and all other research subjects such as the estimation of link travel times.

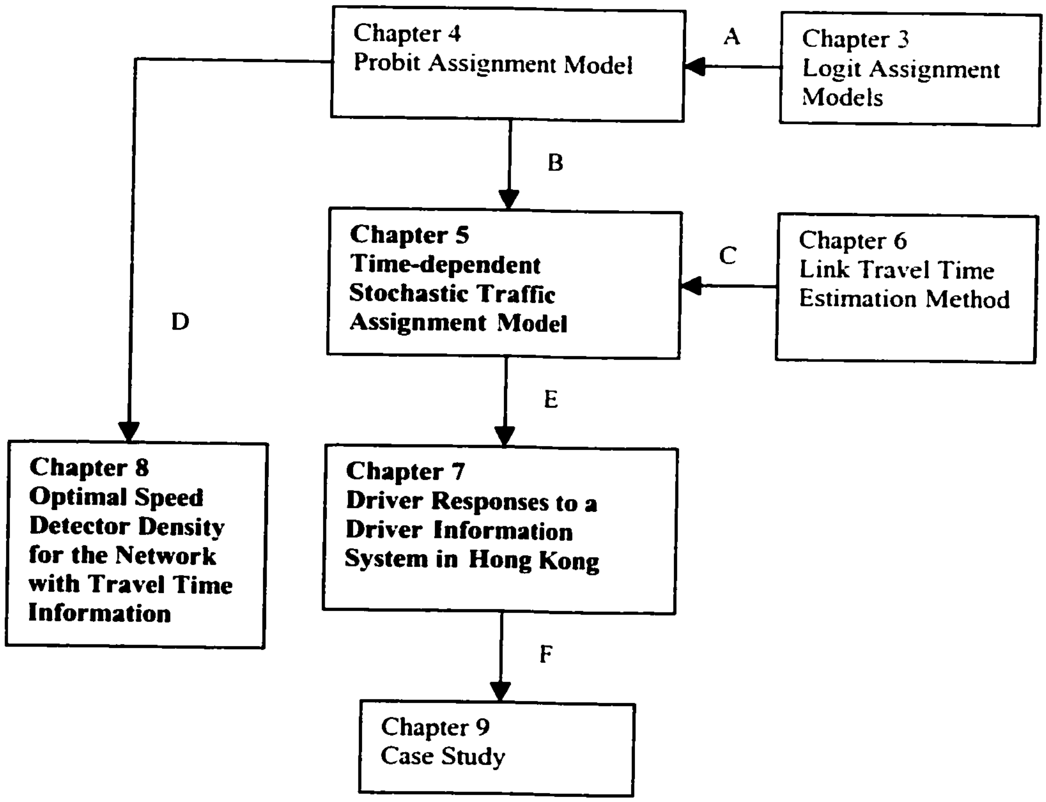

Figure 1.1 Interrelations between the Chapters

In this thesis, the relationships between the chapters are illustrated in Figure 1.1 with arrows from A to F. They are briefly outlined as follows:

A - The logit assignment models in Chapter 3 are enhanced for alleviating the cyclic flow problem and then used to compare with the probit assignment model in Chapter 4.

B – The static probit assignment model in Chapter 4 is firstly calibrated and validated with real data in Hong Kong. In Chapter 5, it is extended to the time-dependent stochastic traffic assignment (or quasi-dynamic probit assignment) model for assessing the drivers' route choices under DIS.

C - The link travel time estimation method in Chapter 6 is related to the measured travel times and its errors presented in Chapter 5. This can be incorporated into the time-dependent stochastic probit assignment model in Chapter 5.

D - The static probit assignment model in Chapter 4 is adopted in the lower level problem of the bilevel programming model in Chapter 8 for determining the optimal speed detector density in the network with travel time information.

E – Interview survey in Chapter 7 is conducted to collect data for calibrating and validating the time-dependent stochastic probit assignment model in Chapter 5.

F – The case study in Chapter 9 presents the model calibration and validation by using the results obtained from Chapter 7.

2 LITERATURE REVIEW

This research is believed to be the first thorough investigation of the driver information system (DIS) by developing a stochastic traffic assignment model which takes account of both the measured and the perceived link travel time error variances.

Both the perceived and measured link travel time error variances are strongly related to the DIS. The perceived link travel time error variances are concerned with the drivers' responses to the DIS. The measured link travel time error variances are related to the accuracy of the provided travel times which are also very important. In this research, the measured link travel time error variances is a function of speed detector density and a bilevel programming approach is proposed to determine the optimal detector density under the DIS environment. Therefore, a review is given for the evaluations and implementations of the DIS. According to the review, stochastic user equilibrium (SUE) assignment models are suitable for investigating the DIS.

Both the logit and probit assignment models are well known SUE models. The SUE assignment models are reviewed to show the advantages and disadvantages of the logit and probit assignment models. The link flow variance-covariance matrix can not be obtained from the logit assignment model due to its assumption of independence between link flows and path flows. Therefore, the probit assignment model is adopted in the bilevel programming approach for determining the optimal detector density. The probit assignment model is also extended to a time-dependent dimension for assessing the benefits of the DIS.

The previous research work shows that the benefits of the DIS are affected by the accuracy of the provided travel time information. Therefore, good link travel time estimation is important. In this study, a link travel time estimation method is proposed and is compared with other existing methods. Thus, the previous link travel time estimation methods in the literature is also outlined.

Consequently, a collective review of literature has been carried out to discover ideas in the evaluation and implementation of the DIS, previous SUE models and the link travel time estimation methods. The outline of this chapter is as follows. Section 2.1 gives a review on the existing DIS evaluations and implementations. Section 2.2 presents some previous related works on SUE assignment models. Section 2.3 outlines the previous link travel time estimation methods. Finally, Section 2.4 gives a summary of this chapter.

2.1 DRIVER INFORMATION SYSTEM (DIS)

Providing DIS to drivers has the potential to get significant benefits in terms of travel time saving. These facts have to be studied in detail. Attention is paid in the literature to the investigation of the drivers' reaction to the DIS and the effect of providing the DIS in this research together with development of models and stated preference (SP) survey for assessing the impacts of the DIS. Section 2.1.1 describes the previous research work in the DIS. Section 2.1.2 gives a review of the applications of the SP approach to investigate the effect of providing the DIS.

2.1.1 Previous Research Work on Driver Information System

In this section, the previous research work on the DIS are outlined. Firstly, Section 2.1.1.1 provides a review of the evaluation works of the DIS in previous work. This is followed by a description of the DIS implementation in practice in Section 2.1.1.2.

2.1.1.1 Driver information system evaluation

Peeta et al. (1991) adopted simulation model for revealing the level of benefits arising from the provision of the DIS. The simulation results found that the location of an incident and its duration are important factors. There is a complex interaction between the parameters of the incident, the information strategy used and the behaviour of the drivers. Mahmassani and Jayakrishnan (1991) proposed a modelling framework to obtain the overall performance of the in-vehicle real time information on a congested network.

Yang et al. (1993) developed a neural network approach to investigate the driver's response to the advanced traveler information system (ATIS). It was found that the route choice behaviour was related to the accuracy of the information provided and the characteristics of the respective routes. Meanwhile, Lotan and Koutsopoulos (1993) used the fuzzy set theory and fuzzy control to model the route choice behaviour under the DIS. Khattak et al. (1993) adopted a multinomial logit model to determine the driver's diversion to alternative routes. It was found that: (a) the benefits of the ATIS on driver's diversion could be increased by giving precise information on the congested road sections, and (b) in case of incidents, knowledge of the nature of the event and the actions to clear it were important.

Emmerink et al. (1995a) focused on the effects of different types of information provision to drivers in a network with recurrent congestion and found that un-informative and inaccurate information causes overreaction. Emmerink et al. (1995b) conclude that it is impossible for the drivers to use the road network efficiently (in terms of total network travel time) if no information is provided on networks with non-recurrent congestion. Emmerink et al. (1995a, 1995b) used a simulation model in which the traffic flows are the aggregation of drivers' decision.

Nihan et al. (1995) investigated the interaction between the DIS, route choice, and optimal traffic signal settings. The logit model and the method of successive averages (MSA) were applied to calculate the route choice probabilities and the stochastic equilibrium assignment. It was concluded that a unique joint signal timing/assignment equilibrium was reached in all cases provided that a certain precision in drivers' perceptions was not reached. If driver information increases in precision, the unique joint signal timing/assignment equilibrium no longer exists.

Nijkamp et al. (1996) presented a case study regarding the variable message sign (VMS) in the Netherlands. It was found that the benefits of the VMS are the reduction in travel time and the reduction of drivers' uncertainty with respect to the traffic situation. Richards et al. (1996) adopted the RGCONTRAM modelling approach to analyze the factors which influence the effectiveness of the VMS. It was assumed in the model that the proportion of drivers who divert at the VMS is user-defined and that drivers are diverted to the user-defined diversionary routes.

Ramsay et al. (1997) evaluated the benefits of the VicRoads' Drive Time System installed on Melbourne's South Eastern Arterial. The Trip information sign of that Drive Time System provides estimated travel times to major arterial exit points. The benefits of Drive Time are in delay reductions due to increase in traffic diversions from the South Eastern Arterial when incidents occur, and also due to less incidents as a result of reduced stress and better predictive information. Catchpole et al. (1995) reported that the DIS on freeways would be considered desirable and useful by the great majority of drivers in the community.

Lim and Lee (1997) proposed an integrated dynamic traffic assignment approach for responsive signal control and VMS information. They expected this model to be useful for evaluating the various diverse strategies of Intelligent Transportation System (ITS). Mammer et al. (1996) adopted the decentralized feedback control method to the Aalborg highway network in Denmark. This approach first calculates each path's time based on the real time detector measurements and a desired diversion rate is approximated by displaying a suitable message to the drivers which are known to have impact to drivers diversion in different degrees. The objective of the decentralized feedback control is to equalize the time for each pair of alternative paths.

Khattak (1998) examined the drivers' spatial knowledge and responses to unexpected delay information. The behavioral responses of drivers to information across Chicago and the San Francisco Bay Area were compared. Data were collected through handout-mailback questionnaires targeting peak-period automobile commuters. Results showed that longer duration of residence, higher propensity for discovering new routes, and locational characteristics tend to increase drivers' spatial knowledge. It was found that drivers with a higher propensity for taking risks to avoid unexpected delays are more likely to divert. It was indicated that delay information received through radio traffic reports, as opposed to other sources such as self-observation of congestion, increases en route diversion propensity in unexpected delay situations. Therefore, this implicated that the potential benefits from the ATIS must compete with the benefits already accruing from radio traffic information.

Al-Deek et al. (1998) developed a framework for evaluating the effect of the ATIS. A composite traffic assignment model which combines a probabilistic traveler behavior model and a queuing model was proposed. They aimed to evaluate the ATIS impacts under incident conditions. Three types of travelers were considered: (a) those unequipped with electronic devices; (b) those who receive delay information from radio only; and (c) those who access ATIS only. Their findings showed that the overall system performance, measured by average travel time, improves marginally with increased market penetration of ATIS. However, the benefits of ATIS under incident conditions are expected to be marginal when there is more information available to travelers through the radio. This is because delay information, received through radio, induced drivers' diversions earlier. This affected the potential benefits of ATIS Systems.

Yang et al. (1998) developed a driving simulator to investigate the types of information that drivers need. For a familiar network and encountering congestion and delay caused by an unexpected traffic incident, drivers only need short and simple information, such as the location of the incident and expected delay time. For unfamiliar networks, the need for information such as alternative route recommendations and directions to alternative routes are strong.

Chatterjee and McDonald (1999) considered the accident risk of different routes as part of the route recommendation process by integrating the accident predictive models with a traffic network model designed to simulate route guidance. They investigated the effect of considering accident risk in route recommendations.

Yang et al. (1999) examined the assumption of "uniform market penetration" in the existing evaluation studies of ATIS. The findings showed that this assumption might possibly lead to underestimation of the benefits derived from ATIS. They indicated that information benefit and the market penetration of ATIS depend strongly on the trip characteristic such as trip length; ignoring such an important factor may give rise to misleading ATIS performance results.

Recently, Chen et al. (2001) developed an individual behavioral-based mechanism for exploring the crucial criteria affecting drivers' route choices. They used a weight-assessing model and the habitual domain theory. The effects of information on drivers' route-formulating behaviors is investigated. An empirical study in Taipei City was conducted to show the feasibility and applicability of their methods and the empirical results indicate good performance in practice.

2.1.1.2 Driver information system implementation

Bieserbos and Zijerhand (1995) described the SOCRATES (System of Cellular Radio for Traffic Efficiency and Safety) concept and system. This is basically a dynamic route guidance and driver information system based on the combination of electronic car navigation and bidirectional communication between the car and the outside world.

Tsugawa et al. (1997) presented a survey of present IVHS activities in Japan. The Japanese Government has been conducting IVHS (Intelligent Vehicle-Highway Systems) projects on ATMS (Advanced Traffic Management Systems), ATIS (Advanced Traveller Information Systems) and AVCS (Advanced Vehicle Control Systems). VICS (Vehicle Information and Communication System) started a driver information service including dynamic route guidance in the spring of 1996. At the same time, ASV (Advanced Safety Vehicle) aiming at active safety for passenger cars was demonstrated. An Automated Highway System was tested in 1995 on a test track. In the spring of 1997, it was then tested on an expressway, with inter-vehicle communication. In addition to Government projects, navigation systems have become widespread, and inter-vehicle distance warning systems for trucks and an intelligent cruise control system for passenger cars have become commercially available.

Messmer et al. (1998) presented the design, implementation, and evaluation work for the development of the DIS in the interurban Scottish highway network. The control strategy employed is based on simple automatic control concepts with both feedback and feedforward terms subject to user-optimum constraints. Feedforward terms are employed for the prediction of travel times and delays along long-distance interurban highway links.

2.1.2 Applications of Stated Preference (SP) Approach in the DIS

Much previous research work investigated drivers' responses to the DIS by using the stated preference (SP) approach and calibrating the route choice model using a logit-type model (Abdel-Aty et al., 1997; Lai and Wong, 2000; Wardman et al., 1997). Logit and probit models have been developed to predict whether commercial drivers or dispatchers use an ITS and to quantify travelers' ratings of the importance of in-vehicle system attributes (Mannering et al., 1995; Ng et al., 1995).

A number of studies have been performed on drivers' route choice. Previous researchers (Duffell and Kalombaris, 1988; Huchingson et al., 1977) have indicated that travel time is the most important factor affecting an individual's route choice. Recent studies (Bonsall, 1992; Bonsall and Palma, 1998) have found that delay and congestion were also important determinants of route choice. Therefore, travel time and congestion conditions are important for the SP hypothesized choice experiment design.

Khattak et al. (1993) evaluated the effects of real-time traffic information along with driver attributes, roadway characteristics and situational factors on drivers' willingness to divert. The SP approach was used to study commuters' diversion propensity. The findings indicated that drivers expressed a higher willingness to divert: (a) if expected delays on their usual route increased; (b) if the congestion was incident-induced as opposed to recurring; (c) if delay information was received from radio traffic reports compared with observing congestion and (d) if trip direction was home-to-work rather than work-to-home. Drivers were less willing to divert if their alternate route was unfamiliar, unsafe or had many traffic stops.

Polak and Jones (1993) adopted a SP approach to study the effects of pre-trip information on travel behaviour. They investigated travellers' requirements for different types of travel information and methods of enquiry and to relate the process of information acquisition to changes in travel behaviour. The SP approach was built on the use of a microcomputer based simulation of an in-home pre-trip information system offering information on travel times from home to City Centre, by bus and car, at different times of the day.

Bonsall and Merrall (1995) used the VLADIMIR route choice simulator to collect data on driver's response to the VMS and found that the journey time information is the prime determinant of route choice. Zhao et al. (1996) investigated driver's en-route diversion behaviour in response to traffic information by calibrating a logit model based on the stated preference data. Emmerink et al. (1996) conducted an empirical analysis to provide insight into the impacts of radio traffic information and the VMS displaying dynamic traffic information on the route choice behaviour.

Wardman et al. (1997) used a SP approach to undertake a detailed assessment of the effect on drivers' route choice of information provided by the VMS. It was found that route choice could be strongly influenced by the provision of information about traffic conditions ahead. This had important implications for the use of VMS systems as part of comprehensive traffic management and control systems. The principal findings were that the impact of VMS information depends on: the content of the message, such as the cause of delay and its extent; local circumstances, such as relative journey times in normal conditions; and drivers' characteristics, such as their age, sex and previous network knowledge.

Abdel-Aty et al. (1997) presented a statistical analysis of commuters' route choice including the effect of traffic information. Two route choice models were estimated. The first one used five hypothetical binary choice sets collected in a computer-aided telephone interview. The first model determined how travel time variation affects route choice, and the potential interplay among travel time variation, traffic information acquisition and route choice. The second model used data collected in a mail survey from three binary route SP scenarios customized according to each respondent's actual commute route and travel time. The aim of this model was to investigate the potential effect of the ATIS on route choice.

Recently, Wong and Lai (1999) determined the effects of VMS display formats in drivers decision-making process. Drivers' behaviour is quantified and expressed by utility functions. The respondents were divided into two categories regarding their listening propensity to radio traffic information. The findings showed that driver preference of travelling on a route could be affected by presenting identical traffic information in different formats.

Lai and Wong (2000) attempted to examine driver comprehension of the traffic information that is presented in three formats: (a) the numerical format; (b) the description format and (c) the switch-on-light format. Binary logit models with respect to drivers' traveling preference of two designated routes under different traffic conditions were developed. The explanatory variables employed in the models include those referring to respondents' socioeconomic background and those characterizing the transport network. The results indicated that drivers have different comprehension of the formats for presenting traffic information on the VMS, and the message formats can induce biases toward a route in drivers' decision-making processes.

There is growing literature on combing supplied information (estimated travel times) with actual experience. Jha et al. (1998) developed a bayesian updating model to capture the mechanism by which travelers update their travel time perceptions from one day to the next in light of information provided by DIS and their previous experience. Adler (2001) investigated the learning effects of route guidance and traffic advisories on driver's route choice behavior. The results indicated that there may be significant short-term advantages to providing in-vehicle routing and navigation information to unfamiliar drivers.

According to the review of the previous works in the DIS, it can be observed that the SUE models are applied for investigating the impacts of the DIS. In this research, the proposed SUE model is also used for evaluating the DIS. Therefore, Section 2.2 will give an overview of the existing SUE models.

2.2 OVERVIEW OF EXISTING STOCHASTIC USER EQUILIBRIUM (SUE) MODELS

It is well known that the user equilibrium (UE) traffic flow pattern (Wardrop, 1952) can be obtained if each driver has perfect knowledge about the network condition, which is nevertheless impossible in practice. However, stochastic user equilibrium (SUE) assignment is a more reasonable approach, in taking account of the individual's perceived travel times as a random variable. Therefore, SUE is a more general statement of equilibrium than the UE conditions (Sheffi, 1985).

The UE definition can be stated as:

"For each O-D pair, at user equilibrium, the travel time on all used paths is equal, and (also) less than or equal to the travel time that would be experienced by a single vehicle on any unused path." The UE objective function can be written as:

$$\sum_k \int_0^{v_k} C_k(x)dx \tag{2.1}$$

where v_k is the flow of link k and $C_k(x)$ is the travel time function of link k.

The definition means that at equilibrium, the paths connecting each O-D pair can be divided into two groups. The first group includes paths that carry flow. The travel time on all these paths will be the same. The other group includes paths that do not carry any flow. The travel time on each of these paths will be at least as large as the travel time on the paths in the first group.

However, with SUE, no motorist can improve his or her perceived travel time by unilaterally changing routes. In other words, the UE condition are a particular case of SUE; when the variance of travel time perception is zero, the SUE conditions are identical to the UE conditions. The SUE objective function is:

$$\sum_k \int_0^{v_k} C_k(x)dx + \sum_j h_j(\ln h_j - 1)/\alpha \qquad (2.2)$$

where v_k is the flow of link k, $C_k(x)$ is the travel time function of link k, h_j is the flow of path j and α is the dispersion parameter.

To determine the SUE route choices of a network, it is necessary to adopt a stochastic network loading model. The stochastic network loading model allocates a set of O-D trips to a transportation network in which the link travel times are fixed. The logit approach to stochastic network loading was suggested by Dial (1971) model in which the perceived travel time errors are distributed using the Gumbel distribution. The application of the probit approach to stochastic network loading was suggested by Daganzo and Sheffi (1977). For the probit approach, the errors of the perceived travel times are normally distributed.

The difference between the stochastic network loading models and the SUE models is that the link travel times are flow dependent in the SUE models. In other words, the link travel times are functions of the link flow in the SUE models. It is well known that there are two categories of the SUE assignment model. The first is the logit assignment model in which the stochastic network loading model is the logit model. The other is the probit assignment model, the stochastic network loading model is the probit model.

Section 2.2.1 describes the logit assignment models and the logit-based stochastic network loading models in the literature. Section 2.2.2 gives the review of the probit assignment models and the probit-based stochastic network loading models. Section 2.2.3 describe the dynamic traffic assignment models in the literature.

2.2.1 Logit Assignment Models

For the logit assignment model, the relationship between the perceived path travel time C_k and the measured path travel time c_k for kth path can be expressed as,

$$C_k=c_k-\varepsilon_k/\alpha \tag{2.3}$$

where ε_k is the random component and α is the dispersion parameter.

A large value of α indicates a small perception error and most of the drivers will select the minimum travel time route. If α is small, the perception error is large and the drivers will choose many routes with large travel time.

In this section, the logit assignment algorithms, the applications of the logit assignment models and the recent modified logit assignment models are described. Section 2.2.1.1 gives a review of the logit assignment algorithms. Section 2.2.1.2

presents the applications of the logit assignment models. Section 2.2.1.3 describes the new modified logit assignment models in the literature.

2.2.1.1 Logit assignment algorithm

In 1971, Dial proposed the STOCH (logit assignmnet) method in which the perceived travel time errors are distributed Gumbel. Dial's stochastic assignment algorithm restricts the assignment path set to an efficient path. As a result, it sometimes produces the unrealistic flow pattern that no flow is loaded on some paths where many vehicles are running in reality. To remove this drawback of Dial's algorithm, Akamatsu (1996) presented the logit assignment method that does not restrict the assignment paths. An algorithm is proposed that does not require the matrix operation nor path enumeration over a network. The algorithm was based on the entropy decomposition derived from the Markov property of the logit model.

Bell (1995) proposed a node-based alternative to Dial's method. But Bell's method suffered from a cycle problem which produced an unrealistic link flow. In order to eliminate the cycle problems, a link-based alternative to Bell's logit assignment method was suggested by Lam et al. (1996) and induced in Bell's approach. Huang and Bell (1998) studied the Van Vliet formula in calculating the link choice probabilities for the logit assignment without cyclic flows. They provided a formula for removing cyclic flow but with the need for path enumeration and presented an approach to generate all non-looping paths and apply it to solve SUE problem in conjunction with the method of successive averages.

Controversally, there were objections to the use of a logit assignement model by some researchers because of the axiom of the Independence of Irrelevant Alternatives (IIA). Recently, a new approach was proposed for overcoming the IIA problems in the route choice logit model by introducing the commonality factor (Cascetta et al., 1996).

A logit-based mathematical programming problem was formulated for SUE by Fisk (1980). In 1995, Huang studied Fisk's SUE assignment model and showed that the stochastic properties of this model completely depend on the calibration parameter. A modified combined algorithm for solving and calibrating Fisk's stochastic traffic assignment model was developed. The algorithm achieved the path enumeration automatically and controlled the number of alternative paths generated by a predetermined function.

Damberg et al. (1996) presented a new algorithm for the approximate solution of the logit assignment problem. The advantage of this algorithm is that it provides route flows explicitly, of particular interest in the evaluation of route guidance and information systems.

Bell et al. (1997) sets out a path flow estimator suitable for use in conjunction with urban traffic monitoring, control and guidance. They partitioned the link travel time into undelayed travel time and delay. An equivalent convex programming problem was formulated and an iterative solution procedure set out. The estimation of the dispersion parameter in the logit model was discussed, and a column generation method to avoid path enumeration proposed.

Maher (1998) proposed an algorithm with optimal step length along the search direction for faster convergence. It was found that for all but the smallest network the version using the standard search direction gave the fastest rate of convergence.

2.2.1.2 Applications of the logit assignment models

Yang (1999) demonstrated that the classical principle of marginal-cost pricing is still applicable by using the logit assignment model. It showed that the marginal-cost link tolls were meaningful from both economic and behavioral viewpoints. It was concluded that the marginal-cost link tolls were a good alternative to drive a SUE flow pattern towards the system optimum.

Asakura (1999) showed that the SUE logit assignment model could be incorporated in the performance reliability model. The effects of providing information were analyzed using the SUE model with two different groups of route choices; informed drivers and non-informed drivers. The results indicated that providing information generally increases network performance reliability.

Lam et al. (1999) proposed a SUE logit assignment model for congested transit networks, together with a solution algorithm. A mathematical programming problem was formulated, that was equivalent to the SUE assignment model for a congested transit system. The proposed model could simultaneously predict how passengers will choose their optimal routes and estimated the total passenger travel time in a congested transit network.

2.2.1.3 Modified logit assignment models

Prashker and Bekhor (1998) investigated the network loading process of a stochastic traffic assignment. Although the multinomial logit model can be implemented efficiently in stochastic network loading algorithms, the model suffers from theoretical drawbacks, some arising from the independence of irrelevant alternatives property. The stochastic loading on routes that share common links is overloaded at the overlapping parts of the routes. Prashker and Bekhor (1998) investigated and compared three modified logit models: (a) the C-logit model, which was specifically defined for route choice; and two general discrete-choice models; (b) the cross-nested logit model; and (c) the paired combinatorial logit model. It was concluded that the cross-nested logit model has an advantage over the two other generalized models because it enables performing stochastic loading without route enumeration.

Vovsha and Bekhor (1998) presented a new link-nested logit route choice model. The model was derived as a particular case of the generalized-extreme-value class of discrete choice models. The model has a flexible correlation structure that allows for overcoming the route overlapping problem. A stochastic network loading procedure that obviates route enumeration was presented.

2.2.2 Probit Assignment Models

The difference between the logit assignment model and probit assignment model is mainly due to their covariance matrix. A logit assignment model has a simple covariance matrix, for example in the binary logit assignment model,

$$\Sigma = \sigma^2 I \tag{2.4}$$

where σ^2 is the variance of each alternative and I is an identity matrix of appropriate order. This covariance matrix is not suitable for the case when alternatives are not independent because the correlation terms will be non-zero. For the binary probit assignment model,

$$\Sigma = \begin{pmatrix} \sigma_1^2 & \rho\sigma_1\sigma_2 \\ \rho\sigma_1\sigma_2 & \sigma_2^2 \end{pmatrix} \tag{2.5}$$

where σ_1^2, σ_2^2 are the variances of the alternatives 1 and 2 respectively and ρ is the correlation coefficient between the two alternatives. Therefore, the probit assignment model has a more general covariance matrix structure and is useful when alternatives are not independent.

However, it is more restricted for solving the probit model than the logit model. The probit model can be solved by the simulation approach or the Clark's approximation. A simulation approach was firstly suggested by Daganzo and Sheffi (1977) for solving the probit assignment model. There is nevertheless no closed form for the probit model (Daganzo, 1979), a simulation assignment algorithm was therefore developed by Powell and Sheffi (1982) using the randomized link travel times and fixed step size. Recently, a new heuristic probit stochastic assignment method was proposed (Maher and Hughes, 1997) which does not require Monte-Carlo simulations but suffers from the cycle problems and need to adopt the Clark's approximation while scanning the network from origin to destination.

Maher and Hughes (1997) described a probit assignment method which does not require path enumeration. They developed a new SUE model by incorporating capacity restraint (in the form of link-based cost-flow functions) into this stochastic loading method. The SUE problem was expressed as a mathematical programming problem, and its solution found by an iterative algorithm with optimal step length.

Fu (1998) defined the dynamic and stochastic shortest path problem (DSSPP) as finding the expected shortest path where the link travel times are modeled as a continuous-time stochastic process. Its objective was to examine the properties of the DSSPP problem and to identify the availability for solving the DSSPP in networks with ITS. A heuristic algorithm based on the k-shortest path algorithm to solve the problem was proposed. The solution quality and computational efficiency of the proposed algorithm was demonstrated.

More recently, Nielsen (2000) presented a framework for a public traffic assignment that builds on the probit model of Sheffi and Powell (1982). The simulation of perceived travel times was extended to describe differences in the distribution of travel- and waiting times for different sub-modes. Preliminary tests showed that the methodology could describe route choices in public transport. This is both due to the model's ability to describe overlapping routes and also to the many different error components and distributions that make it possible to calibrate the model.

Although the computation burden of simulation is substantial, the simulation approach is now widely used in transportation problems. (Benekohala and Zhaob, 2000; Bhat, 2000; Garrido and Mahmassani, 2000; Nielsen, 2000)

In this research, the probit assignment model is proposed. The probit assignment model is incorporated in the proposed bilevel programming approach for determining the optimal detector density. The probit assignment model is also extended to a time-dependent stochastic traffic assignment model which is adopted for analyzing the drivers' reactions to the information provided by the DIS. Therefore, Section 2.3 gives a review of the previous dynamic traffic assignment models.

2.2.3 Dynamic Traffic Assignment Models

The development of the dynamic traffic assignment (DTA) models has been a substantial research topic during the past decade. DTA is given increasing attention due to the potential of the ITS applications. DTA models can be broadly classified into two approaches: mathematical formulation and simulation.

The advantages of the mathematical formulation approach are that the unique and optimal solutions which satisfy the Wardrop's principle can be obtained. The previous related works on DTA include the fixed-point problem approach (Asmuth, 1978), the nonlinear complementarity problem (Aashtiani, 1979) and the variational inequality approach (Friesz et al., 1993). Recently, a dynamic traffic assignment formulation is proposed by incorporating the cell-transmission model (Lo, 1999).

However, the mathematical formulation approach has a disadvantage that involves the difficulties of formulating and solving the mathematical programming problem properly. Therefore, most of the DTA approaches use a simulation platform to model the traffic dynamics (Chang and Mahmassani, 1988; Van Vuren and Watling, 1991; Van Aerde, 1994; Peeta and Mahmassani, 1995). The advantages of the simulation approach are: (1) it is flexible, user classes can be added and defined; (2) the macroscopic traffic flow dynamics can be introduced; and (3) it permits transparent understanding. However, the disadvantages of the simulation approach are that the solution quality and property cannot be guaranteed. Consequently, simulated solutions may not necessarily follow Wardrop's principle, nor guarantee to be globally optimal (Ran et al., 1996).

On the other hand, the previous work on DIS shows that the quality of travel time information is very important. As a result, the accuracy of the link travel time is also a key factor affecting the driver behaviour under DIS environment. Therefore, the link travel time methods are investigated in this research. Section 2.3 gives a review of the previous link travel time estimation methods.

2.3 LINK TRAVEL TIME ESTIMATION METHODS

Detector data have been conventionally collected for traffic surveillance and control purposes, e.g. detection of an accident. Owing to the initiatives of the ITS, there is a growing demand for using the detector data to provide travel time estimates.

More attention has been given to the estimation of freeway travel times using traffic information collected from single-loop detectors, namely, occupancies and flows (Dailey, 1993 & 1999; Pushkar et al., 1995; Sisiopiku et al., 1995; Petty et al., 1998). With the use of the data collected from single-loop detectors, algorithms have to be firstly devised to estimate the vehicle travel speed that can then be used to estimate the link travel time. For example, the travel time from an upstream detector station to a downstream detector station was expressed as a power series function of the speed estimates at the two detectors (Dailey, 1997).

As reported by Sisiopiku and Rouphail (Sisiopiku and Rouphail, 1995), research to date has not yet produced satisfactory formal analytical link travel time functions particularly for application in large-scale transportation networks. Thus, empirically regression-based approaches have been conventionally adopted for link travel time estimation.

Vehicular travel time is increasingly becoming important for assessing the level of mobility in urban areas. Link travel time is considered to be a key variable for real-time network information and traffic control purposes. Hence, travel time estimation is a fundamental input to transport planning and management. It clearly indicates the operation of traffic flow and performance of the transport facility. Although attempts have been made to estimate/forecast travel times on freeways and/or urban roads, more attention has been given to estimate travel times directly from flow measurements.

With the advent of ITS, there is a growing demand for using the detector data to provide link travel time estimates. There is a classical approximate method to compute the space mean speed (or link speed) using the detector data such as the time mean speed (or point speed) and the variance of the time mean speed (Gerlough and Huber, 1975). Recently, more attention has been given to predict travel times using occupancies and flows (Dailey, 1993; Nam and Drew, 1999; Pushkar et al., 1995; Sisiopiku and Rouphail, 1995; Petty et al., 1998). With the use of the data collected from single-loop detectors, algorithms have to be devised firstly to estimate the link travel speed that can then be used to estimate the link travel time.

Various attempts were made during the past two decades to develop link travel time estimation methods using traffic information collected from single-loop detectors, namely, occupancies and flows. Dailey (1993) employed a cross-correlation technique to predict travel time. The model used link flow measurements to determine the maximum correlation between continuous concentration signals generated from link flow measurements. The model requires fewer traffic parameters. However, this model may not work well under congested traffic conditions, because the correlation may disappear under such circumstances.

Dailey (1997) also presented an algorithm for estimating travel time using volume and occupancy data from a series of single inductive loops. Dailey models speed as a stationary Gaussian process plus observer Gaussian error and then uses a Kalman Filtering method for estimating the actual speed of a particular vehicle from single-loop detector data. The algorithm firstly produced an estimation of speed and then predicted the travel time. The model required several parameters that must be properly estimated first. Abours (1986) calibrated regression models to estimate travel times from loop occupancies for a case study in Paris.

Nam and Drew (1996 and 1999) presented a model for predicting freeway travel time directly from the traffic flow measurements. The model was based on the stochastic queuing theory and the principle of conservation of vehicles. The link travel time was determined by measuring the cumulative flow from two loop detectors at each end of the link. The model incorporated several hypotheses of traffic conditions. However, it was required to adjust and/or modify the input data for the model estimation particularly when the cumulative departure and arrival flow curves cross each other due to errors of the detector data.

Petty et al. (1998) presented a methodology to estimate link travel times directly from the single-loop detector's flow and occupancy data based on a stochastic approach, in which vehicles that arrive at an upstream point during a given interval of time have a common probability distribution of travel times to a downstream point.

Cremer (1995) estimated route travel time using a macroscopic simulation model in which the time-dependent speed profile is generated for all the routes within a given network. The model was formulated for the estimation of individual travel time with the use of a concept of virtual vehicle.

Makigami et al. (1996) developed a procedure for estimating travel time on an expressway covering a long distance using a calibrated simulation model. The model estimated travel time by adjusting the origin-destination (O-D) matrix and minimizing the difference between the estimated and detected traffic flows.

As reported by Sisiopiku and Rouphail (1995), satisfactory results on formal analytical link travel time functions have not yet been available particularly for application in large-scale transportation networks. Thus, empirically regression-based approaches have been conventionally adopted for the estimation of link travel time.

2.4 SUMMARY

In this Chapter, the evaluations and implementation of the driver information system (DIS) are examined. Various types of logit and probit stochastic user equilibrium (SUE) assignment models are reviewed for evaluation of the DIS. The link travel time estimation methods in the literature are briefly described.

There are many previous attempts for evaluating the impacts of the DIS. Previous research has shown that the quality of the travel time information is very important. The quality and accuracy of the travel time information depends on the speed detector density. In this research, the measured link travel time error variances which are functions of the speed detector density are considered. By adopting measured link travel time error variances, a bilevel programming approach to determine the optimal detector density under the DIS environment is proposed.

Previous work for investigating the benefits of the DIS showed that SUE models are applied. For the SUE models, there are advantages and disadvantages of the logit and probit assignment models. Bell (1995) proposed a logit assignment method for removing drawbacks of the classical Dial's logit assignment method (1971) but suffered from a cycle problem. An alternative to Bell's method is therefore proposed to reduce that cycle problem. However, a logit assignment model has a simple covariance matrix (see eqn. (2.4)). Nevertheless, the probit assignment model has a more general covariance matrix structure (see eqn. (2.5)) and is useful when alternatives are not independent. In this research, both the measured and perceived link travel time error variances are considered. Therefore, the probit assignment model is more suitable in this study. A probit assignment model is proposed for taking account of both the measured and perceived link travel time error variances. The proposed probit assignment model is extended to a time-dependent stochastic traffic assignment model for assessing the benefits of providing the DIS.

Previous work showed that the benefits of providing the DIS are mainly due to the travel time information provided to the drivers. Therefore, the accuracy of the link travel time is an important factor affecting them. Therefore, a link travel time estimation method is proposed and compared with two other existing methods in this research.

3 LOGIT ASSIGNMENT MODELS

In Chapter 2, a review of the existing logit assignment models is given. In Chapter 3, three alternatives to Bell's logit assignment method are proposed. A Bell's logit assignment method was proposed as an alternative to Dial's algorithm. While retaining the absence of a need for path enumeration, Bell's method dispenses with either a forward or a backward pass. It therefore does not require minimum node-to-node travel time information beforehand. The only constraint on the set of feasible paths imposed is that there are no loops and/or cycles. However, it is difficult to avoid loops in real networks.

In order to minimize the cycle problems, a link-based alternative to Bell's logit assignment method is proposed making use of the method of successive averages (MSA). The absence of any efficiency constraint on the set of feasible paths makes the method attractive for use in stochastic user equilibrium assignments. Two extensions of the proposed method to limit the number and type of cycles permitted in the feasible path set are also discussed. Numerical examples are given to illustrate the applications of the proposed method and to compare the results with other assignment methods.

3.1 INTRODUCTION

Dial's algorithm (1971) has been widely used for solving the fixed-time logit assignment problem. For congested networks, Powell and Sheffi (1982) proposed a stochastic user equilibrium (SUE) assignment method using Dial's algorithm. For solving the network design problem (NDP), a version of Dial's method was adopted by Davis (1994) under the assumption of SUE.

There are a *forward pass* and a *backward pass* in Dial's method. On the *forward pass*, the weights are assigned to all the links, moving from node to node according to increasing minimum time from the origin. For the *backward pass*, the traffic is assigned to the links according to the weights. Path enumeration is not required. Due to the sequence of processing in the forward pass, only those paths which lead away from the origin are considered. Consequently, each link in the path must increase the minimum time from origin. All efficient paths must lead away from the origin which introduce the concept of *efficiency*. A further condition added by Dial, that all efficient paths should lead toward the destination, implies that each link should reduce the minimum time to the destination. This condition slows Dial's method.

A necessary requirement of Dial's algorithm for calculating minimum times is that the minimum time from each origin to any node if the less restrictive definition of efficiency is used. For congested networks, a problem arises because the congestion's level and distribution influences the efficiency or otherwise of a path. Therefore, the problems of convergence may exist for the iterative SUE assignment methods that incorporate Dial's method, such as the method of successive averages proposed by Powell and Sheffi (1982).

Bell (1995) has proposed a simple method for solving a logit assignment model that dispenses with the need for either a forward or a backward pass. As with Dial's method, path enumeration is not required. There is no efficiency constraint on feasible paths and therefore no need to know minimum times beforehand. The only constraint imposed on feasible paths is that there should be no cycles. Since the method is similar in structure to the shortest path algorithm of Floyd (1962) and Warshall (1962), minimum times and their associated paths may be determined simultaneously.

In the early' eighties, the Land Use Transport Optimization (LUTO) model was developed for Hong Kong strategic planning. In the LUTO network analysis submodel, a road assignment is carried out by a multi-path stochastic assignment technique, and subsequently improved by a volume-averaging process until the major link flows are sufficiently close to the equilibrium state (Choi, 1986).

In fact, there are different methods for stochastic traffic assignment and it becomes fashionable to use the analytical stochastic assignment method instead of the simulation approach (Maher, 1992; Akamatsu, 1996). In this chapter, the proposed method is one of the analytical methods. As with Bell's method, path enumeration is not required in the proposed method and the absence of any efficiency constraint on the set of feasible paths makes the proposed algorithm attractive for use in the SUE assignment.

This chapter extends Bell's logit assignment method to eliminate unreasonable cycles from the feasible path set. The purpose of this chapter is to introduce an alternative traffic assignment algorithm proposed by Bell. First, the assumptions and definitions of SUE are briefly described. Second, the basis for Dial's method and its implication are presented. The basis for Bell's methods is briefly reviewed to provide a background for the problem of cycle in the logit assignment. There follows a presentation of the link-based method for removing some of the cycles in the Bell's logit assignment, together with discussions on its extensions in practice. The extent and nature of the censoring of cycles by the proposed method and its applications in conjunction with the MSA are illustrated by numerical examples together with a comparison of other assignment methods.

3.2 ASSUMPTIONS AND DEFINITIONS

The SUE objective function for the logit assignment is:

$$\sum_{u} \int_{0}^{V_u} c_u(x)dx + \sum_{p} h_p(\ln h_p - 1)/\alpha \tag{3.1}$$

where h_p is the traffic flow on path p and α is the dispersion parameter of the perceived travel time error.

For the probit assignment model, the drivers' perceived travel time error ξ_u of each link u can be assumed as normally distributed with mean zero and variance σ_u c_u where σ_u is the dispersion parameter of the perceived travel time error for link u and c_u is the measured travel time of link u.

$$\xi_u \sim N(0, \sigma_u c_u) \tag{3.2}$$

3.3 CYCLE PROBLEM

3.3.1 Basis for Dial's Method

Let

c_u = the travel time of link u

a_{upij} = the number of times link u is included on path p between i and j

c_{pij} = the travel time of path p from i to j

Since the path times are the sum of the link times

$$c_{pij} = \sum_u a_{upij}\, c_u \tag{3.3}$$

In the logit model, the probability that path p is chosen for a trip from i to j is

$$\text{Prob (p chosen}|\text{ij}) = \exp(-\alpha c_{pij}) / \sum_p \exp(-\alpha c_{pij}) \tag{3.4}$$

Substitute (3.3) into (3.4), we obtain

$$\text{Prob (p chosen}|\text{ij}) = \beta \exp(-\alpha \sum_u a_{upij}\, c_u) \tag{3.5}$$

$$\beta = 1/ \sum_p \exp(-\alpha \sum_u a_{upij}\, c_u) \tag{3.6}$$

$$\text{Prob (p chosen}|\text{ij}) = \beta \exp(-\alpha\, a_{1pij}\, c_1) \exp(-\alpha\, a_{2pij}\, c_2) \cdots \exp(-\alpha\, a_{Upij}\, c_U) \tag{3.7}$$

where U is the number of links on path p.

From (3.7), when loops are excluded, the implication is that one can pass through the network assigning each link u a weight equal to $\exp(-\alpha c_u)$. The product of these weights for a path is proportional to the probability that the path is chosen. The constant of proportionality is calculated so that the sum of these probabilities is equal to one for the feasible path by O-D pair. This is the basis of the forward pass of Dial's algorithm. The link flows are then assigned for conforming to the multinomial logit model which is the basis of the backward pass. The methods described as below are concerned with processing these weights.

3.3.2 Bell's Logit Assignment Method

The logit assignment method presented in Bell (1995) dispenses with the need for either a forward or a backward pass. As with Dial's method, path enumeration is not required. There is no efficiency constraint on feasible paths and therefore no need to know minimum centroid-to-node times beforehand. The Bell's logit assignment algorithm is as follows:

Bell's logit assignment algorithm

Algorithm A3.1

Step 1 (initialization of weight matrix)

for all nodes and centroids k and l

if a link joins k to l

then $w_{kl} \leftarrow \exp(-\alpha \text{ time})$

otherwise $w_{kl} \leftarrow 0$

time $\leftarrow$ 99999

Step 2 (process matrix of weights)

for all nodes m

for all nodes and centroids k not equal to m

for all nodes and centroids l not equal m or k

$$w_{kl} \leftarrow w_{kl} + w_{km} w_{ml}$$

Step 1 initializes the matrix of weights. For each link or connector present in the network the exponential of minus α times its time is entered; all other elements of the matrix are assigned the value zero. In Step 2, each node is processed once. When a connection is found between any node or centroid and any other node or centroid via the node being processed, the existing weight for the connection (which will be zero if the connection is new) is increased by the product of the two weights involved.

After completion of Step 2, the probability that a trip from node k to node l chooses link r can be calculated using the Van Vliet (1981) method, namely:

$$p_{klr} = w_{km} \exp(-\alpha c_r) w_{nl} / w_{kl} \qquad (3.8)$$

where link r connects node m to node n.

The Bell's logit assignment algorithm admits some paths without cycles and some with. One of the difficulties in admitting cycles is that paths with short cycles will tend to be assigned too much traffic due to the assumed independence of alternatives which are in fact to some extent dependent. This is partly due to perceptual reasons (drivers do not perceive two substantially overlapping paths as two independent alternatives) and partly due to behavioural reasons (driver learning capabilities discourage cycles). In practice, it is not reasonable to admit 2-node cycles. In the following section, the link-based logit assignment method is proposed to remove the 2-node cycles.

3.4 SOLUTION ALGORITHM

3.4.1 Link-based Logit Assignment Method

Inspired by the logit assignment method presented in Bell (1995), the following link-based logit assignment algorithm is proposed to eliminate all the 2-node cycles.

Algorithm A3.2

Step 1 (initialization of weight matrix)

for all links and centroid connectors r and s

if a turn e joins r and s where $r \neq s$

then turn time $c_e \leftarrow$ average of link time $\frac{1}{2}(c_r + c_s)$

$+$ junction delay (if known)

and $w_{rs} \leftarrow \exp(-\alpha\ c_e)$

otherwise $w_{rs} \leftarrow 0$

for all centroid connectors r,

add a dummy centroid turn e to connect centroid connector r and dummy centroid connector s

$c_s \leftarrow 0$

$c_e \leftarrow \frac{1}{2}(c_r + c_s)$

$w_{rs} \leftarrow \exp(-\alpha\, c_e)$

Step 2 (process of matrix of weights)

for all links and centroid connectors u

for all links and centroid connectors r not equal u

for all links and centroid connectors s not equal u or r

$w_{rs} \leftarrow w_{rs} + w_{ru}\, w_{us}$

After the completion of the algorithm, the probability that a trip from link r to link s uses turn e can be calculated using the Van Vliet (1981) method, namely, the turn choice proportion:

$$p'_{rse} = w_{ru} \exp(-\alpha\, c_e)\, w_{vs} / w_{rs} \qquad (3.9)$$

where turn e connects link u to the link v. The turning movement is therefore obtained by the following conservation relationship

$$q_e = \sum_i \sum_j p'_{ije} t_{ij} \qquad (3.10)$$

Using arguments similar to those presented by Bell (1995), it can be shown that the probability that a trip from link r to link s chooses link u is given by $P_{rsu}=w_{ru}\ w_{us}\ /\ w_{rs}$. The link flow is therefore obtained as follows,

$$V_u = \sum_i \sum_j P_{iju} t_{ij} \tag{3.11}$$

Consider a 2-node cycle as shown in Figure 3.1,

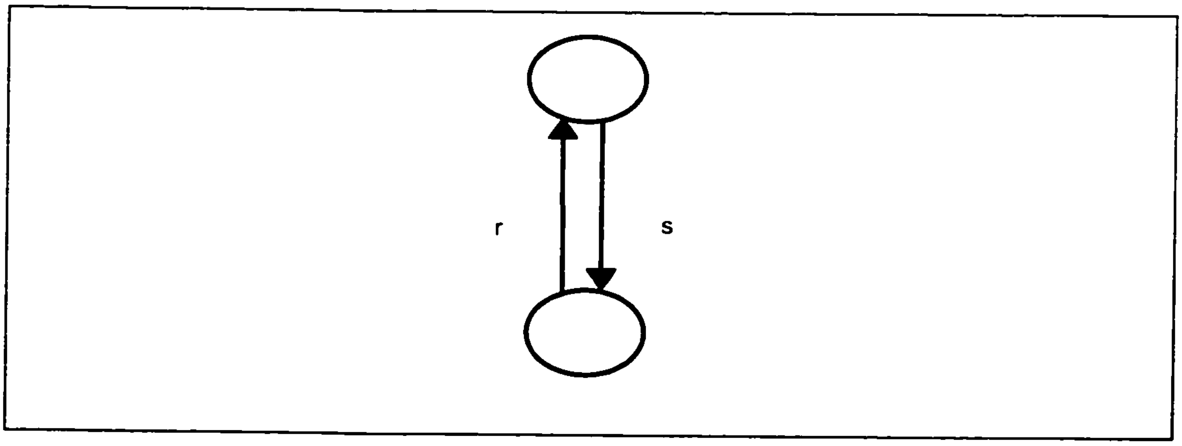

Figure 3.1 A 2-node Cycle

The turns between link r and link s are omitted when $w_{rs} \leftarrow 0$ initially, thereby eliminating the 2-node cycles. The procedure for generating the turns are as follows,

Generation of turns

For all links and centroid connectors r, s

if $M^{l}_{r,2} = M^{l}_{s,1}$ and $M^{l}_{r,1} \neq M^{l}_{s,2}$

then there is a turn from r to s

add r, s to the indicator matrix M^{t}

$d_{rs} \leftarrow 1$

otherwise, $d_{rs} \leftarrow 0$.

For example, consider the network in Figure 3.2,

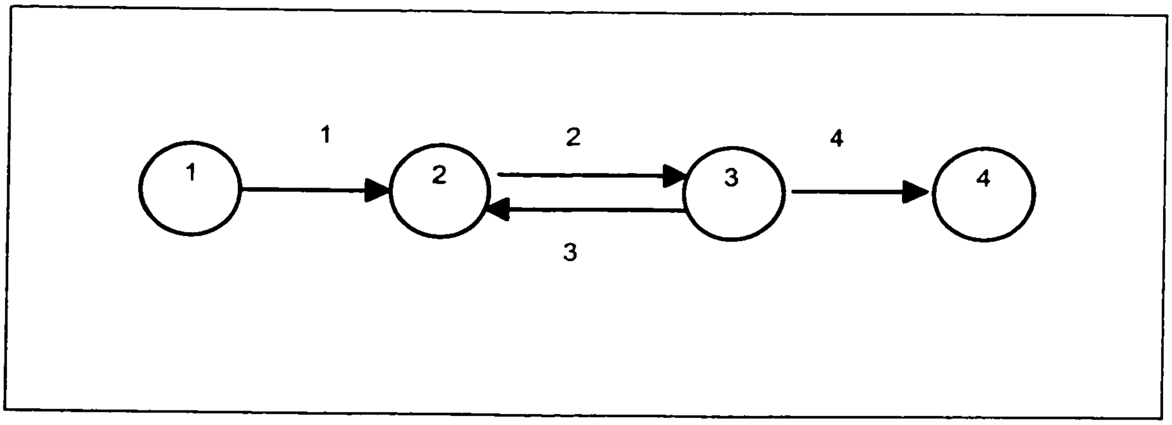

Figure 3.2 Example Network with a 2-node Cycle

For this network, the indicator matrix M^l is,

$$M^l = \begin{pmatrix} 1 & 2 \\ 2 & 3 \\ 3 & 2 \\ 3 & 4 \end{pmatrix}$$

After the generation of turns, the indicator matrix M^t can be obtained,

$$M^t = \begin{pmatrix} 1 & 2 \\ 2 & 4 \end{pmatrix}$$

Therefore, there are only two turns in the network. Turn 1 is from link 1 to link 2. Turn 2 is from link 2 to link 4. The turns between link 2 to link 3 are omitted because $M^l_{2,1} = M^l_{3,2} = 2$. In this example, $d_{12} = d_{24} = 1$ while $d_{23} = d_{32} = 0$.

However, only the 2-node cycles can be removed in the link-based logit assignment method. In order to eliminate more short cycles, the extensions of the link-based logit assignment method are presented in the following sections.

3.4.2 Turn-based Assignment Method

In order to eliminate more short cycles, the following turn-based logit assignment algorithm is proposed which can remove all the 2-node and 3-node cycles.

Algorithm A3.3

Step 1 (initialization of weights matrix)

for all turns and centroid turns e and f

if an arc x joins e and f where $e \neq f$

then arc time $c_x \leftarrow$ average of turn time $\frac{1}{2}(c_e + c_f)$

$w_{ef} \leftarrow \exp(-\alpha\ c_x)$

otherwise $w_{ef} \leftarrow 0$

for all centroid turns e,

add a dummy centroid arc x to connect centroid turn e and dummy centroid turn f

$c_f \leftarrow 0$

$c_x \leftarrow \frac{1}{2}(c_e + c_f)$

$w_{ef} \leftarrow \exp(-\alpha\ c_x)$

Step 2 (process of matrix of weights)

for all turns and centroid turns g

for all turns and centroid turns e not equal g

for all turns and centroid turns f not equal g or e

$$w_{ef} \leftarrow w_{ef} + w_{eg}\, w_{gf}$$

The probability that a trip from turn e to turn f uses turn g is given by $P'_{efg}=w_{eg}\, w_{gf} / w_{ef}$. The link choice proportions can be obtained as follows.

For all links r, s, u,

$P_{rsu} \leftarrow 0$.

For all turns g,

$P_{rsu} \leftarrow P_{rsu} + P'_{efg}$

where $r= M^t_{e,1}$, $s= M^t_{f,2}$, $u= M^t_{g,1}$.

Then the P_{rsu} is the probability that a trip from link r to link s uses link u.

Consider a 3-node cycle as shown in Figure 3.3.

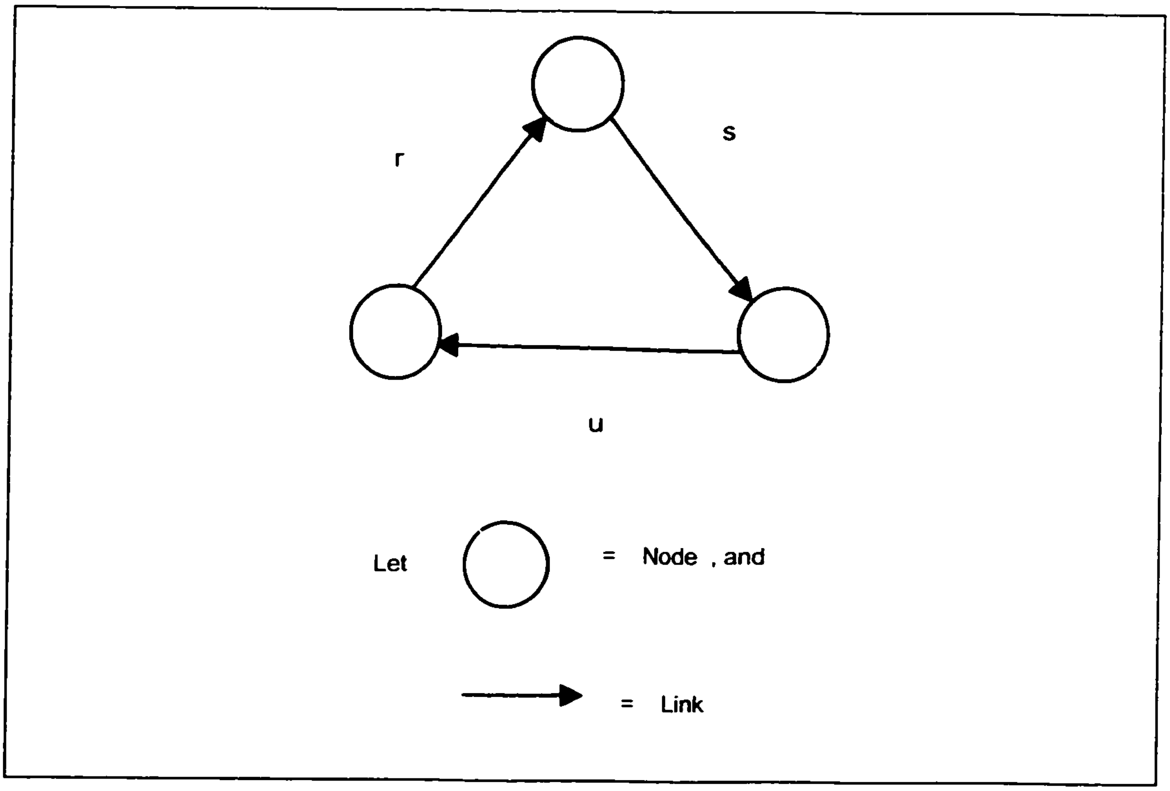

Figure 3.3 A 3-node Cycle

By generating the turns as before, a new network can be obtained as shown in Figure 3.4.

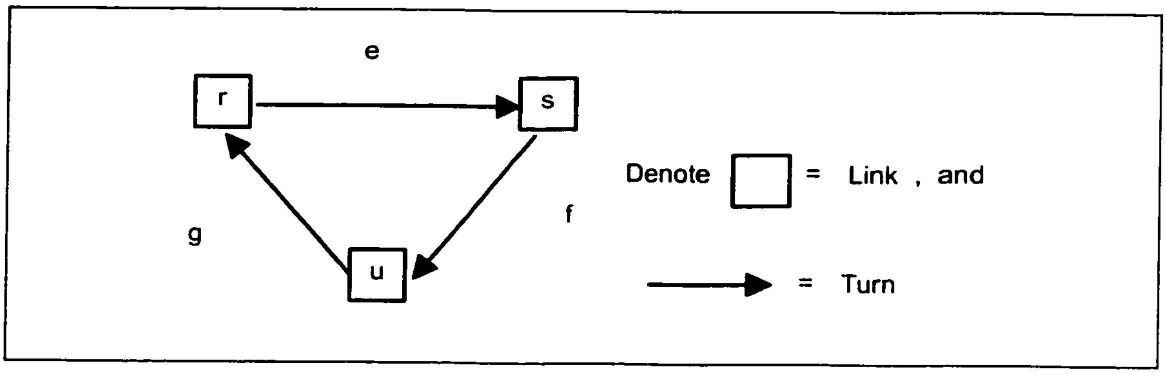

Figure 3.4 A 3-link Cycle

The arcs from turn e to turn f, from turn f to turn g and from turn g to turn e are omitted so that all the 3-node cycles are removed by setting $w_{fg} = w_{ge} = w_{ef} = 0$. For example, the arc from turn g to turn e is omitted, which is equivalent to a 3-node cycle from link u via link r to link s.

Similar to the generation of the turns, the procedure for generating the arcs are as follows,

Generation of arcs

For all turns and centroid turns e, f

if $M^t_{e,2} = M^t_{f,1}$ and $d_{rs} = 0$

where $s = M^t_{e,1}$, $r = M^t_{f,2}$

then there is an arc from e to f

add e,f to indicator matrix M^a

where $d_{rs}=0$ if no turns from link r to link s.

3.4.3 Arc-based Assignment Method

On the basis of the turn-based logit assignment method, it is possible to extend the work to eliminate all the cycles with 2 to 4 nodes. The following arc-based logit assignment algorithm which can remove all the 2-node, 3-node and 4-node cycles is proposed.

Algorithm A3.4

Step 1 (initialization of weights matrix)

for all arcs and centroid arcs x and y

if a route h joins x and y where $x \neq y$

then route time $c_h \leftarrow$ average of arc time $\frac{1}{2}(c_x + c_y)$

$w_{xy} \leftarrow \exp(-\alpha\ c_h)$

otherwise $w_{xy} \leftarrow 0$

for all centroid arcs x,

add a dummy centroid route h to connect centroid arc x and dummy centroid arc y

$c_y \leftarrow 0$

$c_h \leftarrow \frac{1}{2}(c_x + c_y)$

$w_{xy} \leftarrow \exp(-\alpha\ c_h)$

Step 2 (process of matrix of weights)

for all arcs and centroid arcs z

for all arcs and centroid arcs x not equal z

for all arcs and centroid arcs y not equal z or x

$w_{xy} \leftarrow w_{xy} + w_{xz}\, w_{zy}$

The probability that a trip from arc x to arc y uses arc z is given by $P^{xy}_{xyz} = w_{xz}w_{zy}/w_{xy}$.

The link choice proportions can be found by the following steps.

For all turns e, f, g,

$P'_{efg} \leftarrow 0.$

For all links r, s, u,

$P_{rsu} \leftarrow 0.$

For all arcs z,

$P'_{efg} \leftarrow P'_{efg} + P''_{xyz}$

where $e=M^a_{x,1}$, $f=M^a_{y,2}$, $g=M^a_{z,1}$.

For all turns g,

$P_{rsu} \leftarrow P_{rsu} + P'_{efg}$

where $r= M^t_{e,1}$, $s= M^t_{f,2}$, $u= M^t_{g,1}$.

The P_{rsu} is then the probability that a trip from link r to link s uses link u.

It must be born in mind that when the routes are generated, all the routes with 4-node cycles are omitted. Using arguments similar to the turn-based logit assignment method, the routes can be generated as follows,

Generation of routes

For all arcs and centroid arcs x, y

if $M^a_{x,2}=M^a_{y,1}$ and $d_{rs}=0$

where $s=M^t_{e,1}$ $r=M^t_{f,2}$

and $e=M^a_{x,1}$ $f=M^a_{y,2}$

then there is a route from x to y

Obviously, the same approach can be adopted to eliminate cycles with more than 4 nodes. However, it may not really be necessary to remove larger cycles because the number of trips involved will be small. The time of travelling on the cycle is increasing with the size of the cycle.

3.4.4 Iterative Assignment Algorithm

The structure of the above proposed method makes it suitable for combination with the volume successive average algorithm, leading to the following iterative assignment.

Algorithm A3.5

Step 0 Select a suitable initial set of current link travel times, usually free-flow travel times. Initialize all flows V; let n=0.

Step 1 Use the link-based logit assignment method (or its extensions as presented in Sections 3.4.2 and 3.4.3) to derive the set of link choice proportions with the current travel times; set n=1. Compute the link flow V_u^1 by eqn. (3.11).

Step 2 Update the link travel times with current link flows.

Step 3 Build the set of link choice proportions with the current link travel times; make n=n+1.

Step 4 Compute the auxiliary flows E_u by eqn. (3.11).

Step 5 Calculate the current flows as:

$$V_u^n=(1-\phi)\ V_u^{n-1} + \phi\ E_u \qquad (3.12)$$

with $0 \leq \phi \leq 1$.

Step 6 If the link flows have not been changed significantly in two consecutive iterations, stop; proceed to Step 2. The convergence condition for stopping is as follows

$$|V_u^n - V_u^{n-1}| \leq \varepsilon \qquad (3.13)$$

where ε is the convergence criterion. Another common criterion for stopping is simply to fix the maximum number of iterations. It is necessary to adopt a small value of ε. The maximum number of iterations is set to be 1,000 in this study. Iterative assignment algorithms differ in the method used to give a value to ϕ. A simple rule to make it constant, for example $\phi=0.5$. However, Lam (1988) demonstrated that the volume averaging method may not produce a convergent sequence with a numerical example. In the MSA, $\phi = 1/(n-1)$.

In this study, MSA is used instead of using volume averaging technique with a constant value of ϕ. "The advantage of using the above MSA method is the guarantee of the convergence without evaluating the objective function." (Chen and Alfa, 1991). "The convergence of this algorithm is not monotonic because the search direction is only a descent direction on average." (Ortúzar and Willumsen, 1994). Actually, the results obtained by MSA in practice will depend on the chosen value of ε and the maximum number of iterations used. More stable solutions can be obtained by the proposed iterative assignment algorithm for smaller values of ε.

3.5 NUMERICAL EXAMPLES

Three numerical examples are presented in this chapter. Example 1 is designed to demonstrate the effectiveness of the link-based logit assignment method with fixed link travel time. Example 2 is used to study the performance of the iterative assignment algorithm on network with flow-dependent link travel times. Note that there is only one Origin-Destination (O-D) pair in these examples and each cycle includes two U-turns in the networks. Example 3 is presented to illustrate the solution algorithm in real situation where the Tuen Mun Road Corridor is used.

In addition, calibration is carried out for the logit model on the Tuen Mun Road Corridor. A simulation method (Sheffi and Powell, 1982) is adopted to compute the flow pattern of the SUE probit model in the three numerical examples. Convex combination method (Sheffi, 1985) is also applied to obtain the solution of the UE problem for the three numerical examples.

3.5.1 Example 1

Consider the example network in Figure 3.5, where there is only one 2-node cycle formed by links 4 and 6. It is supposed that all the links and the centroid links in this example have a fixed travel time of 1.0.

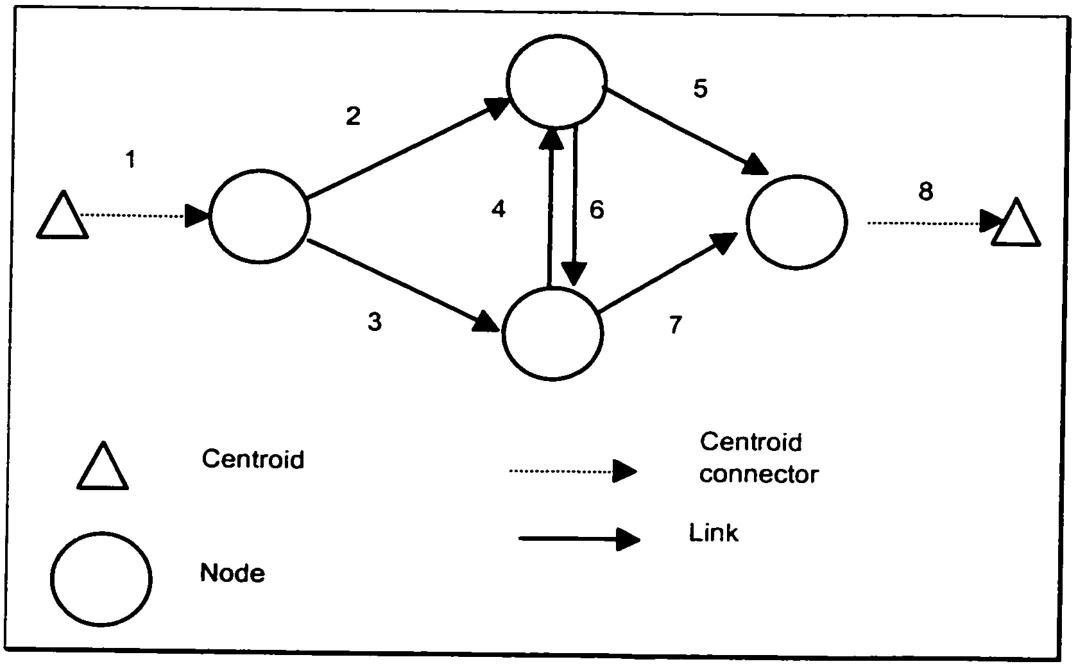

Figure 3.5 Example Network

The link-based logit assignment method when applied this example yields the results given in Table 3.1. given α=0.5. Since Bell's node-based logit assignment method admits 2-node cycles, there are some trips cycling round links 4 and 6. The paths through links 2, 6, 4, 5 and links 3, 4, 6, 7 are feasible for Bell's logit assignment method so the sum of the link choice proportions on links 2 and 3 is equal to 1.048 which is greater than 1.0. However, the sum of link choice proportions on link 2 and link 3 is exactly equal to 1.0 for the link-based logit assignment method as the 2-node cycle has been eliminated. The link choice proportions obtained by the simulation method have close values with results of the link-based method.

Table 3.1 The Link Choice Proportions (Example 1)

Traffic assignment methods	Link					
	2	3	4	5	6	7
Bell's method	0.5149	0.5331	0.6863	0.4358	0.6384	0.4851
Link-based method	0.5000	0.5000	0.1888	0.5000	0.1888	0.5000
Probit assignment method	0.5000	0.5000	0.0780	0.5000	0.0780	0.5000
UE method	0.5000	0.5000	0	0.5000	0	0.5000

* Note : α (in eqn. (3.1)) = 0.5 for the Bell's method and link-based method.

σ_u (in eqn. (3.2)) = 0.5 for the probit assignment method.

Suppose that the junction delays on turns from link 2 to link 6 (turn 3) and from link 3 to link 4 (turn 5) are equal to 1.0. The link-based logit assignment method can be used to compute the turn choice proportions. The results are shown in Table 3.2.

It can be seen that the turn choice proportions of turns 3, 5, 7, 9 have been decreased if junction delays are introduced. In contrast, the turn choice proportions of turns 4 and 6 are increased as some drivers will change to use turns 4 and 6 instead of turns 3 and

5 when there are junction delays on turns 3 and 5. Once the O-D trip rates are available, the turning movements can then be obtained by eqn. (3.10).

Table 3.2 The Turn Choice Proportions (Example 1)

Turn	From link	To link	No junction delay	Junction delay=1.0 on turns 3 and 5
1	1	2	0.5000	0.5000
2	1	3	0.5000	0.5000
3	2	6	0.1888	0.1345
4	2	5	0.3112	0.3655
5	3	4	0.1888	0.1345
6	3	7	0.3112	0.3655
7	4	5	0.1888	0.1345
8	5	8	0.5000	0.5000
9	6	7	0.1888	0.1345
10	7	8	0.5000	0.5000

3.5.2 Example 2

In the second example, the network in Figure 3.5 is still adopted. The O-D trip rate is assumed to be 4 units. The travel time on each link is a function of the link flow in the following BPR (Bureau of Public Roads, 1964) form:

$C_u = \beta_u + \lambda_u (V_u / \mu_u)^4$, where μ_u is the capacity of link u and u=1,2,...8.

Link u	1	2	3	4	5	6	7	8
β_u	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
λ_u	0.0	25.6	25.6	12.8	12.8	5.12	5.12	0.0
μ_u	4.0	4.0	4.0	4.0	4.0	4.0	4.0	4.0

By applying the iterative assignment algorithm combined with MSA, the results are shown in Table 3.3, given α=0.5. Let the convergence criterion ε be 0.01.

Table 3.3 The Link Flows (Example 2)

Number of iterations	Link					
	2	3	4	5	6	7
1	2.0000	2.0000	0.7551	2.0000	0.7551	2.0000
2	1.9714	2.0286	0.7080	1.8797	0.7997	2.1203
3	2.0027	1.9973	0.6981	1.8904	0.8104	2.1096
4	1.9925	2.0075	0.7010	1.8869	0.8066	2.1131
5	1.9931	2.0069	0.7007	1.8871	0.8067	2.1129

The iterative assignment algorithm is converged in five iterations. Since β_u =1 for all u, the link travel times depend on λ_u. From Table 3.3, link flows on link 2 and 3 are similar. However, the flow on link 5 is less than that on link 7 because $\lambda_5 > \lambda_7$. Similarly, there are more flows on link 6 than link 4 due to $\lambda_5 > \lambda_7$ and $\lambda_4 > \lambda_6$ so that the path using links 2, 6, 7 is more attractive than the path via links 2, 4, 5.

To demonstrate how to obtain the approximation of user equilibrium (UE) through SUE, the convergent solutions are computed by the iterative assignment algorithm for different α. Table 3.4 shows the resultant link flows for α=0.5, 1.0, 2.0 and 5.0.

It is found from Table 3.4 that the flows of links 4 and 6 decrease as α increases with link travel times on these two links. The link flows become 0.0030 and 0.0503, only for links 4 and 6 respectively when α=5.0. This is because the SUE link flow pattern approaches to the UE link flow pattern for large α. This is equivalent to small perception error of the drivers. In this example, the SUE results are the approximation of UE results when α=5.0.

Table 3.4 Link Flows with Various α and Other Assignment Results (Example 2)

		Link					
		2	3	4	5	6	7
α	0.5	1.9931	2.0069	0.7007	1.8871	0.8067	2.1129
	1.0	1.9891	2.0109	0.4675	1.8579	0.5986	2.1421
	2.0	1.9823	2.0177	0.1699	1.8511	0.3010	2.1489
	5.0	1.9577	2.0423	0.0030	1.9103	0.0503	2.0897
Probit assignment method		1.9655	2.0345	0.1013	1.8485	0.2183	2.1515
UE method		1.9440	2.0560	0.0000	1.9440	0.0000	2.0560

* Note : α (in eqn. (3.1)) = 0.5, 1.0, 2.0 and 5.0 for the proposed iterative assignment method. σ_u (in eqn. (3.2)) = 0.5 for the probit assignment method.

3.5.3 Example 3

To illustrate the solution algorithm in the real case, the method is applied to the Tuen Mun Road Corridor which connects Tuen Mun and Kowloon. The study network, which consists of 3 zones and 10 links, is shown in Figure 3.6.

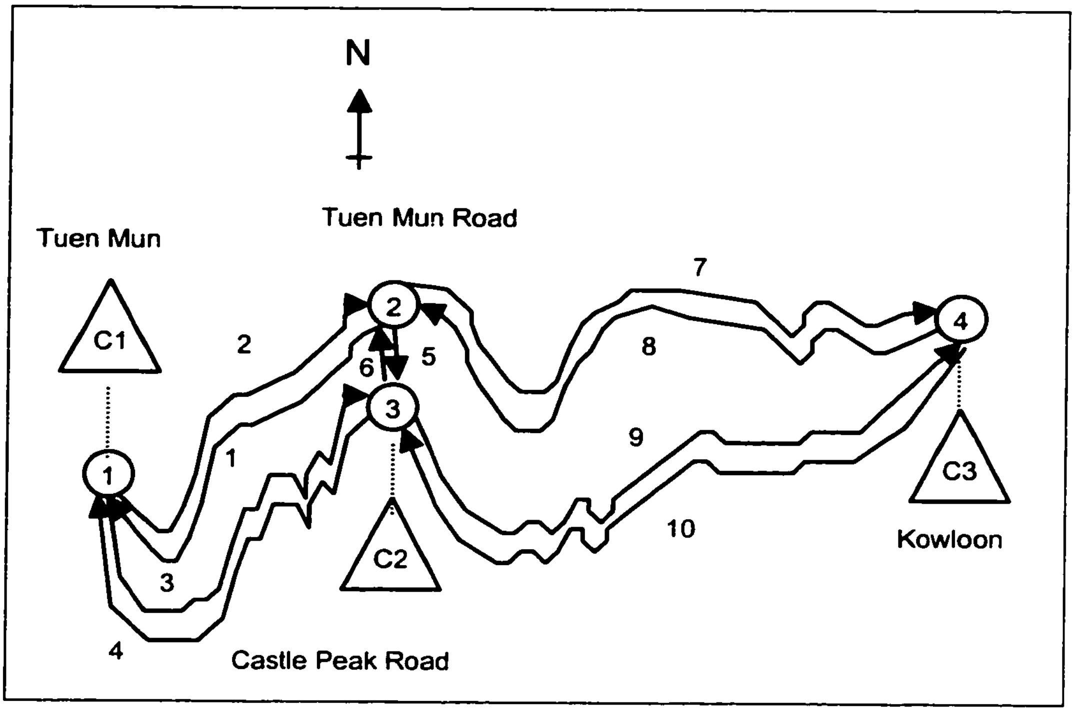

Figure 3.6 Tuen Mun Road Corridor Network

The link travel time functions with respect to link flows are given as follows:

$$C_u = \beta_u + \lambda_u (V_u / \mu_u)^{\rho_u} ,$$

where μ_u is the capacity of link u and u=1,2,..10, β_u is the free flow time. λ_u and ρ_u are the calibration parameters of link u. The link data on the study network for the p.m. peak hours are given in Table 3.5.

Table 3.5 The Link Data of the Network

Link no.	1,2	3,4	5	6	7,8	9,10
β_u (hrs)	0.0975	0.0922	0.0043	0.0043	0.0315	0.23
λ_u (hrs)	0.0975	0.0922	0.0037	0.0037	0.0280	0.23
μ_u (pcu/hr)	5175	1000	730	950	4800	850
parameter ρ_u	3.5	3.6	3.6	3.6	3.6	3.6

The travel demand (pcu/hr) is presented in the O-D matrix as shown in Table 3.6. The empirical work is carried out for calibrating the logit model on the Tuen Mun Road Corridor by using the data from the enhanced CTS-3 transport model (Hong Kong Transport Department and Wilbur Smith Associates, 1999). The observed link flows are given in Table 3.7. The dispersion parameter α is calibrated to be 12.6 for the p.m. peak hours.

Table 3.6 O-D Matrix

		Destination zones			
		C1	C2	C3	pcu/hr
Origin zones	C1	-	32	3859	3891
	C2	16	-	205	221
	C3	4012	309	-	4321
		4028	341	4064	8433

By using the proposed iterative assignment algorithm, the estimated link flows for α=12.6 are obtained and are presented in Table 3.7. They are also compared against the link flows estimated by the UE assignment method, the probit-based simulation method and Bell's method. The calculated ratio of the estimated and observed link flows are between 0.9 and 1.1 as indicated in Table 3.7.

Table 3.7 Resultant Link Flows (pcu/hr)

Link	Bell's method	Probit assignment method	UE method	Estimated Link Flows by the proposed method	Observed Link Flows	Ratio (Est. Link Flows/ Obs. Link Flows)
1	5456	3143	3415	3071	2930	1.1
2	3376	3004	3254	2905	2800	1.0
3	6570	887	637	1001	1091	0.9
4	4316	885	613	973	1098	0.9
5	34733	1201	906	1298	1253	1.0
6	36904	1024	810	1278	1125	1.1
7	4653	4001	4064	3785	3756	1.0
8	4453	4316	4321	3969	4013	1.0
9	5087	63	0	281	308	0.9
10	5177	5	0	353	308	1.1

* Note : α (in eqn. (3.1)) = 12.6 for the Bell's method and the proposed iterative assignment method.

σ_u (in eqn. (3.2)) = 0.5 for the probit assignment method.

It can be observed in Table 3.7 that the estimated link flows are closer to the observed link flows while the UE results are comparatively less accurate particularly on links 9 and 10. The link flows obtained by the probit-based simulation method, which are not closed to the observed link flows especially on links 9 and 10, are between the estimated link flows and the UE link flow pattern. The resultant link flows by Bell's method are not reasonable because there are some trips cycling round the loops so that the flows on links 5 and 6 are extremely large. The advantages of Bell's method include: (1) path enumeration is not required, (2) there is no efficiency constraint on feasible paths, (3) there is no need to know minimum times beforehand. However, the only disadvantage is that there should be no cycles in the network. After removing the cycles by the proposed algorithm, the estimated link flows can be an approximation of the observed link flows.

To demonstrate the convergence of the proposed iterative assignment algorithm, Figure 3.7 shows the descent direction of the SUE objective value as the number of iterations for α=12.6; where one of the stopping criterion ε=1.0. The required number of iterations is 32 to reach this stopping criterion. Figure 3.7 indicates that the reduction of the SUE objective function value is higher for the first two iterations while the improvement of the SUE objective function value is not significant at the latter stage.

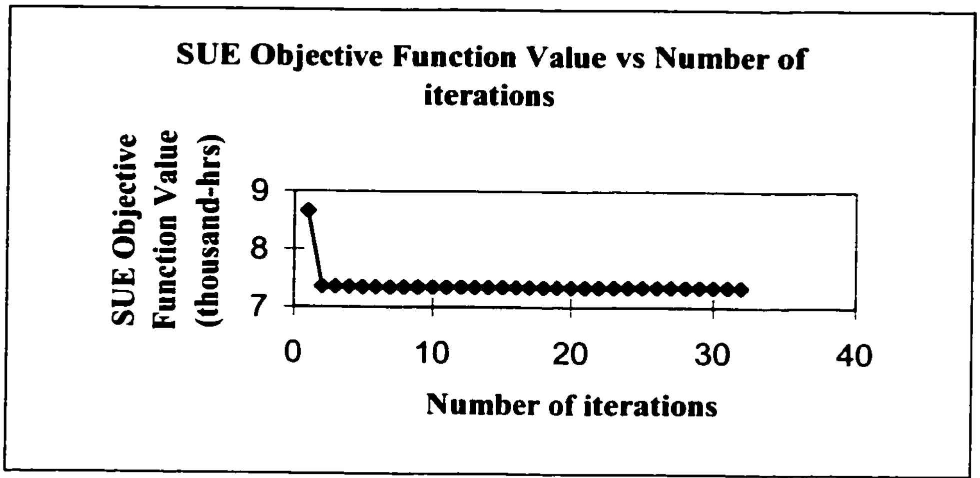

Figure 3.7 SUE Function Objective Value vs Number of Iterations

3.6 SUMMARY

In this chapter, alternatives to Bell's node-based logit assignment method designed to progressively eliminate cycles is proposed. The proposed link-based logit assignment method can remove all the 2-node cycles, and the turn-based logit assignment method can eliminate all the 2-node and 3-node cycles, while the arc-based logit assignment method can eliminate all the 2-node, 3-node and 4-node cycles. By extending the approach to exclude cycles with greater number of nodes, sub-paths and/or complete paths without cycles will progressively be generated but the indicator matrices and/or path-node matrix will be very large. It may not be practical for a large network. In fact, it is sensible to remove all the short cycles. This is because drivers do not perceive two substantially overlapping paths as two independent alternatives and they will avoid short cycles because of their driving experience. However, paths with short cycles will tend to be assigned too much traffic. It seems sensible to admit some large cycles as drivers have incomplete knowledge of the network in practice. However, these trips should be very few as the travel time increases with the size of the cycle permitted in the feasible path set.

The absence of any efficiency constraint on the set of feasible paths makes the link-based logit assignment method attractive for use in stochastic user equilibrium method or in the approximation of UE through SUE. Moreover, junction delays can be incorporated into the turn time and the turning movements can be obtained explicitly. A case study was carried out to calibrate the value of the dispersion parameter α for the Tuen Mun Road Corridor. Numerical examples are used to illustrate the applications of the link-based logit assignment method and demonstrate the convergence of the iterative assignment algorithm, together with a comparison of other assignment methods.

4 PROBIT ASSIGNMENT MODEL

In Chapter 3, three logit assignment methods were proposed for minimizing the cycle problems in Bell's logit assignment. In Chapter 4, a probit assignment model is proposed for estimating the link flow and its variance. The estimated link flow and the covariance matrix of the link flow for each origin-destination (O-D) pair can be obtained by the solution algorithm proposed in this chapter.

In the proposed probit assignment model, the perceived and measured travel time errors are considered separately and assumed to be distributed Normal. The variance of the link travel time error of the measured and perceived error of the drivers are modelled as functions of volume/capacity (v/c) ratio. The effects of the perceived and measured travel time errors are assessed. A numerical example on the Tuen Mun Road Corridor is used to illustrate this model.

4.1 INTRODUCTION

The user equilibrium (UE) traffic flow pattern arises if each driver has perfect knowledge about network conditions and all had identical perceptions of travel time, which is scarcely possible. However, a stochastic user equilibrium (SUE) assignment can overcome these limitations by considering the individual's perceived travel times as a random variable.

Dial (1971) proposed the STOCH (logit assignment) method in which the perceived travel time errors are distributed Gumbel. A simulation (probit assignment) approach was suggested by Daganzo and Sheffi (1977) where the perceived travel time errors are distributed Normal. Logit-based optimization analogues were formulated for SUE by Fisk (1980) and by Sheffi (1985). Bell (1995) developed a node-based alternative to Dial's method. In order to eliminate the cycle problems, a link-based alternative to Bell's logit assignment method was suggested by Lam et al. (1996).

There are objections to use logit model because of the axiom of the Independence of Irrelevant Alternatives (IIA). The IIA can be stated as "where any two alternatives have a non-zero probability of being chosen, the ratio of one probability over the other is unaffected by the presence or absence of any additional alternative in the choice set" (Luce and Suppes, 1965). This property makes the model fail in the presence of the correlated alternatives. Unrealistic path choice probabilities can be derived from the IIA property of logit model (Sheffi, 1985; Daganzo and Sheffi, 1977).

Cascetta et al. (1996) proposed a C-logit model for overcoming the IIA problems in the route choice logit model by introducing a commonality factor. The idea of the C-logit model is to deal with similarities among overlapping paths through an additional travel time attribute, named a commonality factor, in the utility function of a logit model. For the probit model, the route choice probabilities cannot be expressed in a closed form (Daganzo, 1979). A simulation assignment algorithm was adopted using the randomized link travel times and fixed step size approach of Powell and Sheffi (1982).

In the above probit and/or logit models, the perceived travel time errors are assumed to be distributed by Normal and Gumbel respectively but the measured travel time errors and the variance of link choice proportion (i.e. the proportion of traffic between a zone pair that uses the corresponding link) are not considered. From a series of computer test runs carried out on some small hypothetical networks, Lo et al. (1996) showed that the effect of using incorrect link choice proportions would be significant and could lead to serious errors in the estimation of an O-D matrix from traffic counts. Lo et al. (1996) therefore proposed a model that incorporates the randomness of the link choice proportions in the estimation of the O-D matrix.

A logit model has a simple covariance matrix, for example in the binary logit model,

$$\Sigma = \sigma^2 I \tag{4.1}$$

where σ^2 is the variance of each alternative and I is an identity matrix of appropriate order. This covariance matrix is not suitable for the case when alternatives are not independent because the correlation terms will be non-zero. For the binary probit model,

$$\Sigma = \begin{pmatrix} \sigma_1^2 & \rho\sigma_1\sigma_2 \\ \rho\sigma_1\sigma_2 & \sigma_2^2 \end{pmatrix} \tag{4.2}$$

where σ_1^2, σ_2^2 are the variance of the alternatives 1 and 2 respectively and ρ is the correlation coefficient between the two alternatives. Therefore, the probit model has a more general covariance matrix structure and is useful when alternatives are not independent.

However, it is more restricted for solving the probit model than the logit model. The probit model can be solved by Clark's approximation or the simulation approach. Therefore, Maher et al. (1997) proposed a new heuristic probit stochastic assignment method which does not require Monte-Carlo simulations but suffers from the cycle problems and needs to adopt the Clark's approximation. In this chapter, the simulation approach based on the simulation assignment algorithm of Powell and Sheffi (1982) is used for solving the probit model. Although the computation burden of simulation is substantial, the simulation approach is now widely used in transportation problems (Benekohala and Zhaob, 2000; Bhat, 2000; Garrido and Mahmassani, 2000; Nielsen, 2000).

In this chapter, the stochastic link travel times are input to the proposed model, while the outputs are the stochastic link flows. The resulting stochastic link flows can be used to estimate the time mean speed. The estimated time mean speed can be used for checking the accuracy of the detector data. The difference between the space mean speed and time mean speed can also be calculated.

In Figure 4.1, a road section is used to illustrate the space and time mean speeds.

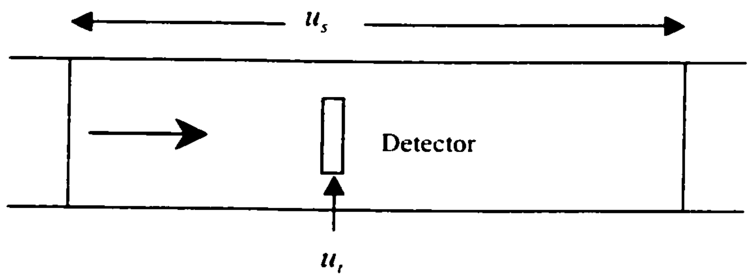

Figure 4.1 Illustration of the Space and Time Mean Speeds

Let u_s and u_t respectively be the space mean speed and time mean speed. The space mean speed can be calculated by eqn. (4.3) by dividing the length of the section by the average travel time of the cars for a study period.

$$u_s = \frac{L}{\frac{1}{n}\sum_{i=1}^{n} t_i} \tag{4.3}$$

where L is the length of the study section, n is the number of cars travelling in the study period and t_i is the individual car i ($1 \leq i \leq n$) travel time in the study period.

The time mean speed can be found from eqn. (4.4) by computing the average point speed of the cars for a study period. The point speed can be obtained from the detector. Therefore, the time mean speed can easily be measured by the detector.

$$u_t = \frac{1}{n}\sum_{i=1}^{n} u_i \tag{4.4}$$

Wardrop (1952) derived the relationship between the space mean speed and time mean speed as,

$$u_t = u_s \{1 + (\sigma_s/u_s)^2\} \tag{4.5}$$

where σ_s is the standard deviation of the space speed of the cars in the study period.

Therefore, the time mean speed and space mean speed are equal only if the standard deviation of the space speed is zero. The difference in the two speeds is larger when that standard deviation is larger. This standard deviation can be calculated in the proposed model. Therefore, the time mean speed can be computed.

In this chapter, a probit assignment model for estimating the variance of link flow and of the link choice proportion is proposed. The perceived travel time errors of the drivers and the measured travel time are considered as Normally distributed random variables. The form for the variance of the link travel time measurement and drivers' perceived travel time error are assumed to be functions of volume/capacity (v/c) ratio which have different properties. As the v/c ratio increases, the variation of individual travel time in the survey data will decrease and the variance of the measured errors will also decrease. Thus, the variance of the measured errors should decrease with the v/c ratio. However, it is more difficult for drivers to perceive the travel time correctly as congestion and/or incidents occur. Therefore, the perceived error of the drivers increase as the v/c ratio increases. Therefore, the variance of the perceived travel time errors of the drivers should be an increasing function of the v/c ratio.

The structure of the chapter is as follows. The probit assignment model is formulated, together with a solution algorithm. A numerical example is then used to illustrate the application of the proposed model and algorithm. Finally, a summary is given.

4.2 MODEL FORMULATION

4.2.1 The Perceived Path Travel Time Errors

As drivers are usually unable to have complete knowledge of the traffic conditions on the road network, the perceived path travel time errors should be introduced into the traffic assignment model. The perceived and measured travel times on path k between origin r and destination s have the following relation,

$$C_k^{rs} = c_k^{rs} + \xi_k^{rs} \tag{4.6}$$

where ξ_k^{rs} is the perceived path travel time errors and are here assumed to be distributed Normal.

Thus, the drivers' perceived travel time errors ξ_l of each link l along the path k can be assumed as normally distributed with mean zero and variance $\alpha_l c_l$ where α_l is the dispersion parameter of the perceived travel time error for link l where α_l is the dispersion parameter of the perceived error for link l and c_l is the travel time of link l.

$$\xi_l \sim N(0, \alpha_l c_l) \tag{4.7}$$

The drivers' perceived travel time errors vary between links. As the v/c ratio increases, the perceived travel time errors of the drivers will also increase because the correct perception of travel time for drivers is particularly difficult in congested situations. Consequently, the variance of the perceived errors should be assumed as a proportional function of the v/c ratio. Thus the dispersion parameter of perceived error α_l is expressed as follows,

$$\alpha_l = f_p(V_l / S_l) \tag{4.8}$$

where V_l is the flow of link l and S_l is the capacity of link l.

The function $f_p(V_l/S_l)$ is an increasing function of V_l/S_l. The variation of the perceived errors is high when congestion occurs. Therefore, α_l becomes large when the ratio of V_l/S_l approaches to 1. The dispersion parameter function $f_p(V_l/S_l)$ can be calibrated by the survey data. A survey can be designed for collecting the data of the perceived travel times and link flows in the network so as to establish the relationship between the perceived travel time errors and the v/c ratio.

4.2.2 Measurement Errors

The perceived travel time errors are due to effects observable in principle but not calibrated in a survey and may be different for each individual. The measurement errors are due to the errors from the survey. If the measurement errors are also taken into account for each path, the perceived path travel time becomes

$$C_k^{rs} = c_k^{rs} + \varepsilon_k^{rs} + \xi_k^{rs} \tag{4.9}$$

where ε_k^{rs} is the measured error of path k and is here assumed to be Normally distributed. Hence, the measured error ε_l of each link l along the path k is here assumed as a normal variate with mean zero and variance $\beta_l c_l$ where β_l is the dispersion parameter of the measured error for link l.

$$\varepsilon_l \sim N(0, \beta_l c_l) \tag{4.10}$$

In effect, the travel time measured errors are different for each link. In Figure 4.2, the relationships between individual travel times and the v/c ratio on a certain road link in Hong Kong are shown together with the calibrated link travel time function. If the v/c ratio increases, the variation of individual travel times will decrease and the variance of the measured errors will also decrease. Thus, the variance of the measured errors should be a decreasing function of the v/c ratio. Hence the dispersion parameter β_l is expressed as shown below,

$$\beta_l = f_m(V_l / S_l) \tag{4.11}$$

The function $f_m(V_l / S_l)$ is a decreasing function of V_l / S_l. The change of the measured errors is small when congestion occurs. Therefore, the β_l becomes small when the ratio of V_l / S_l approaches to 1. The function $f_m(V_l / S_l)$ is a calibrated function which can be obtained by conducting an appropriate survey.

In the proposed model, both the path and link choice proportions are considered as random variables. Consequently, the link flow can also be considered as a random variable and its variance can be obtained by the proposed solution algorithm.

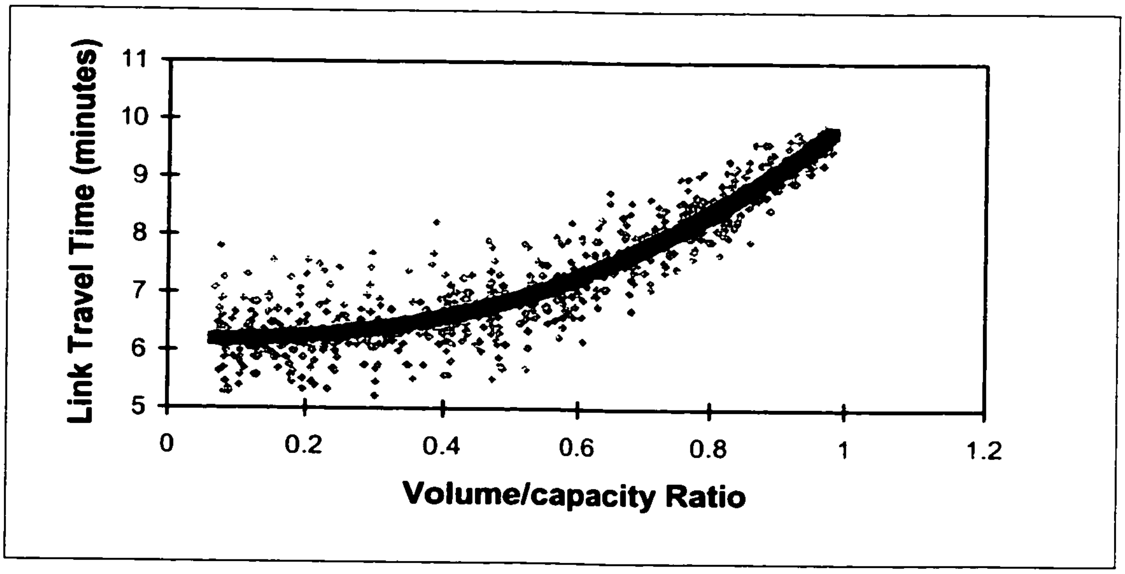

Figure 4.2 Link Travel Time vs V/c Ratio

4.2.3 Uniqueness of Solution

The proposed model is a probit assignment model because the travel time errors are assumed as normal variates. The steady-state traffic assignment on the network is equivalent to the following minimization problem (Sheffi and Powell, 1982).

$$\underset{v}{\text{Minimize}} \quad z(v) = -\sum_{a} \int_{0}^{v_a} C_a(v)dv + \sum_{a} C_a(v_a)v_a - \sum_{rs} T_{rs}S_{rs}(v)$$

where T_{rs} is the O-D demand form origin r to destination s and S_{rs} is the expected perceived minimum time (the satisfaction function between origin r and destination s) which depends on link travel time and link flow. The uniqueness of solution for this problem was proved by Sheffi and Powell (1982). The link flow pattern of the probit assignment model is unique if the link travel time functions are monotonic (Sheffi and Powell, 1982). The SUE probit assignment model does not possess the nonuniqueness of path flows property (Clark and Watling, 2001). On the basis of the monotonic characteristic of the link travel time function, the link flow pattern is unique but the path flow pattern is not guaranteed to be unique.

4.3 SOLUTION ALGORITHM

Because no closed form expression exists for the probit-based path choice model, it is difficult to have an analytical approach for deriving the path choice proportions. Maher et al. (1997) proposed a heuristic probit assignment method which used the Clark's approximation and had the cycle problems. However, the simulation assignment can be used for computing the link flow and the covariance matrix of the link flow. One of the advantages of the simulation approach is that the random errors can have any type of distribution. The column generation algorithm proposed by Bell et al. (1993) can be used to identify the set of feasible paths. By applying the Monte-Carlo simulation and the method of successive averages, the solution algorithm is proposed as shown below,

Algorithm A4.1

Step 0 Initialization. Let N be the maximum number of simulations. Set iteration n=1 and flow $V_l^n=0$ for all links l.

Step 1 Update the link travel times. Build the minimum travel time paths. Add any new paths into the link-path incidence matrix A. Compute the path travel times.

Step 2 Simulation assignment

Adopt the Monte-Carlo simulation to generate Normal variates for each link. Compute the path choice proportion. Calculate α_l and β_l by eqn. (4.8), (4.11) respectively.

Adopt the Monte-Carlo simulation to generate the Normal variates ε_l and ξ_l

$$\varepsilon_l \sim N(0, \beta_l c_l),\ \xi_l \sim N(0, \alpha_l c_l) \tag{4.12}$$

Calculate the auxiliary link flow x_l^n and link choice proportion $y_l^{rs,n}$ for link l from origin r to destination s.

Step 3 Perform method of successive average (MSA).

$$V_l^{n+1} = V_l^n + (x_l^n - V_l^n)/n, \quad p_l^{rs,n+l} = p_l^{rs,n} + (y_l^{rs,n} - p_l^{rs,n})/n$$

Record the current link flow V_l^{n+1} and the link choice proportion $p_l^{rs,n+l}$ for link l from origin r to destination s.

Step 4 Check the stopping criteria

If $|V_l^{n+1} - V_l^n| \leq \phi$, $|p_l^{rs,n+l} - p_l^{rs,n}| \leq \phi$ where ϕ is a small value or n=N, go to Step 5. Otherwise, n=n+1 and go to Step 1.

Step 5 Compute the entries σ_{ll} and σ_{lm} of the covariance matrix Ω, where σ_{ll} and σ_{lm} are computed as follows,

$$\sigma_{ll} = [\sum_{i=1}^{n} (x_l^i)^2 - (\sum_{i=1}^{n} x_l^i)^2 / n] / [n(n-1)] \tag{4.13}$$

$$\sigma_{lm} = [\sum_{i=1}^{n}(\mathbf{x}_l^i \mathbf{x}_m^i) - (\sum_{i=1}^{n}\mathbf{x}_l^i)(\sum_{i=1}^{n}\mathbf{x}_m^i)/n]/[n(n-1)] \tag{4.14}$$

n is the total number of iterations.

Similarly, the variance of the link choice proportion for link l (σ_{ll}^{rs}) and the covariance of the link choice proportion for the links l and m (σ_{lm}^{rs}) can be estimated as below:

$$\sigma_{ll}^{rs} = [\sum_{i=1}^{n}(y_l^{rs,i})^2 - (\sum_{i=1}^{n}y_l^{rs,i})^2/n]/[n(n-1)] \tag{4.15}$$

$$\sigma_{lm}^{rs} = [\sum_{i=1}^{n}(y_l^{rs,i}y_m^{rs,i}) - (\sum_{i=1}^{n}y_l^{rs,i})(\sum_{i=1}^{n}y_m^{rs,i})/n]/[n(n-1)] \tag{4.16}$$

These estimates of variance and covariance of the link choice proportion are useful particularly in connection with Lo et al. (1996) proposal of a model that incorporates the randomness of the link choice proportions which can be adopted for estimating the O-D matrix.

4.4 NUMERICAL EXAMPLE

Figure 4.3 shows the network of the Tuen Mun Road Corridor which connects the Tuen Mun and Kowloon urban areas in Hong Kong. The network consists of 3 zones, 4 nodes and 10 links.

The link travel time function (Bureau of Public Roads, 1964) with respect to link flow is given as follows:

$$C_l = \gamma_l + \eta_l (V_l / S_l)^{\rho} \tag{4.17}$$

where S_l is the capacity of link l and l=1,2,..10, γ_l is the free flow time, η_l and ρ_l are the measurement parameters of link l. The O-D matrix and the link data for the example network are given in Tables 4.1 and 4.2 respectively.

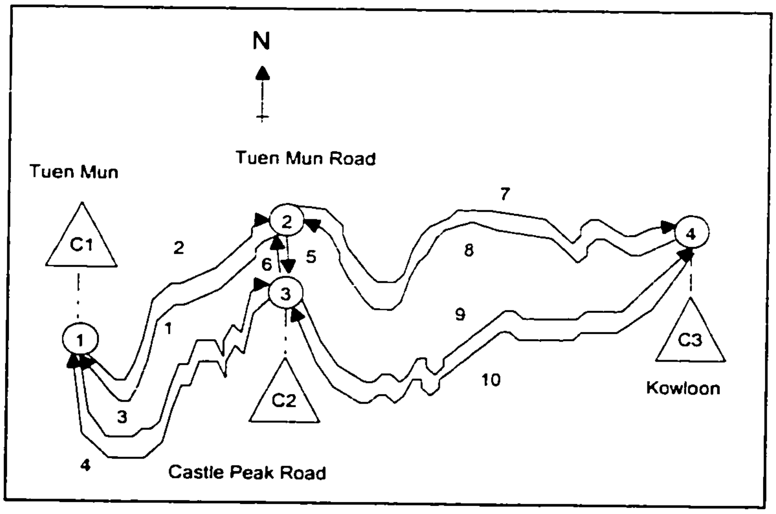

Figure 4.3 Tuen Mun Road Corridor Network

Table 4.1 The Link Data of the Network

Link no.	γ_l (hrs)	S_l (pcu/hr)	Parameter ρ_l	Parameter η_l
1,2	0.0975	5175	3.5	0.0975
3,4	0.0922	850	3.6	0.0922
5	0.0043	730	3.6	0.0037
6	0.0043	950	3.6	0.0037
7,8	0.0315	4800	3.6	0.0280
9,10	0.2300	1000	3.6	0.2300

Table 4.2 O-D Matrix (Passenger Car Units per Hour)

		Destination	zones		pcu/hr
		C1	C2	C3	Total
Origin	C1	-	32	3859	3891
zones	C2	16	-	205	221
	C3	4012	309	-	4321
	Total	4028	341	4064	8433

Since the dispersion parameter function is a positive value, an exponential function with positive coefficient is used and which is then positive for all v/c ratios. The dispersion function of the measured error variance for each link β_l can be assumed as a negative exponential function which is a decreasing function of the v/c ratio as shown below,

$$\beta_l = \lambda_l \exp(-\tau_l \; V_l / S_l) \qquad (4.18)$$

where λ_l and τ_l are positive measurement parameters for link l. For simplicity, λ_l and τ_l are the same for all links l. Let $\lambda_l = \lambda$ and $\tau_l = \tau$ for every link l. Therefore, eqn. (4.18) becomes

$$\beta_l = \lambda \exp(-\tau V_l / S_l) \qquad (4.19)$$

where λ is the proportional positive coefficient of the measured error variance.

The dispersion parameter function of the perceived travel time variance α_l for each link l is here assumed to be an exponential function which is an increasing function of v/c ratio as follows,

$$\alpha_l = \nu_l \exp(\mu_l \; V_l / S_l) \tag{4.20}$$

where ν_l and μ_l are positive measurement parameters. We assume that ν_l and μ_l are the same for all links l. Let $\nu_l = \nu$ and $\mu_l = \mu$ for all links l. Thus, eqn. (4.20) becomes

$$\alpha_l = \nu \exp(\mu \, V_l / S_l) \tag{4.21}$$

where ν is the proportional positive coefficient of the perceived travel time error variance.

In this numerical example, the stopping parameter ϕ used in step 4 of the algorithm is set to be 0.1 pcu/hr. The value of the parameters τ (in eqn. (4.19)) and μ (in eqn. (4.21)) in this chapter are fixed to be 0.5 for all the numerical testing. The link flows for different numbers of simulations when the value of the parameters λ=0.1 pcu/hr and ν=0.1 pcu/hr are shown in Table 4.3. Δ_1 and Δ_2 are the absolute differences between the link flows for simulations 5,000 and 10,000, 10,000 and 15,000 respectively.

From Table 4.3, the maximum Δ_1 and Δ_2 are 1.67 and 0.19 respectively, and their totals are 6.28 and 0.83. The change of the link flow from 10,000 to 15,000 simulations is comparatively small and indicates that good convergence has been achieved. The maximum number of simulations N is then set to be 10,000. The results in this chapter are obtained using 10,000 simulations.

Table 4.3 The Resulting Link Flows (pcu/hr) for Different No. of Simulations

Link	No. of simulations (N)			Absolute Difference	
	5,000	10,000	15,000	Δ_1 (pcu/hr)	Δ_2 (pcu/hr)
1	3411.96	3411.54	3411.47	1.67	0.15
2	3254.77	3253.1	3252.95	0.42	0.07
3	636.23	637.9	638.05	1.67	0.15
4	616.04	616.46	616.53	0.42	0.07
5	928.82	929.25	929.36	0.43	0.11
6	829.02	830.69	830.88	1.67	0.19
7	4064.00	4064.00	4064.00	0.00	0.00
8	4321.00	4321.00	4321.00	0.00	0.00
9	0.00	0.00	0.00	0.00	0.00
10	0.00	0.00	0.00	0.00	0.09
			Total	6.28	0.83

In order to assess the effects of adopting different values for ν (in eqn. (4.21)) when λ=0.1, the resulting link flows obtained are shown in Table 4.4. With various values of λ, assuming ν=0.1, the resultant link flows are presented in Table 4.5.

Table 4.4 indicates that the larger the value of ν, the greater the dispersion of the link flow because a larger ν corresponds to a larger perceived travel time error (see eqn.

(4.21)). As the value of λ increases, the measured error also increases (see eqn. (4.19)). The consequence of this is shown in Table 4.5. The above properties are illustrated and indicated that the dispersion of the link flow increases when λ increases.

Tables 4.5 and 4.6 also show that the flows on links 9 and 10 are very low because they are on urban roads with higher travel times. The variances of the link flows for different ν for the same set of fixed parameter values as in Table 4.4 are displayed in Table 4.6. For different values of λ as shown in Table 4.5, the resulting variances of the link flow are given in Table 4.7.

Table 4.4 The Resulting Link Flows (pcu/hr) for Different ν when λ=0.1 hrs

Link	ν=0.01	ν=0.1	ν=0.5
1	3447	3412	3264
2	3283	3253	3027
3	608	638	864
4	581	616	764
5	881	929	1181
6	789	831	1063
7	4064	4064	3937
8	4321	4321	4292
9	0	0	127
10	0	0	29

Table 4.6 shows as would be expected that the larger the value of the proportional positive coefficient of the perceived travel time error variance ν, the greater the obtained variance of the link flow due to the larger perceived travel time error. Also

from Table 4.7, the obtained link flow variance increases when the value of λ increases. This leads to the increases of the variance for the measured travel time error.

Table 4.5 The Resulting Link Flows (pcu/hr) for Different λ when ν=0.1 hrs

Link	λ=0.01	λ=0.1	λ=0.5
1	3405	3412	3315
2	3240	3253	3156
3	651	638	735
4	623	616	713
5	936	929	918
6	844	831	940
7	4064	4064	4064
8	4321	4321	4201
9	0	0	0
10	0	0	120

Table 4.6 The Variances of Link Flow (pcu^2/hr^2) for Different ν, λ=0.1 hrs

Link	ν=0.01	ν=0.1	ν=0.5
1	6.36	40.34	61.20
2	19.20	47.07	103.74
3	19.20	47.07	103.16
4	6.36	40.34	62.82
5	5.38	34.46	48.29
6	5.68	33.00	45.43
7	6.15	37.24	117.63
8	1.36	6.31	43.20
9	6.13	37.12	116.67
10	1.37	6.35	53.49

Table 4.7 The Variances of Link Flow (pcu^2/hr^2) for Different λ, ν=0.1 hrs

Link	λ=0.01	λ=0.1	λ=0.5
1	8.26	40.34	52.31
2	13.80	47.07	60.78
3	13.80	47.07	60.86
4	8.26	40.34	52.31
5	5.93	34.46	59.39
6	4.79	33.00	45.63
7	5.94	37.24	89.25
8	0.77	6.31	58.70
9	5.93	37.12	88.97
10	0.78	6.35	43.29

The covariance matrix obtained for ν=0.1 hrs and λ=0.1 hrs as shown in Table 4.8,

Table 4.8 Covariance Matrix Obtained for ν=0.1 hrs, and λ=0.1 hrs

		Link number									
		1	2	3	4	5	6	7	8	9	10
Link number	1	40.3	33.3	-33.3	-40.3	-33.5	17.7	12.6	3.8	-12.5	-3.7
	2	33.3	47.1	**-47.1**	-33.3	26.3	-18.7	**24.6**	3.2	-24.5	-3.1
	3	-33.3	-47.1	47.1	33.3	-26.3	18.7	-24.6	-3.2	24.5	3.1
	4	-40.3	-33.3	33.3	40.3	33.5	-17.7	-12.6	-3.8	12.5	3.7
	5	-33.5	-26.3	-26.3	33.5	34.5	-20.0	-4.7	2.6	9.6	-2.7
	6	17.7	18.7	18.7	-17.7	-20.0	33.0	14.7	-2.7	-14.8	2.8
	7	12.6	24.6	-24.6	-12.6	-4.7	14.7	37.2	-5.8	-37.2	5.7
	8	3.8	3.2	-3.2	-3.8	2.6	-2.7	-5.8	6.31	5.8	-6.3
	9	-12.5	-24.5	24.5	12.5	9.6	-14.8	-37.2	5.8	37.12	5.8
	10	-3.7	-3.1	3.1	3.7	-2.7	2.8	5.7	-6.3	5.8	6.4

The effect on the variance and covariance of the link flows if the measured error is increased as v=0.5 is now investigated. The covariance matrix is obtained and given as shown in Table 4.9:

Table 4.9 Covariance Matrix Obtained for v=0.5 hrs, and λ=0.1 hrs

Link number		1	2	3	4	5	6	7	8	9	10
	1	61.2	40.9	-40.9	-61.2	-43.8	44.3	39.5	44.7	-41.2	-44.6
	2	40.9	103.7	**-103.2**	-41.2	38.8	-50.9	**67.8**	10.8	-55.6	-9.3
	3	-40.9	-103.2	103.1	40.9	-38.8	50.9	-66.7	-10.9	56.8	9.6
	4	-61.2	-41.2	40.9	62.8	43.9	-44.1	-39.2	-44.5	41.6	44.3
	5	-43.8	38.8	-38.8	43.9	48.3	-22.9	-56.1	21.3	49.5	-21.1
	6	44.3	-50.9	50.9	-44.1	-22.9	45.4	43.3	-5.9	-43.2	7
	7	39.5	67.8	-66.7	-39.2	-56.1	43.3	117.6	-58.6	-115.9	58.7
	8	44.7	10.8	-10.9	-44.5	21.3	-5.9	-58.6	43.2	43.8	-43.1
	9	-41.2	-55.6	56.8	41.6	49.5	-43.2	-115.9	43.8	116.7	50.9
	10	-44.6	-9.3	9.6	44.3	-21.1	7	58.7	-43.1	50.9	53.5

From these covariance matrices, both positive and negative values of covariance are shown. The covariance is an indication of how one link flow varies with another link flow. If the covariance between two link flows is positive, the two link flows are positively correlated. For instance, covariances between flows on links 2 and 7 in the two covariance matrices are 24.6 and 67.8 respectively. The positive covariance shows that the larger the flow of link 2, the larger is the flow of link 7. As shown in Figure 4.3, links 2 and 7 are along the same major route for the travel from Tuen Mun to Kowloon. Therefore, the flow on link 7 increases when the flow on link 2 increases.

However, if the covariance between two link flows is negative, the two link flows are negatively correlated. For example, covariances between flows on links 2 and 3 are -

47.1 and -103.2 in the two covariance matrices respectively. The negative covariance indicates that the larger the flow of link 2, the smaller the flow of link 3. From Figure 4.3, it can be seen that links 2 and 3 are the two alternative routes from Tuen Mun to Kowloon. Hence, when the flow on link 2 increases, the flow on link 3 would decrease.

To demonstrate the convergence of the proposed iterative assignment algorithm, we consider the root mean square difference between the current and auxiliary solutions (RMS(X,V)). This is a convenient measure of convergence (Maher and Hughes, 1997) and is defined as

$$\mathrm{RMS}(X,V) = \sqrt{\frac{1}{N}\sum_{a}\frac{(x_a - v_a)^2}{0.5(x_a + v_a)}} \tag{4.22}$$

where x_a and v_a are respectively the auxiliary and current link flows, and N is the number of links in the network. Figure 4.4 shows values of RMS(X,V) for a various number of iterations. This indicates that the reduction of the RMS(X,V) value is higher for the first 200 iterations while the RMS(X,V) becomes a very small value at the latter stage. The total network travel times for a different number of iterations are shown in Figure 4.5. The change in the total network travel time is small after the first 200 iterations. This indicates the convergence of the model and algorithm.

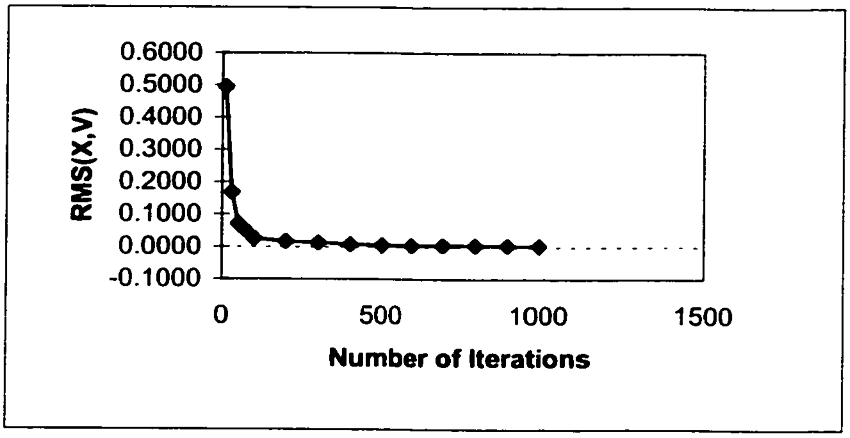

Figure 4.4 RMS(X,V) vs Number of Iterations (n)

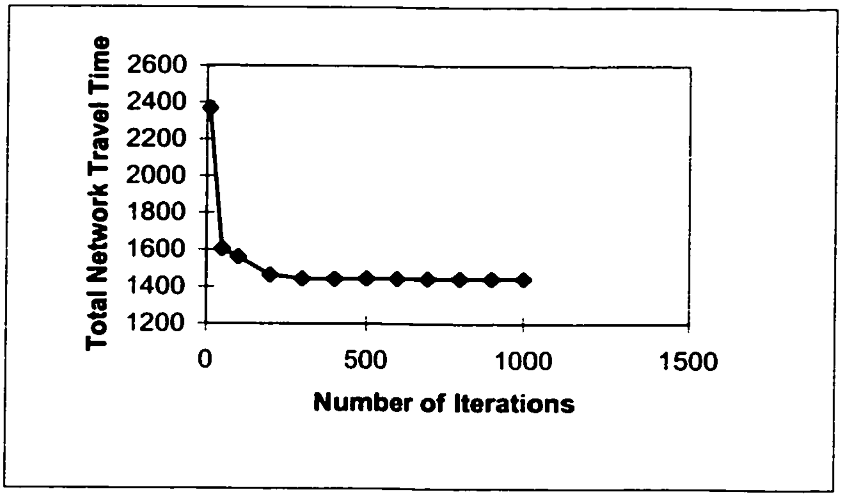

Figure 4.5 Total Network Travel Time vs Number of Iterations (n)

Table 4.10 shows the link flows resulting from different assignment models considered in this study of equilibrium, logit, C-logit and probit in comparison with the observations. The suggested commonality factor (Cascetta et al., 1996) is as follows:

$$CF_k = \beta_0 \ln \sum_h \left(\frac{L_{hk}}{L_h^{1/2} L_k^{1/2}} \right)^{\gamma} \qquad (4.23)$$

where L_{hk} is the length of links common to paths h and k, while L_h and L_k are the overall lengths of paths h and k respectively; β_0 and γ are dimensionless parameters.

The link-based method (Lam and Chan, 1998) is used for solving the logit assignment model where the dispersion parameter is set to be 12.6 hr^{-1}. It can be observed that the probit link flows are closer to the observed link flow pattern when the calibrated parameters of λ=0.86 and ν=0.87 are used. The obtained link flow of the link-based method is also close to the observed link flow when the dispersion parameter of logit assignment model is 12.6 hr^{-1}.

To validate the calibrated probit assignment model, the C-logit model and the logit assignment model, we consider RMS and average relative error (ARE) differences between observed and estimated link flows (Maher and Hughes, 1997). The ARE is defined as follows:

$$\text{ARE}=\frac{1}{N}\sum_{a}\frac{x_a - v_a}{x_a} \tag{4.24}$$

where x_a and v_a are respectively the observed and estimated link flows, and N is the number of links in the network.

The RMS and ARE differences between the observed link flows and resulting link flows for each of these three models are computed. The resultant RMS are 14.66, 2.04, 2.27 and 2.52 for the UE, probit, C-logit and the logit assignment models respectively. The resultant ARE are –29.28, 2.16, 3.17 and 3.36 for the UE, probit, C-logit and the logit assignment models respectively.

Both the RMS and ARE of the probit assignment model are lower than the C-logit and logit assignment models. The percentage ratio of the difference between each resulting and observed link flow is shown in the corresponding bracket. The highest percentage ratio between resulting and observed link flows are -100, 12.66, 23.38 and 14.61 for the UE, probit, C-logit and logit assignment models respectively. In view of the above findings, the calibrated probit assignment model performs better than the other two models.

Table 4.10 Link Flows (pcu/hr) Resulting from Different Models

Link	UE	Probit assignment model (λ=0.86 hrs, ν=0.87 hrs)	C-logit (β_0=0.21, γ=1)	Logit Assignment model (dispersion parameter=12.6 hr^{-1})	Observed Link Flows (pcu/hr)
1	3415 (16.55)	3053 (4.20)	3045 (3.92)	3071 (4.81)	2930
2	3254 (16.21)	2855 (1.69)	2898 (3.50)	2905 (3.75)	2800
3	637 (-41.61)	1053 (-3.48)	1021 (-6.42)	1001 (-8.25)	1091
4	613 (-44.17)	992 (-9.65)	1011 (-7.92)	973 (-11.38)	1098
5	906 (-27.69)	1301 (3.83)	1301 (3.83)	1298 (3.59)	1253
6	810 (-28.00)	1249 (11.02)	1250 (11.11)	1278 (13.60)	1125
7	4064 (8.20)	3819 (1.68)	3745 (-0.29)	3785 (0.77)	3756
8	4321 (7.68)	3988 (-0.62)	3943 (-1.74)	3969 (-1.10)	4013
9	0 (-100.00)	339 (10.06)	321 (4.22)	281 (-8.77)	308
10	0 (-100.00)	347 (12.66)	380 (23.38)	353 (14.64)	308
RMS	14.66	2.04	2.27	2.52	-
ARE	-29.28	2.16	3.17	3.36	-

Note: the value in the bracket =
(resulting link flow-observed link flow)/ observed link flow *100%

4.5 SUMMARY

In this chapter, a probit traffic assignment model for estimating the variance of the link flow and of the link choice proportion is proposed. The perceived and measured path travel time errors are both assumed to be distributed Normal. The measurement errors and perception errors are considered separately in this chapter. Therefore, the Monte-Carlo simulation is used for simulating the measurement errors and perception errors which violate the advantage of the logit model (closed form solution). Consequently, the probit model is chosen. In principle, a logit model has a simple covariance matrix but the probit model has a more general covariance matrix structure and is appropriate, particularly when alternatives are not always independent in practice. Therefore, the probit model should be more accurate than the logit model. However, some recent development of efficient algorithms for solving probit model (Clark and Watling, 2001) and quasi-simulation approach (Bhat, 2000) have been carried out.

From the numerical results, the higher the proportional coefficient of the perceived travel time error variance ν, the higher the perceived error and hence the variance of the link flow increases. The variance of the link flow increases with the value of the proportional coefficient of the measured error variance λ because the variance of the measured error is proportional to λ. The covariance of the link flows can be viewed as an indicator of how one link flow varies with another. The root mean square difference and the total network travel time are adopted for demonstrating the convergence of the solution. The effectiveness of the probit model and solution method are illustrated in the numerical example. The resulting RMS and ARE are lower than that obtained by the other two models.

The proposed model and solution algorithm will be extended to a time-dependent dimension in Chapter 5, in order that the application of the proposed model can be used to assess the effects of the driver information system.

5 TIME-DEPENDENT STOCHASTIC TRAFFIC ASSIGNMENT MODEL FOR NETWORK WITH VARIABLE MESSAGE SIGNS

In view of the serious traffic congestion during peak hours in most metropolitan areas around the world and the recent improvement of information technology, there is a growing aspiration to alleviate road congestion by the application of electronic information and communication technology. Providing drivers with dynamic travel time information such as estimated journey times on major routes should help drivers to select better routes and guide them to utilise existing expressway networks. This can be regarded as one possible strategy for effective traffic management.

In Chapter 4, a probit assignment model is proposed for estimating the link flow and its variance. In Chapter 5, the proposed model and solution algorithm are extended to a time-dependent dimension for assessing the effects of the driver information system. This chapter aims to investigate the effects and benefits of providing dynamic travel time information to drivers via variable message signs on the expressway network. In order to assess the effects of the dynamic driver information system by making use of the variable message signs, a time-dependent stochastic traffic assignment model is proposed. A numerical example is used to illustrate the effects of the dynamic travel time information via variable message signs. It should be noted that the proposed stochastic traffic assignment model is also referred to as the probit assignment model in the remaining chapters of the thesis.

5.1 BACKGROUND

It is noteworthy that Hong Kong has been at the forefront of practical applications of information technology in transport; the pilot area pricing scheme in Hong Kong has excited interest throughout the transport planning community, the real time traffic information has been used to adjust signal timings at major road intersections so as to improve the efficiency of road networks, and a dynamic driver information system is being introduced.

Although Hong Kong has made use of information technologies in transport, growing pressures on the transport system necessitates consideration of additional or alternative information technologies. The provision of dynamic driver information system via variable message signs (VMS) on the major routes such as Tuen Mun Road Corridor in Hong Kong (see Figure 5.2) can be an alternative to address the traffic congestion problem. In fact, the evaluation of this system is very important. This chapter proposes a time-dependent traffic assignment model for assessing the effects of providing dynamic travel time information via variable message signs. The total network travel time can be compared for the evaluation of the system.

The structure of this chapter is organised as follows. First, the dynamic driver information system being proposed for the Tuen Mun Road Corridor in Hong Kong is briefly described together with its potential extension. It is followed by the review of previous related literature research. The assumptions of this chapter are also given. The proposed model for assessing the effects of dynamic travel time information on drivers' route choices is then presented together with a numerical example. Finally, a summary will be given and a discussion of the effectiveness of the proposed dynamic driver information system.

5.1.1 Dynamic Driver Information System for the Tuen Mun Road Corridor

The expressway network in Hong Kong represents a small proportion of the total length of road network, but nonetheless carries a disproportionately high amount of traffic. Growing demand for use of the network cannot be accommodated by further extension. This causes an increasing incidence of congestion, with the consequent delay, accidents and environmental pollution.

Given this context, the Hong Kong Transport Department has investigated the feasibility of implementing a Dynamic Driver Information System covering the Tuen Mun Road (Delcan and Parsons Brinckerhoff, 1995), and extending along the corridor between the Tuen Mun New Town and the Kowloon urban area (see Figure 5.2).

The project includes the installation of 19 Closed Circuit Television (CCTV) cameras and 21 VMS gantries at various locations on the Tuen Mun Road corridor to provide drivers dynamic information so as to alleviate the effects of two types of congestion:

(i) Recurrent congestion - predictable traffic conditions caused by an excess of demand over supply, following a defined pattern e.g. peak period traffic and seasonal variations.

(ii) Non-recurrent congestion - situations resulting from a temporary reduction in the capacity of a length of road due to accidents, construction works or other short-term disruptions to traffic flow.

The non-recurrent incidents with lane blockage, such as a disabled vehicle, can generate substantial congestion. The incidents can cause significant traffic capacity reductions and costly delay. For example, reductions in capacity of around 50 percent are found on a three-lane roadway when one lane is closed (Pfefer and Raub, 1998). In the event of heavy congestion, or a major incident on the expressway network, a pre-planned control strategy is implemented utilizing a roadside VMS system. This enables diversion of traffic onto other expressways or parallel distributors. The VMS system would be linked via the existing cable network to a control centre located near the Traffic Control and Surveillance Division (TCSD) office of Transport Department. The overall aim would be to create a facility for positive traffic management on the Tuen Mun Road expressway network and to use this as a model for the rest of the territory expressway network.

The proposed VMS system utilises vehicle detection technology to collect traffic data and variable message signs, on gantries at regular intervals, to supply recommended speed limits and lane control information to drivers. The overall concept could be to extend and supplement the capabilities of the proposed system with a dedicated dynamic driver information system capable of providing dynamic travel time information based on actual and predicted traffic conditions.

The concept of providing dynamic travel time information to drivers via VMS has the potential to accrue significant benefits in terms of reduced delay and environmental pollution. However, the exact value of these benefits will depend on the design of the system to accommodate variations in reliability of travel time estimation and driver behaviour. These facts would have to be studied in more detail prior to the assessment of cost benefit values.

It is particularly important to gain more insight into the impacts of variable message sign information, since these might provide a relatively cheap alternative for the very sophisticated and expensive on-board navigation systems. The Dutch government is planning to substantially increase the number of variable message signs that provide dynamic traffic information (Dutch Ministry of Transport, 1992). It is expected that these will play an important role in improving both the efficiency and control of traffic flows (Emmerink et al., 1996).

Ramsay et al. (1997) presents the findings of an evaluation of the VicRoads' Drive Time System installed on Melbourne's South Eastern Arterial. The Trip information sign of that Drive Time System provides estimated travel times to major arterial exit points. The benefits of Drive Time are delay reductions due to increases in traffic diversion from the South Eastern Arterial when incidents occur, and also due to less incidents as a result of reduced stress and better information ahead. Catchpole et al. (1995) reported that a system of dynamic traffic information signs on freeways would be considered desirable and useful by the great majority of drivers in the community. However, it is necessary to evaluate the effects of providing dynamic travel time information via VMS on the network performance.

5.1.2 Previous Related Works

Peeta et al. (1991) using simulation modelling indicated that the level of benefits that can be achieved by the provision of dynamic information is particularly sensitive to the location of an incident and its duration. Mahmassani and Jayakrishnan (1991) developed a modelling framework to investigate the effect of the in-vehicle real time information on the overall performance of a congested network.

Yang et al. (1993) proposed a neural network model to reveal the driver's response to the advanced traveler information system. Meanwhile, Lotan and Koutsopoulos (1993) applied the fuzzy set theory and fuzzy control to model the route choice behaviour under the dynamic information system.

Emmerink et al. (1995a, 1995b) used a simulation model to analyze the effects of different types of information provision to drivers in a network. However, the above models may not be applicable to expressway networks where travel time information is only provided on the major routes via VMS.

Nijkamp et al. (1996) presented a case study regarding VMS in the Netherlands and found that the benefits of the VMS are not only confined on the reduction in travel time, but also on the reduction of uncertainty with respect to the traffic situation. Richards et al. (1996) used the RGCONTRAM model to investigate the factors which influence the effectiveness of VMS. It was assumed in the model that the proportion of drivers, who divert at the VMS, is user-defined. Thus, drivers are diverted to the user-defined diversionary routes.

Lim and Lee (1997) developed an integrated dynamic traffic assignment model for responsive signal control and variable message sign information and the model is expected to be useful for evaluating the various diverse strategies of Intelligent Transport Systems (ITS). Mammer et al. (1996) adopted the decentralized feedback control method to the Aalborg highway network in Denmark.

In view of the above, it is necessary to evaluate the effects of the VMS on drivers' route choices, particularly in the case where dynamic travel time information is only provided on the major route but not on the parallel distributors. And the location of VMS is to the key strategic locations that are the principal roads before the intersections between the motorways and other major roads (Nijkamp et al., 1996; Ramsay et al., 1997). This chapter proposes a traffic assignment model for road networks with dynamic travel time information via VMS. Both the steady state and time-dependent state assignment algorithms are presented. Finally, a numerical example is given to illustrate the effects of dynamic travel time information on the expressway network.

5.2 ASSUMPTIONS

Throughout this chapter, the following assumptions are made:

1. The origin-destination (O-D) demands are assumed to be functions of time.

2. Travel times on both expressways and local distributor roads are continuous and strictly increasing functions of traffic flows such as the typical (BPR Bureau of Public Roads, 1964) link travel time function.

3. Drivers don't have sufficient knowledge of traffic condition on the road network if the VMS are turned off, and make routing decisions in a stochastic user optimal manner.

4. The stochastic network loading is simulated by a probit assignment model where the perceived link travel time and measured link travel time are normally distributed.

5. The measured link travel time error variance is assumed as the product of the actual link travel time and a measured travel time error dispersion function. The measured travel time error dispersion function is assumed as a function of the detector density. If the number of detectors in a road increases, the detector measurement errors are reduced. Thus, the variance of the measurement errors is smaller if the detector density is higher. We can assume that the dispersion function with respect to types of detectors is an inversely proportional function to the detector density. In fact, the findings of Sen et al. (1997) support this assumption. Sen et al. (1997) found that the variance of the mean of the travel times obtained from n probes for the same link over a fixed time period is shown to be inversely proportional to n. It was found the standard error of the travel time decreases as the number of probe vehicles increases. Note that the estimation of link speeds by using probe vehicles or speed detectors is similar in principle as both probe vehicles and speed detectors can provide the sample link speed estimates on the road section concerned. Therefore, the effect of increasing the number of probe vehicles is more or less equivalent to that of increasing the

number of speed detectors. Consequently, it can be implied that the measured travel time dispersion decreases as the number of speed detectors increases.

6. The perceived link travel time error variance is assumed as the product of the measured link travel time and a perceived travel time error dispersion parameter.
7. The stochastic equilibrium is assumed in the proposed model. If the duration of the non-recurrent congestion is short and its impact is insignificant, the stochastic equilibrium can be reached after the short-duration incident. If the non-recurrent congestion is held for a longer duration, the drivers should be able to adapt to the new condition on the basis of the dynamic information from the VMS and then the stochastic equilibrium can be reached at a later stage.

5.3 PROPOSED STOCHASTIC TRAFFIC ASSIGNMENT MODEL

Basically, there are two types of link on the road network. The first type of link contains the vehicle detectors and the VMS which can provide the travel time information to the drivers passing through these links. For the first type of link, the travel time measurement errors due to the detectors are taken into account as the accuracy of the measured link time depends on the detector density. The second type of link does not have any vehicle detectors and VMS, on which the perceived errors of the driver are also considered. No travel time information is provided on these links.

Link l belongs to the first type. For this link, the measured link time C_{ml} is a random variable and can be expressed as the sum of the actual link time C_l and the travel time measurement error ε_{ml},

$$C_{ml} = C_l + \varepsilon_{ml} \quad , \ \forall l \in L_{vms} \qquad (5.1)$$

where the travel time measurement error is assumed to be normally distributed with the mean equal to zero and with a variance that is proportional to the actual link time, $\varepsilon_{ml} \sim N(0, \beta_{ml}\, C_l)$. Therefore, the measured link time is normally distributed with the mean equal to the actual link time and a variance that is proportional to the actual link time, $C_{ml} \sim N(C_l, \beta_{ml}\, C_l)$.

Usually, the dispersion parameter β_{ml} is considered to be a constant. In fact, β_{ml} can be interpreted as the variance of the measured travel time error over a road segment where the unit travel time is dependent on the vehicle detector density. In this chapter, it is assumed that $\beta_{ml} = f_d(d_{sl})$. Note that $f_d(d_{sl})$ is a non-increasing function of the detector density on link l because the measurement error decreases as the detector density increases.

The perceived travel time C_{pl} and the measured travel time C_{ml} of link l can be related as follow,

$$C_{pl} = C_{ml} + \varepsilon_{pl} \quad , \ \forall l \in L_{vms} \qquad (5.2)$$

where the perceived error ε_{pl} can be assumed to be normally distributed with mean zero and variance that is proportional to the measured link time, i.e. $\varepsilon_{pl} \sim N(0, \beta_{pl} C_{ml})$. Consequently, the perceived travel time of link l is a random variable with a mean equal to the measured link time and the variance is the product of the dispersion parameter β_{pl} and the measured link time, $C_{pl} \sim N(C_{ml}, \beta_{pl}\, C_{ml})$.

In practice, there are some links in the network which do not need to provide travel time information. For these links l, the perceived time is assumed as below,

$$C_{pl} = C_l + \varepsilon_{fl} \quad , \ \forall l \in L'_{vms} \tag{5.3}$$

where the perceived time error ε_{fl} is assumed to be normally distributed, $\varepsilon_{fl} \sim N(0, \beta_{fl} C_l)$. The dispersion parameter β_{fl} is assumed as a constant. The perceived link time is a random variable and normally distributed with the mean equal to the actual link time and the variance proportional to the actual link time, $C_{pl} \sim N(C_l, \beta_{fl} C_l)$.

The perceived time of path k is the sum of the corresponding perceived link time, that is,

$$C_k = \sum_{l \in L_k} C_{pl} \tag{5.4}$$

For a link l with travel time information, the perceived link time (C_{pl}) is the sum of the actual link time (C_l), the measured link time error (ε_{ml}) and the perceived link time error (ε_{pl}) with travel time information (from eqns. (5.1) and (5.2)). For a link l without travel time information, the perceived link time (C_{pl}) is the sum of the actual link time (C_l) and the perceived link time error (ε_{fl}) without travel time information (from eqn. (5.3)). Therefore, the perceived path time can be obtained

$$C_k = \sum_{l \in L_k \cap L_{VMS}} C_{pl} + \sum_{l \in L_k \cap L'_{VMS}} C_{pl} \tag{5.5}$$

$$= \sum_{l \in L_k \cap L_{VMS}} (C_l + \varepsilon_{ml} + \varepsilon_{pl}) + \sum_{l \in L_k \cap L'_{VMS}} (C_l + \varepsilon_{fl}) \tag{5.6}$$

$$= \sum_{l \in L_k} C_l + \sum_{l \in L_k \cap L_{VMS}} (\varepsilon_{ml} + \varepsilon_{pl}) + \sum_{l \in L_k \cap L'_{VMS}} \varepsilon_{fl} \tag{5.7}$$

$$= \sum_{l \in L_k} C_l + \sum_{l \in L_k} \varepsilon_l \tag{5.8}$$

$$\mathbf{C}^k = A^T\mathbf{c} + A^T\boldsymbol{\varepsilon} \tag{5.9}$$

$$\text{where } \varepsilon_l = \begin{cases} \varepsilon_{pl} + \varepsilon_{ml}, & \text{if } l \in L_{VMS} \\ \varepsilon_{fl}, & \text{if } l \in L'_{VMS} \end{cases} \tag{5.10}$$

Consequently, the perceived path time vector $\mathbf{C}^k$ is the sum of the actual path time vector $A^T\mathbf{c}$ and the perceived error vector $A^T\varepsilon$. For a link l with travel time information, the total link time error (ε_l) is the sum of the measured link time error (ε_{ml}) and the perceived link time error (ε_{pl}). For a link l without travel time information, the total link time error (ε_l) is the perceived link time error (ε_{fl}) without travel time information.

5.4 SOLUTION ALGORITHM

5.4.1 Steady State Traffic Assignment Algorithm for Network with VMS

The steady state traffic assignment algorithm for VMS system is presented as in Figure 5.1. The algorithm includes the stochastic user equilibrium (SUE) probit assignment and the VMS assignment. Firstly, the SUE probit assignment for the whole network is conducted. Secondly, the VMS assignments for each sub-network are conducted where the intersections with VMS are treated as the origin and the traffic flow assigned according to the effect of the VMS information. Therefore, the network is treated as having no VMS on all links, except the one which has been traversed immediately before the diversion point for which path choice probabilities are evaluated.

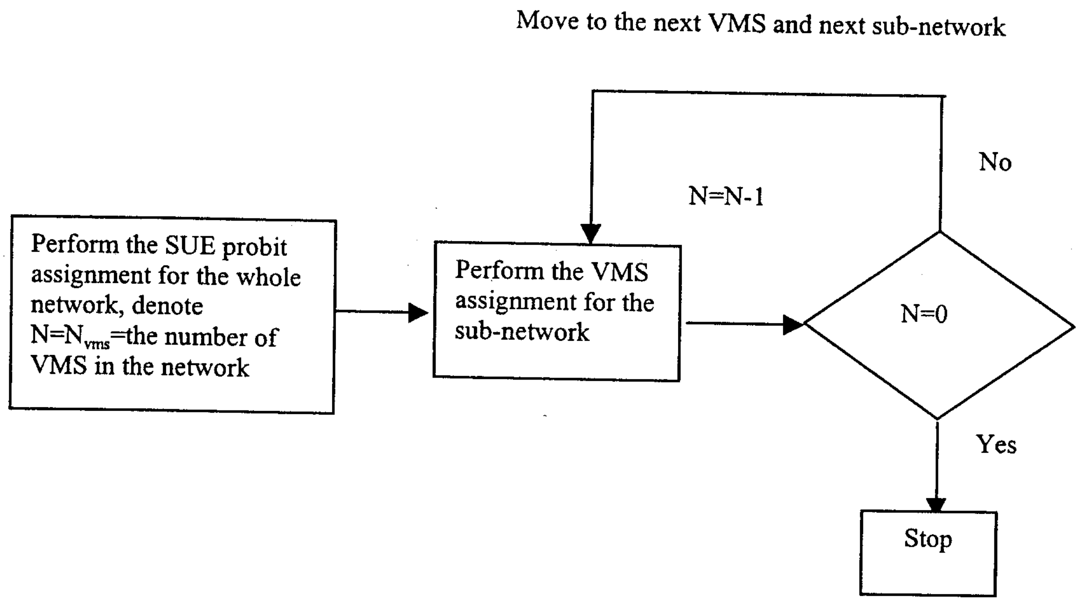

Figure 5.1 Steady State Traffic Assignment Algorithm for Network with VMS

The Monte-Carlo simulation, shortest path algorithm and method of successive average are used to solve the VMS assignment problem for each sub-network. The advantage of the simulation method is that it does not require the sampling of the perceived path time; the perceived link time is sampled only at each iteration thus avoiding the problem of path storage. The VMS assignment algorithm for each sub-network is presented below,

Algorithm A5.1

Step 0: Initialization.

Step 1: Update the travel time. Adopt the Monte-Carlo simulation to generate the measured link time $C_{ml} \sim N(C_l, \beta_{ml} C_l)$ $\forall l \in L_{vms}$. Generate the perceived link time $C_{pl} \sim N(C_{ml}, \beta_{pl} C_{ml})$ $\forall l \in L_{vms}$. For the links without travel time information, generate the perceived link time $C_{pl} \sim N(C_l, \beta_{fl}\ C_l)\quad \forall l \in L'_{vms}$. Perform shortest path algorithm for network.

Step 2: Perform Method of Successive Average (MSA) for estimating the link flows (Y. Sheffi, 1985).

Step 3: If the differences of the estimated link flows in the consecutive iterations are smaller than a given value θ then stop. Otherwise, go to Step 1.

5.4.2 Time-dependent Traffic Assignment Algorithm for VMS

By considering the queues and delay at each time interval, the following time-dependent traffic assignment algorithm for VMS is proposed by modifying the time-dependent stochastic traffic assignment algorithm adopted by Bell et al. (1996). A general difficulty with dynamic assignment is related to the first-in first-out (FIFO) principal, FIFO leads to a non-convex set of feasible link flows (Carey, 1992). By considering the steady state networks, the above difficulty does not arise (Bell et.al., 1996; Lam and Yin, 2001). Therefore, the time-dependent (or quasi-dynamic) SUE probit assignment model proposed in this study is based on the steady state networks for each time interval. The microscopic effects of the flow propagation are not considered in the proposed model, but the macroscopic effects of flow propagation are enforced. The queues at the end of one time interval are carried over to the next time interval. The queues existing at the previous time interval are processed before the new arrivals at current time interval, and new queues are only formed when the exit capacities are reached. It should be noted that the proposed quasi-dynamic probit assignment model was used for long-term strategic planning purpose.

Although the proposed model is considered as analysis tool for long-term strategic planning purpose, the adopted BPR link travel time function is however restricted to the application in estimating the steady state traffic flow and the delay function should be considered in the time-dependent state (Ran et al., 1997). Therefore, the delay function is also incorporated in the time-dependent probit assignment model in this chapter.

Algorithm A5.2

Step 0: Set time interval t=1, give initial queues q_{i0} for all links, determine the study period.

Step 1: Set iteration k=0,

Let the traffic arrival $D_{it}^{(k)}=D_{it}^{(0)}=0$, the link flow $v_{it}^{(k)}=v_{it}^{(0)}=0$ and queue $q_{it}^{(k)}=q_{it}^{(0)}=0$ on link i.

Step 2: Generate link time $c_i^{(k)}$ and delay $d_i^{(k)}$

Total time $C_i^{(k)} = c_i^{(k)}+d_i^{(k)}$.

Step 3: By solving the Steady State Traffic Assignment Algorithm for VMS to find $D_i^{(k)}$.

Step 4: Obtain the auxiliary link flow and queue. If $D_i^{(k)} + q_{i,t-1} < s_i$, obtain the auxiliary link flow $x_i^{(k)} = D_i^{(k)} + q_{i,t-1}$ and auxiliary queue $y_i^{(k)} =0$; otherwise, let $x_i^{(k)} = s_i$ and $y_i^{(k)} = D_i^{(k)} + q_{i,t-1} - s_i$.

Step 5: Find the updated link flow, queue and traffic arrival.

Compute $v_{it}^{(k+1)}$, $q_{it}^{(k+1)}$, $D_{it}^{(k+1)}$ (by MSA)

$$v_{it}^{(k+1)} = v_{it}^{(k)} + (x_i^{(k)} - v_{it}^{(k)})/k \tag{5.11}$$

$$q_{it}^{(k+1)} = q_{it}^{(k)} + (y_i^{(k)} - q_{it}^{(k)})/k \tag{5.12}$$

$$D_{it}^{(k+1)} = D_{it}^{(k)} + (D_i^{(k)} - D_{it}^{(k)})/k \tag{5.13}$$

Step 6: Check stopping criteria.

If $|v_{it}^{(k+1)} - v_{it}^{(k)}| \le \phi$, $|D_{it}^{(k+1)} - D_{it}^{(k)}| \le \phi$ and $|q_{it}^{(k+1)} - q_{it}^{(k)}| \le \phi$ then stop, where ϕ is a small value. Otherwise, k=k+1, go to step 2.

Step 7: If $t \ge$ study period, stop; otherwise, set t=t+1, go to step 1.

5.5 NUMERICAL EXAMPLE

In Figure 5.2, the example network of the Tuen Mun Road Corridor which connects Tuen Mun (new town in the outlying area) and Kowloon (urban area in Hong Kong) is shown. The network consists of 3 zones and 10 links. In the network, the detectors are introduced only on links 1, 2, 7 and 8. We decide two scenarios for locating VMS: (I) number of VMS (v_s) is 1 and the VMS is on node 1, and (II) number of VMS is 2 and the VMS are installed on nodes 1 and 2. The example is designed for two purposes, namely (a) to demonstrate the effects of the dynamic travel time information via VMS in situations of recurrent and non-recurrent congestion, and (b) to test the feasibility of providing dynamic travel time information by minimizing the total network travel time.

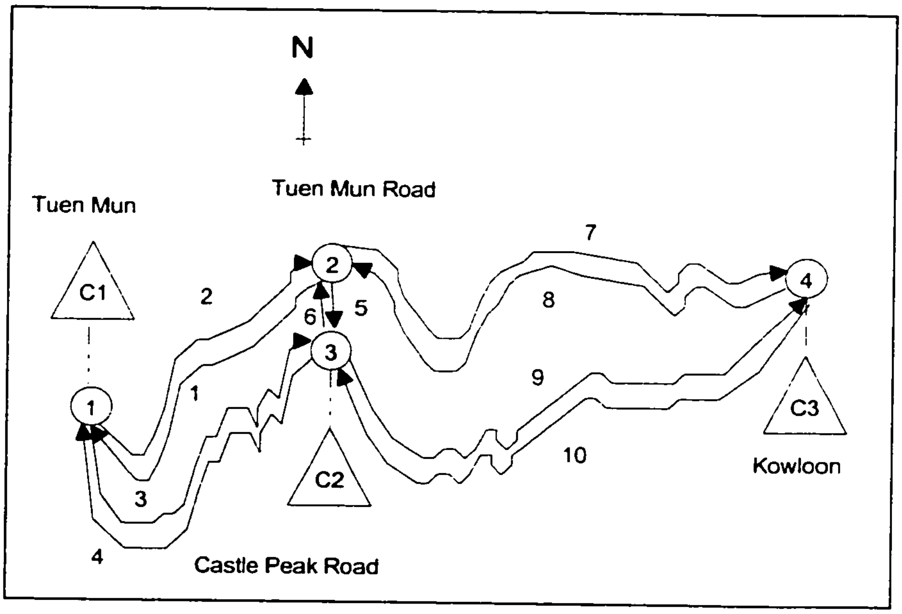

Figure 5.2 Tuen Mun Road Corridor Network

To illustrate the solution algorithm in real case, the model proposed in the last section is applied to the Tuen Mun Road Corridor in Figure 5.2 where the dynamic travel time information are provided on links 1, 2, 7 and 8 via VMS. Suppose the dispersion parameters of the normally distributed errors are assumed as follows:

Measurement Error,	$\beta_{ml} = f_d(d_{sl}) = \lambda e^{-1.2\, d_{sl}}$	
Perceived Error with VMS,	$\beta_{pl} = 0.1,$	$\forall l \in L_{vms}$
Perceived Error without VMS,	$\beta_{fl} = 1,$	$\forall l \in L'_{vms}$

where $L_{vms} = \{1, 2, 7, 8\}$, and $L'_{vms} = \{3, 4, 5, 6, 9, 10, 11\}$. The parameter λ is assumed to be 0.5.

The time-dependent O-D demand functions are given on the basis of unit time period T as below:

$$OD(T)[C1 \rightarrow C2] = 220+30(1-\cos(2\pi T/120)$$

$$OD(T)[C1 \rightarrow C3] = 4952+350(1-\cos(2\pi T/120))$$

$OD(T)[C2 \rightarrow C1] = 313+56(1-\cos(2\pi T/120))$

$OD(T)[C2 \rightarrow C3] = 127+20(1-\cos(2\pi T/120))$

$OD(T)[C3 \rightarrow C1] = 4492+200(1-\cos(2\pi T/120))$

$OD(T)[C3 \rightarrow C2] = 78+20(1-\cos(2\pi T/120))$.

where $0 \le T \le 120$ (in minutes). The study period is from 7:00 a.m. to 9:00 a.m.

The following link travel time function with respect to link flows is adopted:

$$C_u = \gamma_u + \alpha_u \, (v_u / s_u)^{\rho_u} . \tag{5.14}$$

Kytes and Marek (1989) found that the overflow queue delay increases exponentially as the flow increases. The following overflow queue delay time function (Meneguzzer, 1995; Boyce et al.,1997) is used:

$$d_u = \exp[3.802(1+(q_u / s_u))] \tag{5.15}$$

where s_u is the capacity of link u per hour and u=1,2,...10, γ_u is the free flow time, α_u, ρ_u are the calibration parameters of link u and q_u is the overflow queue on link u. The link data on the example network are given in Table 5.1.

Table 5.1 The Link Data of the Network

Link no.	γ_u (hrs)	s_u (veh/hr)	Parameter ρ_u	α_u	Distance (m)
1,2	0.090	5,175	3.5	0.1050	5850
3,4	0.1106	850	3.6	0.1408	5530
5	0.0056	730	3.6	0.0071	280
6	0.0056	950	3.6	0.0071	280
7,8	0.0335	4,800	3.6	0.0335	2680
9,10	0.0767	1,000	3.6	0.1073	4600

The Highway Capacity Manual (Transportation Research Board, 1985) has introduced the concept of level of service (LOS) as a qualitative measure of the degree on congestion of a road network. In practice, the volume/capacity (v/c) ratio can be used to identify the LOS. The six LOS (A to F) are presented in Table 5.2.

Table 5.2 Levels of Service of a Road Network

Levels of service (LOS)	Volume/capacity (v/c) ratio
A	0 - 0.35
B	0.35 - 0.54
C	0.54 - 0.77
D	0.77 - 0.93
E	0.93 - 1.00
F	>1.00

In the recurrent congestion situation, the network vehicle-hour distributions by 5-minute intervals for the two-hour study period are displayed in Figures 5.3 and 5.4 for the network without and with the VMS system. Figure 5.3 shows that during the study period the highest LOS is D only. In other words, the v/c ratios of the links in the network are all greater than 0.77 during the two-hour study period. Compared with the VMS system where both v_s and d_s are equal to 2.0, it can be seen in Figure 5.4 that the percentage of vehicle flow with the LOS F is much smaller.

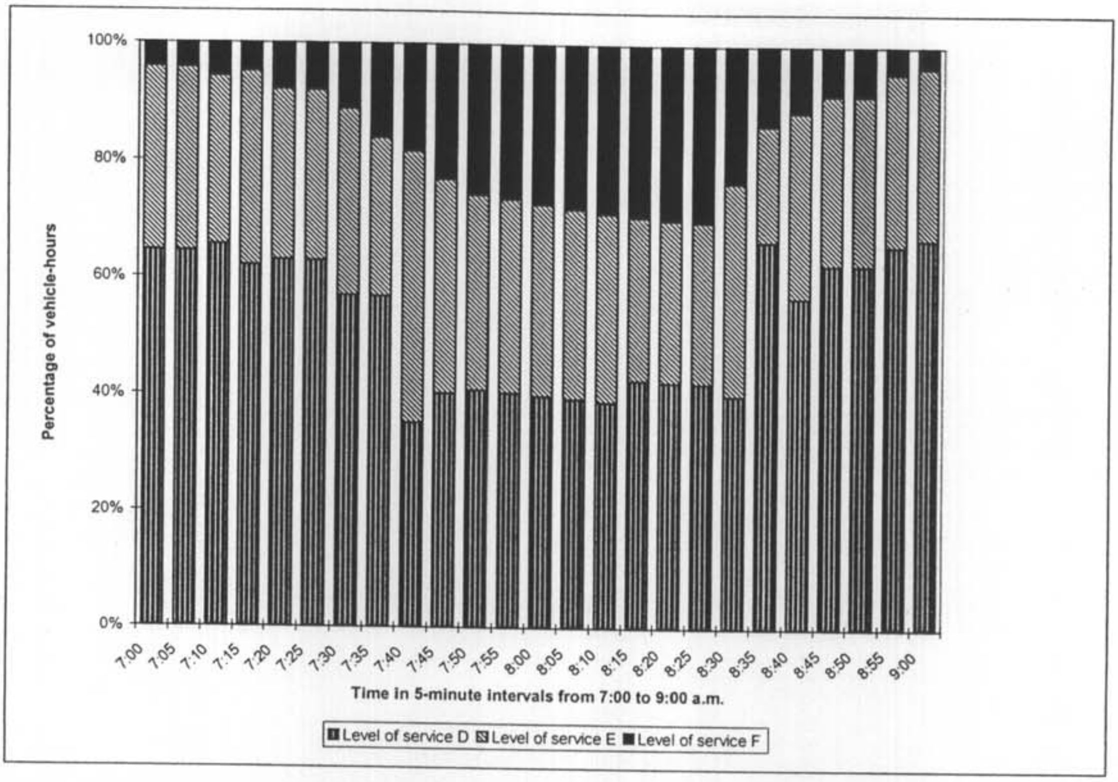

Figure 5.3 Vehicle-hour Distribution without VMS for Recurrent Congestion Situation

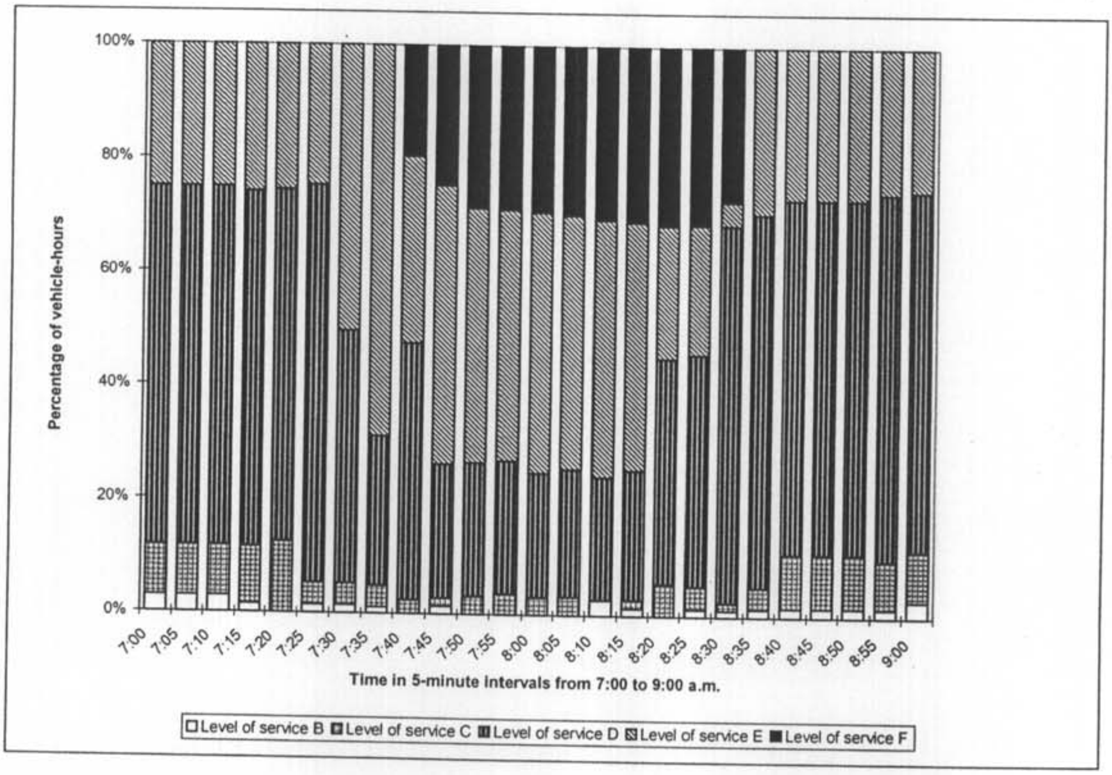

Figure 5.4 Vehicle-hour Distribution with VMS (v_s and d_s=2.0) for Recurrent Congestion Situation

In order to evaluate the benefit of the VMS and to determine the most appropriate number of VMS and detector density, the total network travel times in the cases with and without VMS are compared. The network travel time (NTT) can be represented as

$$\mathrm{NTT} = \sum_{u} (C_u v_u + d_u q_u) \tag{5.16}$$

The total network travel time (TNTT) is the sum of the network travel time for different time intervals in the study period.

Table 5.3 shows the results of the total network travel time against the values of detector density and number of VMS for the two-hour period. It can be seen that the total network travel time decreases as the detector density increases for different number of VMS. Also, the total network travel time is decreasing when the number of VMS is increasing for various values of detector density. It is because the measurement and perceived errors would be reduced as the detector density and number of VMS increase respectively.

Table 5.3. The Total Network Travel Time for the Two-hour Study Period in Recurrent Congestion Situation

		Detector density (detectors/km)					
		0	0.5	1.0	1.5	2.0	4.0
Number of VMS	0	88.26	-	-	-	-	-
	1	-	86.66	86.17	85.62	85.21	85.13
	2	-	85.84	85.09	84.55	84.19	84.17

Note : The dimension of the total network travel time is in thousand vehicle-hours.

In Table 5.3, it can been seen that the most desirable detector density is 2 detectors/km. It is because the improvement is very small even if the detector density increases from 2 detectors/km to 4 detectors/km. However, in the situation of recurrent congestion, the reduction in the total network travel time is very small even when increasing the numbers of VMS and detectors.

The effects of providing dynamic travel time information in situations of non-recurrent congestion are also considered. This congestion, which is the result of a temporary reduction in the capacity of a length of road due to accidents and/or construction works, can also be evaluated. Assuming that there is an accident on link 7 from 7:30 to 8:00 a.m, the road capacity will be reduced from 4,800 veh/hr to 3,200 veh/hr.

Table 5.4 shows the variation of the total network travel time against the detector density for various numbers of VMS for the non-recurrent congestion situation. The total network travel time is very large compared with that for recurrent congestion situation. This is because the overflow queue and delay due to the accident are significant.

The total network travel time decreases when the number of VMS increases. Also, the total network travel time decreases as the detector density increases. This is because the measurement error and perceived error are reduced as the detector density and number of VMS increase. The most desirable detector density is still 2 detectors/km. The reduction in the total network travel time becomes comparatively small as the detector density is further increased.

Table 5.4. The Total Network Travel Time for the Two-hour Study Period in Non-recurrent Congestion Situation

		Detector density (detectors/km)					
		0	0.5	1.0	1.5	2.0	4.0
Number of VMS	0	548.57	-	-	-	-	-
	1	-	453.96	449.09	437.22	414.25	408.85
	2	-	446.62	431.92	422.53	410.77	404.89

Note : The dimension of the total network travel time is in thousand vehicle-hours.

To illustrate the significance and effectiveness of the VMS, the ratio of the total network travel time with and without VMS is defined. The ratio of the total network travel time (RTNTT) is defined by

$$RTNTT(v_s, d_s)=TNTT(v_s, d_s)/TNTT(0) \qquad (5.17)$$

where $TNTT(v_s, d_s)$ is the total network travel time for the case with number of VMS v_s and detector density d_s while TNTT(0) is the total network travel time for the case without VMS and detector.

Figures 5.5 and 5.6 show the ratio of the total network travel time for the recurrent and non-recurrent congestion situation respectively. The effectiveness of the VMS system is significant in the non-recurrent congestion condition because the ratio can be 0.70 when the number of VMS and detector density are 2 VMS and 2 detectors/km respectively. However, the effectiveness is less significant in the recurrent congestion condition because the ratio is more than 0.94 for various values of VMS number and detector density.

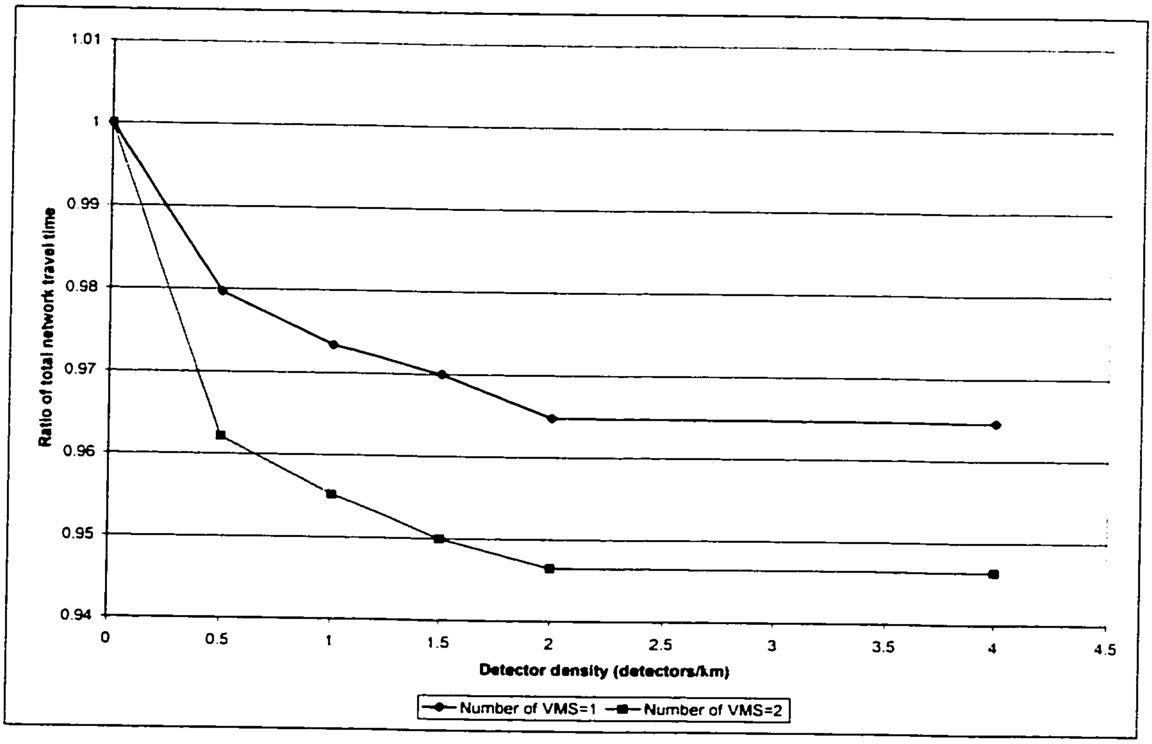

Figure 5.5 The Ratio of Total Network Travel Time for Two-hour Study Period in Recurrent Congestion Situation

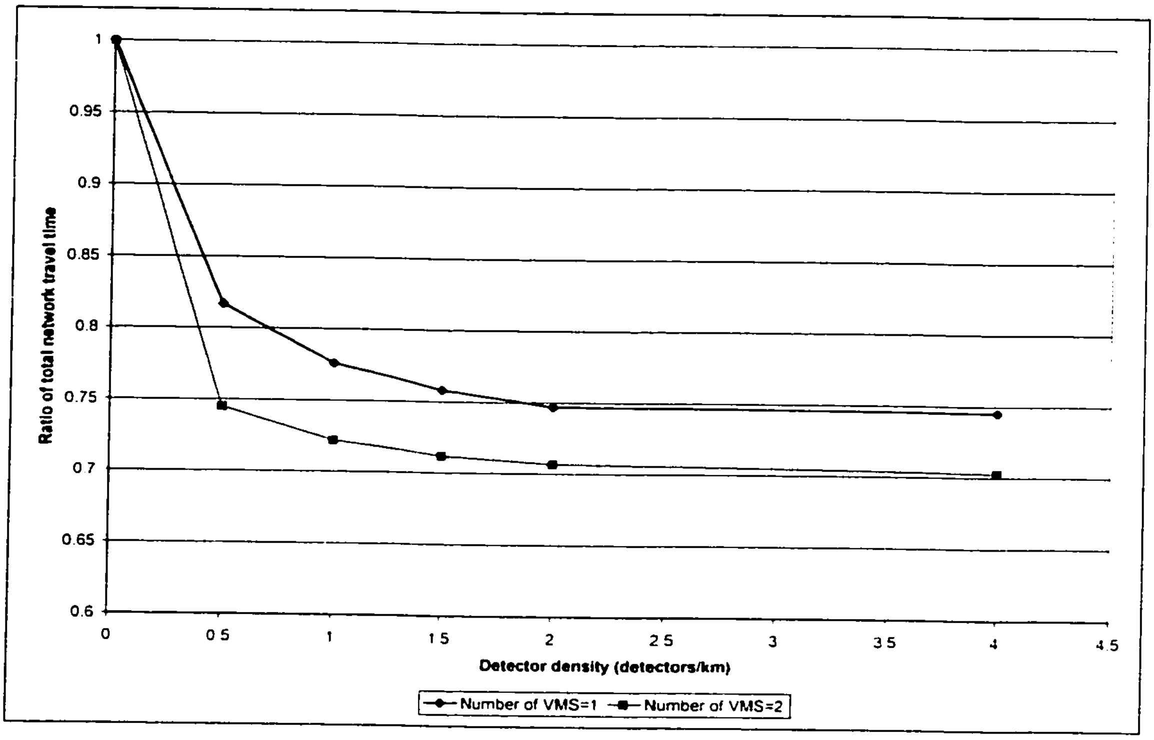

Figure 5.6 The Ratio of Total Network Travel Time for Two-hour Study Period in Non-recurrent Congestion Situation

Three scenarios are tested for the total network travel time by using different values of the dispersion parameter for the links without travel time information (β_{n}). They are assumed to be 0.5, 0.7 and 1.0. Table 5.5 shows the total network travel time for the recurrent and non-recurrent congestion situations in different values of β_{n}. It can be observed that the increase of the dispersion parameter β_{n} will result in the increase of the total network travel time especially for the case without information.

Table 5.5. The Total Network Travel Time for Different β_{n}

		Dispersion parameter β_{n}		
Congestion situation	Information provision	0.5	0.7	1.0
Recurrent	No information	58.77	72.84	88.26
	v_s and d_s=2.0	55.72	68.77	84.17
Non-recurrent	No information	443.63	499.48	548.57
	v_s and d_s=2.0	248.45	321.27	404.89

Note : The dimension of the total network travel time is in thousand vehicle-hours.

Three scenarios, which adopt various values of the parameter of the measurement error dispersion function (λ) which are supposed to be 0.1, 0.3, 0.5 and β_{n}=0.5, are used to test the effect of the measurement error on the total network travel time for the recurrent and non-recurrent congestion situation. The results shown in Table 5.6 indicate that the measurement error has effect on the network travel time for non-recurrent congestion situations because there is growth of the total network travel time when λ rises from 0.1 to 0.5. However, the measurement error has less impact on the total network travel time for the recurrent congestion situation.

Table 5.6 The Total Network Travel Time for Various λ

Congestion situation	Information provision	parameter λ 0.1	0.3	0.5
Recurrent	No information	58.77	58.77	58.77
	v_s and d_s=2.0	54.26	54.38	55.72
Non-recurrent	No information	443.63	443.63	443.63
	v_s and d_s=2.0	223.61	236.03	248.45

Note : The dimension of the total network travel time is in thousand vehicle-hours.

5.6 SUMMARY

In this chapter, a time-dependent traffic assignment model for assessing the effects of providing dynamic travel time information via VMS is proposed. The measurement errors on travel times by detectors are taken into account in the proposed model. The perceived errors of the drivers due to the drivers' responses to the dynamic travel time information provided via VMS are assumed. However, the perceived errors of the drivers due to no dynamic information provided on the parallel links are also considered. The simulation technique, shortest path algorithm and MSA are adopted in the proposed model.

By applying the time-dependent traffic assignment algorithm to the Tuen Mun Road Corridor with VMS, the total network travel time can be computed and compared. The total network travel time is used to compare the effectiveness of the VMS. In the numerical example, the most desirable detector density is 2 detectors/km. The effects of providing dynamic travel time information in the situation of non-recurrent congestion are more significant because the reduction of the total network travel time is much greater than that for the recurrent congestion. The sensitivity test is carried out for a set of different values of the dispersion parameter without travel time information and for the parameter of the measurement error dispersion function.

Further research should be carried out to develop the link travel time estimation models. In Chapter 6, models are developed for estimating travel times on expressways with the use of speed detector data.

6 LINK TRAVEL TIME ESTIMATION METHOD

In Chapter 5, a time-dependent stochastic traffic assignment model is proposed and a numerical example is used to find the desirable detector density. In Chapter 6, methods are developed for estimating travel times on expressways with the use of speed detector data. Three methods are investigated in this chapter, the first is the classical BPR (Bureau of Public Roads, 1964) function, the second is Dailey's method for estimation of link travel times. And the third is a new method which makes use of point speed data at two successive time intervals to estimate the average travel time of the traffic stream entering the study link during a time interval. The effect of time lag in speed measurement on the expressway with a long section of carriageway is taken into account in the new method. These three methods for estimating the link travel time are validated with data collected at the Tsing Ma Control Area (TMCA) in Hong Kong. A manual license plate number survey was conducted at the TMCA to collect the observed link flow, link speeds and link travel times for validation of the three methods. Results show that the new method can give a more accurate estimation of link travel time.

This chapter is organised as follows. Firstly, the introduction is given in Section 6.1. Secondly, the two existing methods and the proposed approach for estimation of link travel times are presented in Section 6.2. In Section 6.3, the data collection are described and the collected data are checked. The validation results of three methods are presented and discussed in Section 6.4. Finally, summary is given in Section 6.5.

6.1 INTRODUCTION

Vehicular travel time is becoming increasingly important for assessing the level of mobility in urban areas. Link travel time is considered to be a key variable for real-time network information and traffic control purposes. Hence, travel time estimation is a fundamental input to transport planning and management. It definitely indicates the operation of traffic flow and the performance of transport facilities. Although attempts have been made to estimate/forecast travel times on freeways and/or urban roads, more attention has been given to estimate travel times directly from flow measurements.

With the advent of Intelligent Transportation System (ITS), there is a growing demand for detector data to be used to provide link travel time estimates. There is a classical approximate method to compute the space mean speed (or link speed) using the detector data such as the time mean speed (or point speed) and the variance of the time mean speed (Gerlough and Huber, 1975). Recently, more attention has been given to predict travel times using occupancies and flows (Dailey, 1993; Nam and Drew, 1999; Pushkar *et al.*, 1995; Sisiopiku *et al.*, 1995; Petty *et al.*, 1998). With the use of the data collected from single-loop detectors, algorithms have to be devised firstly to estimate the link travel speed that can then be used to estimate the link travel time.

Various attempts have been made in the past two decades to develop link travel time estimation methods using traffic information collected from single-loop detectors, namely, occupancies and flows. Dailey (1993) employs a cross-correlation technique to predict travel time. The method uses link flow measurements to determine the maximum correlation between continuous concentration signals generated from link flow measurements. The method requires fewer traffic parameters. However, this method may not work well under congested traffic conditions, because the correlation may disappear under such circumstances. Dailey (1997) also presents an algorithm for estimating travel time using volume and occupancy data from a series of single inductive loops. Dailey models the speed as a stationary Gaussian process plus an observer Gaussian error and then uses a Kalman Filtering method for estimating the actual speed of a particular vehicle from single-loop detector data. The algorithm firstly produces an estimation of speed and then predicts the travel time. The model requires several parameters that must be properly estimated first. Abours (1986) calibrated regression models to estimate travel times from loop occupancies for a case study in Paris.

Nam and Drew (1996 and 1999) presented a model for predicting freeway travel time directly from the traffic flow measurements. The model is based on stochastic queuing theory and the principle of conservation of vehicles. The link travel time is determined by measuring the cumulative flow from two loop detectors at each end of the link. The model incorporates several hypotheses of traffic conditions. However, it is necessary to adjust and/or modify the input data for the model estimation particularly when the cumulative departure and arrival flow curves cross each other due to errors of the detector data. Petty et al. (1998) present a methodology to estimate link travel times directly from single-loop detector's flow and occupancy data based on a stochastic approach, in which vehicles that arrive at an upstream point during a given interval of time have a common probability distribution of travel times to a downstream point. Cremer (1995) estimated route travel time using a macroscopic simulation model in which the time-dependent speed profile is generated for all the routes within a given network. The model is formulated for the estimation of individual travel time with the use of a concept of a virtual vehicle. Makigami et al. (1996) developed a procedure for estimating travel time on expressway of long distance using a calibrated simulation model.

The model estimates travel time by adjusting the origin-destination (O-D) matrix that minimizes the difference between the estimated and detected traffic flows.

As reported by Sisiopiku and Rouphail (1995), satisfactory results on formal analytical link travel time functions have not yet been available particularly for application in large-scale transportation networks. Thus, empirically regression-based approaches have been conventionally adopted for the estimation of link travel time.

Little attention has been given to the effect of time lag in speed measurement in the previous related works. In this chapter, a method is developed for estimating link travel times on expressways with speed detectors. A new method is proposed for estimating the average travel time of the traffic stream entering the study link during a time interval. In the new approach, the point speed data at two successive time intervals is made use of and takes into account the effect of time lag in speed measurement on an expressway with a long section of carriageway.

A case study in Hong Kong is carried out to evaluate the proposed approach and the other two existing methods for the estimation of link travel times. These two estimation methods are as follows. The BPR link travel time function (Bureau of Public Roads, 1964) is calibrated using the observed data collected by the manual license plate survey. Dailey's method (1997) is used for estimating average travel time on a link section. To examine the reliability of the various estimation methods, their estimated link travel times were validated by the observed link travel times on an expressway in Hong Kong.

6.2 LINK TRAVEL TIME ESTIMATION METHODS

Two existing methods for estimating the link travel times are firstly presented in this section. The classical BPR function is shown. Dailey's method (1997) for estimating average travel time on a link section is presented. Finally, the proposed approach for estimating average travel time of the traffic stream during a time interval is shown.

6.2.1 BPR Function

A well-known BPR function (Bureau of Public Roads, 1964), which has been widely used for the prediction of link travel times and travel speeds, is adopted for the estimation of link travel time using the detector data. The BPR travel time function is given below:

$$T(q) = t_o + \alpha \times \left(\frac{q}{C}\right)^{\beta} \tag{6.1}$$

where $T(q)$ is the travel time in seconds; q is the traffic flow, C is the capacity, t_o is the travel time at zero flow, α, β are parameters which have to be estimated by use of observed link flow and travel time data.

The results from eqn. (6.1) can be converted to speed/flow relationship using the transformation:

$$S = 3600D/T(q) \tag{6.2}$$

where S is the vehicle speeds (km/hr) and D is the length (km) of the study section.

6.2.2 Estimated Average Travel Time on a Link Section

When point speeds are available at both ends (i.e. the locations of the two successive speed detectors) of a section, the average speed of the traffic may be assumed to change linearly between the two ends (Dailey, 1997). The average travel speed as a function of position can then be written as:

$$s(x) = s_{i-1} + \frac{s_i - s_{i-1}}{x_i - x_{i-1}} x \tag{6.3}$$

where $s(x)$ is the point speed at location x. s_i is the point speed at the end of the i th section. x_i, x_{i-1} are positions of the two ends of the section i.

The average travel time between any two ends located at x_{i-1} and x_i is derived as:

$$T_a(i) \approx 2l_i \left\{ \frac{1}{s_{i-1} + s_i} + \frac{(s_i - s_{i-1})^2}{3} \left(\frac{1}{s_{i-1} + s_i} \right)^3 + \frac{(s_i - s_{i-1})^4}{5} \left(\frac{1}{s_{i-1} + s_i} \right)^5 + \ldots \right\} \tag{6.4}$$

where $T(i)$ is the average travel time of the section terminated at x_{i-1} and x_i. l_i is the length of the ith section. s_i is the point speed at the end of the i th section.

$$v_i(i) \approx 0.5 \Bigg/ \left\{ \frac{1}{s_{i-1}+s_i} + \frac{(s_i - s_{i-1})^2}{3}\left(\frac{1}{s_{i-1}+s_i}\right)^3 + \frac{(s_i - s_{i-1})^4}{5}\left(\frac{1}{s_{i-1}+s_i}\right)^5 + \cdots \right\} \tag{6.5}$$

Where v_i is the average link speed (or space mean speed) on the i th section.

6.2.3 Average Link Travel Time of the Traffic Stream during a Time Interval

The traffic flow entering a link during a time interval is considered as a continuous flow q with two categories. The first category is the vehicles that traverse the link within a time interval, denoted by q_0. The second category is the vehicles that enter a link at a time interval but leave at the next interval, denoted by q_1. Figure 6.1 shows the propagation process of the traffic flows q_0 and q_1. The average travel time of the traffic stream entering a link during time interval τ can then be calculated as follows:

$$TT(\tau) = \frac{q_0}{q} T_{qo} + \frac{q_1}{q} T_{q1} \tag{6.6}$$

where $TT(\tau)$ is the average link travel time of the traffic entering a link during interval τ, T_{qo} and T_{q1} are the travel times of traffic flow q_0, q_1 respectively.

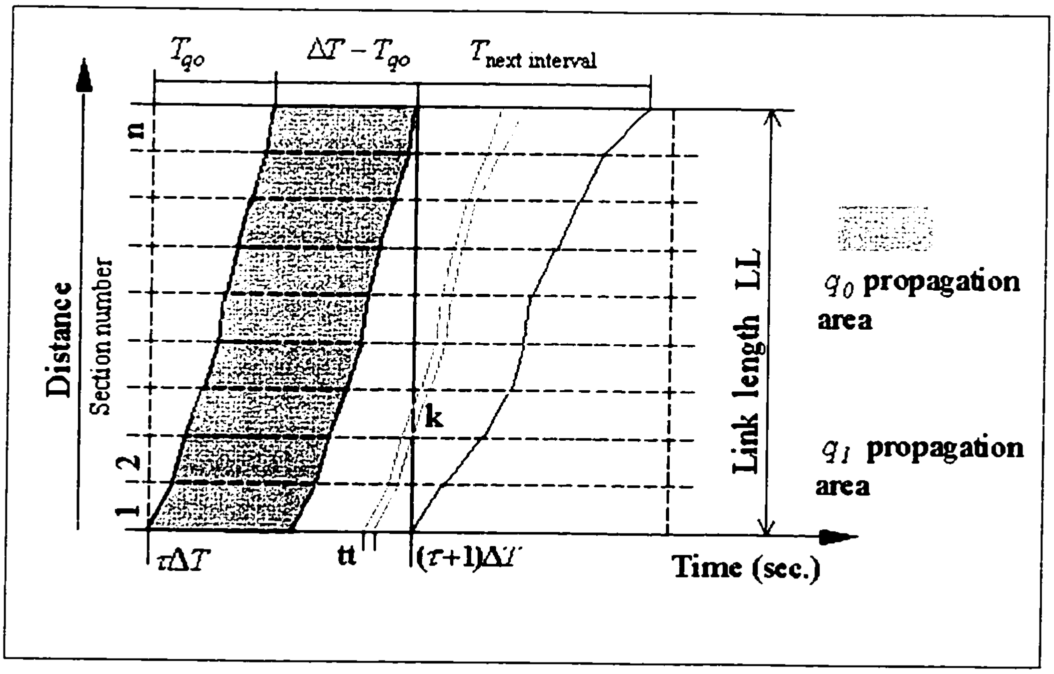

Figure 6.1. Distance-time Diagram for Link Travel Time Estimation

To estimate $TT(\tau)$, the values of q_0, q_1, T_{qo} and T_{q1} must be firstly determined respectively. T_{qo} can be easily calculated using eqn. (6.7):

$$T_{qo} = \sum_{i=1}^{n} \frac{l_i}{v_i(\tau)} \qquad \tau = 1,2,...T \; ; \; i = 1,2,....,k,...,n \tag{6.7}$$

where $v_i(\tau)$ is the average link speed at time interval on the ith section that can be calculated by eqn. (6.5); l_i is the length of the section i; T is the total number of time intervals during the measurement period; n is the total number of sections of the link.

Let ΔT denote the length of a time interval for measurement in seconds. Suppose that the first vehicle entering the study link during interval τ will leave the link after T_{qo} seconds. The following traffic stream during the period of ($\Delta T - T_{qo}$) will exit the link within interval τ (as shown in Figure 6.1). Subsequently, the traffic stream entering the link later during period from $(\tau \times \Delta T + \Delta T - T_{qo})$ to $(\tau + 1)\Delta T$ will exit the link in the next time interval $(\tau + 1)$. If the vehicles arrive with even distribution, the traffic traversing the link within a time interval can be calculated with the following equation:

$$\frac{q_0}{q} = (\Delta T - T_{q0})/\Delta T \tag{6.8}$$

which may be expressed as:

$$\frac{q_0}{q} = 1 - (\sum_{i=1}^{n} \frac{l_i}{v_i(\tau)}) \Big/ \Delta T \tag{6.9}$$

Obviously,

$$q_1 = q(\sum_{i=1}^{n} \frac{l_i}{v_i(\tau)}) \Big/ \Delta T \tag{6.10}$$

To estimate the average travel time of q_1, we may divide q_1 into n groups according to the number of sections on the study link. Let $qq(i) = q_1/n$, where n is the total number of sections of the study link; i =1, 2, ..., n. Similarly, we may also divide the period from $(\tau \times \Delta T + \Delta T - T_{qo})$ to $(\tau+1)\Delta T$, in which q_1 enters the link, into n sub-intervals u. We denote the vehicles that enter the link between time $(\tau+1)\Delta T - i \times {}^{T_{qo}}\!/_{n}$ to time $(\tau+1)\times\Delta T - (i-1)\times {}^{T_{qo}}\!/_{n}$, by $qq(i)$ e.g., $qq(3)$ enters the link during the period $(\tau+1)\Delta T - 3\times {}^{T_{qo}}\!/_{n}$ to $(\tau+1)\Delta T - 2\times {}^{T_{qo}}\!/_{n}$.

The average travel time of $qq(i)$ can be computed in the following two steps. Firstly, the number of sections through which the $qq(i)$ passes before $(\tau+1)\times\Delta T$ is calculated. Let k_i denote the number of the section at which $qq(i)$ passes at time $(\tau+1)\times\Delta T$. k_i can be determined by the following equation: $\sum_{j=1}^{k_i} \frac{l_j}{v_j(\tau)} > i \times u \geq \sum_{j=1}^{k_i-1} \frac{l_j}{v_j(\tau)}$. Then the number of sections that $qq(i)$ has traversed before time $(\tau+1)\times\Delta T$ is $k_i - 1$. Secondly, the travel time of $qq(i)$ can be calculated by the following equation:

$$T_{qq}(\tau) = \sum_{j=1}^{k_i-1} \frac{l_j}{v_j(\tau)} + \frac{1}{2}\sum_{j=k_i}^{k_i} \frac{l_j}{v_j(\tau)} + \frac{1}{2}\sum_{j=k_i}^{k_i} \frac{l_j}{v_j(\tau+1)} + \sum_{j=k_i+1}^{n} \frac{l_j}{v_j(\tau+1)} \tag{6.11}$$

The average travel time of traffic flow q_1 can be derived as:

$$
\begin{aligned}
q_1 \times T_{q1} &= \frac{q_1}{n}\Big[\frac{l_1}{2v_1(\tau)} + \frac{l_1}{2v_1(\tau+1)} + \sum_{j=2}^{n} \frac{l_j}{v_j(\tau+1)}\Big] \\
&+ \sum_{i=2}^{n-1} \frac{q_1}{n}\Big\{\sum_{j=1}^{k_i-1} \frac{l_j}{v_j(\tau)} + \frac{1}{2}\sum_{j=k_i}^{k_i} \frac{l_j}{v_j(\tau)} + \frac{1}{2}\sum_{j=k_i}^{k_i} \frac{l_j}{v_j(\tau+1)} + \sum_{j=k_i+1}^{n} \frac{l_j}{v_j(\tau+1)}\Big\} \\
&+ \frac{q_1}{n}\Big[\frac{l_n}{2v_n(\tau)} + \frac{l_n}{2v_n(\tau+1)} + \sum_{j=1}^{n-1} \frac{l_j}{v_j(\tau)}\Big]
\end{aligned}
\tag{6.12}
$$

where k_i is the number of the section on which $qq(i)$ traverses in the two successive time intervals.

The average travel time T_{q1} is computed as below:

$$
\begin{aligned}
T_{q1} &= \frac{1}{2n}\Big[\frac{l_1}{v_1(\tau)} + \frac{l_1}{v_1(\tau+1)} + \sum_{j=2}^{n} \frac{l_j}{v_j(\tau+1)} + \frac{l_n}{v_n(\tau)} + \frac{l_n}{v_n(\tau+1)} + \sum_{j=1}^{n-1} \frac{l_j}{v_j(\tau)}\Big] \\
&+ \frac{1}{n}\sum_{i=2}^{n-1}\Big\{\sum_{j=1}^{k_i-1} \frac{l_j}{v_j(\tau)} + \frac{1}{2}\sum_{j=k_i}^{k_i} \frac{l_j}{v_j(\tau)} + \frac{1}{2}\sum_{j=k_i}^{k_i} \frac{l_j}{v_j(\tau+1)} + \sum_{j=k_i+1}^{n} \frac{l_j}{v_j(\tau+1)}\Big\}
\end{aligned}
\tag{6.13}
$$

On the basis of eqns. (6.6) and (6.7), the average travel time of the traffic stream entering a link during time interval τ can be derived as follows:

$$
TT(\tau) = \Big(1 - \frac{\sum_{i=1}^{n} \frac{l_i}{v_i(\tau)}}{\Delta T}\Big)\Big(\sum_{i=1}^{n} \frac{l_i}{v_i(\tau)}\Big) + \frac{\sum_{i=1}^{n} \frac{l_i}{v_i(\tau)}}{\Delta T} T_{q1}
\tag{6.14}
$$

Consequently, from eqns. (6.13) and (6.14), we obtain the following eqn. (6.15):

$$
\begin{aligned}
TT(\tau) &= \Big(\sum_{i=1}^{n} \frac{l_i}{v_i(\tau)}\Big)\Big(1 - \frac{\big(\sum_{i=1}^{n} \frac{l_i}{v_i(\tau)}\big)}{\Delta T}\Big) \\
&+ \frac{\sum_{i=1}^{n} \frac{l_i}{v_i(\tau)}}{2n\Delta T}\Big\{\Big[\frac{l_1}{v_1(\tau)} + \frac{l_1}{v_1(\tau+1)} + \frac{l_n}{v_n(\tau)} + \frac{l_n}{v_n(\tau+1)} + \sum_{j=2}^{n} \frac{l_j}{v_j(\tau+1)} + \sum_{j=1}^{n-1} \frac{l_j}{v_j(\tau)}\Big] \\
&+ \sum_{i=2}^{n-1}\Big[2\sum_{j=k_i}^{k_i-1} \frac{l_i}{v_i(\tau)} + \sum_{j=k_i}^{k_i} \frac{l_j}{v_j(\tau)} + \sum_{j=k_i}^{k_i} \frac{l_j}{v_j(\tau+1)} + 2\sum_{j=k_i+1}^{n} \frac{l_j}{v_j(\tau+1)}\Big]\Big\};
\end{aligned}
\tag{6.15}
$$

6.3 EVALUATION DATA

6.3.1 Data Collection

In order to collect the observed and detected link travel times, a survey was conducted at the Tsing Ma Control Area (TMCA) in Hong Kong. TMCA consists of the Tsing Ma Bridge, Ma Wan Viaduct and Kap Shui Mun Bridge as shown in the location map in Figure 6.2. In this chapter, four types of data were collected from 10:30 a.m. to 3:00 p.m. on 23-4-2000 (Sunday) and 24-4-2000 (Monday) at the TMCA with RTMS (microwave) detectors installed.

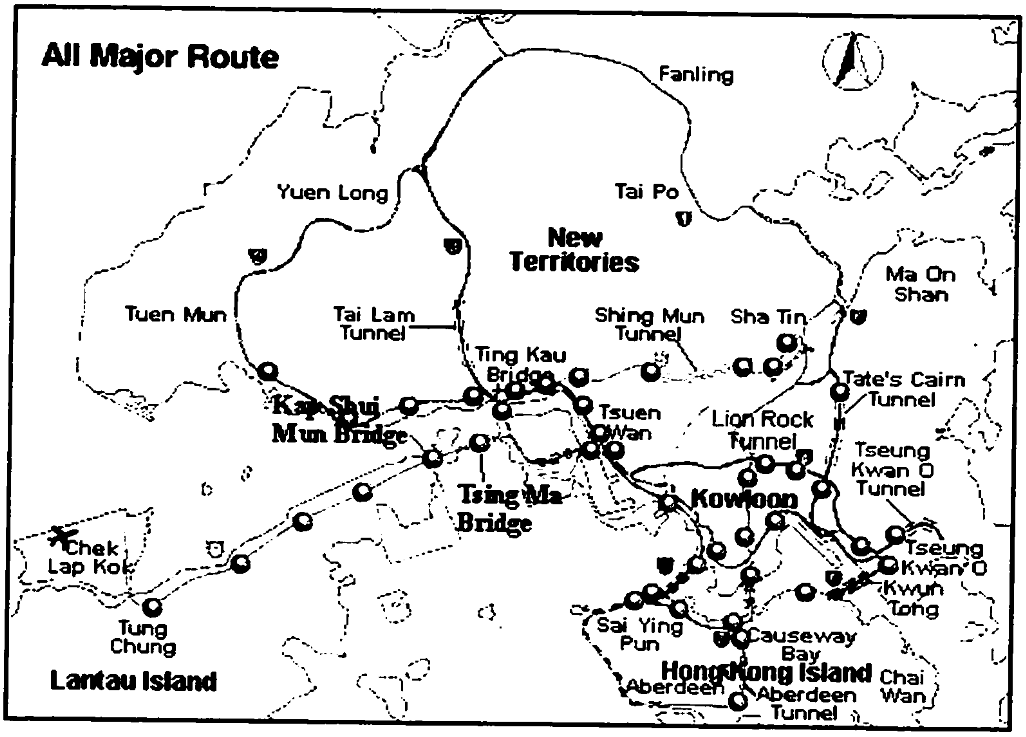

Figure 6.2. Location Map of Tsing Ma Control Area (TMCA)

Table 6.1 shows different survey methods and the four types of data collected, the data description and the usage of the data. The first was collected from the manual recording of vehicle license plate numbers, and the second was collected from RTMS detectors at TMCA. The others are the traffic flow data from video records and the sampling travel time data from digital video records. The detector data consists of the detected traffic flows and speeds at the locations with RTMS detectors. It is collected at 5-minute interval during the survey period.

Table 6.1 Category of Survey Data

Survey method	Data description	Usage of data
Manual license plate survey	Observed travel times and traffic flows on survey section of the road by each 5-minute interval during the survey period	For validation of the estimated travel times and calibration of the BPR function
Detector	Detected spot speeds and traffic flows at a point with RTMS detector by each 5-minute interval during the survey period	For input to the link travel time estimation methods
Video record	Traffic flows on survey section of the road	For independent check of the observed traffic flows obtained by the manual license plate survey
Digital video record	Link travel times on survey section of the road	For independent check of the observed travel times obtained by the manual license plate survey

Figure 6.3 shows the two locations for the manual license plate survey at gantry M25a3 and gantry M25k.

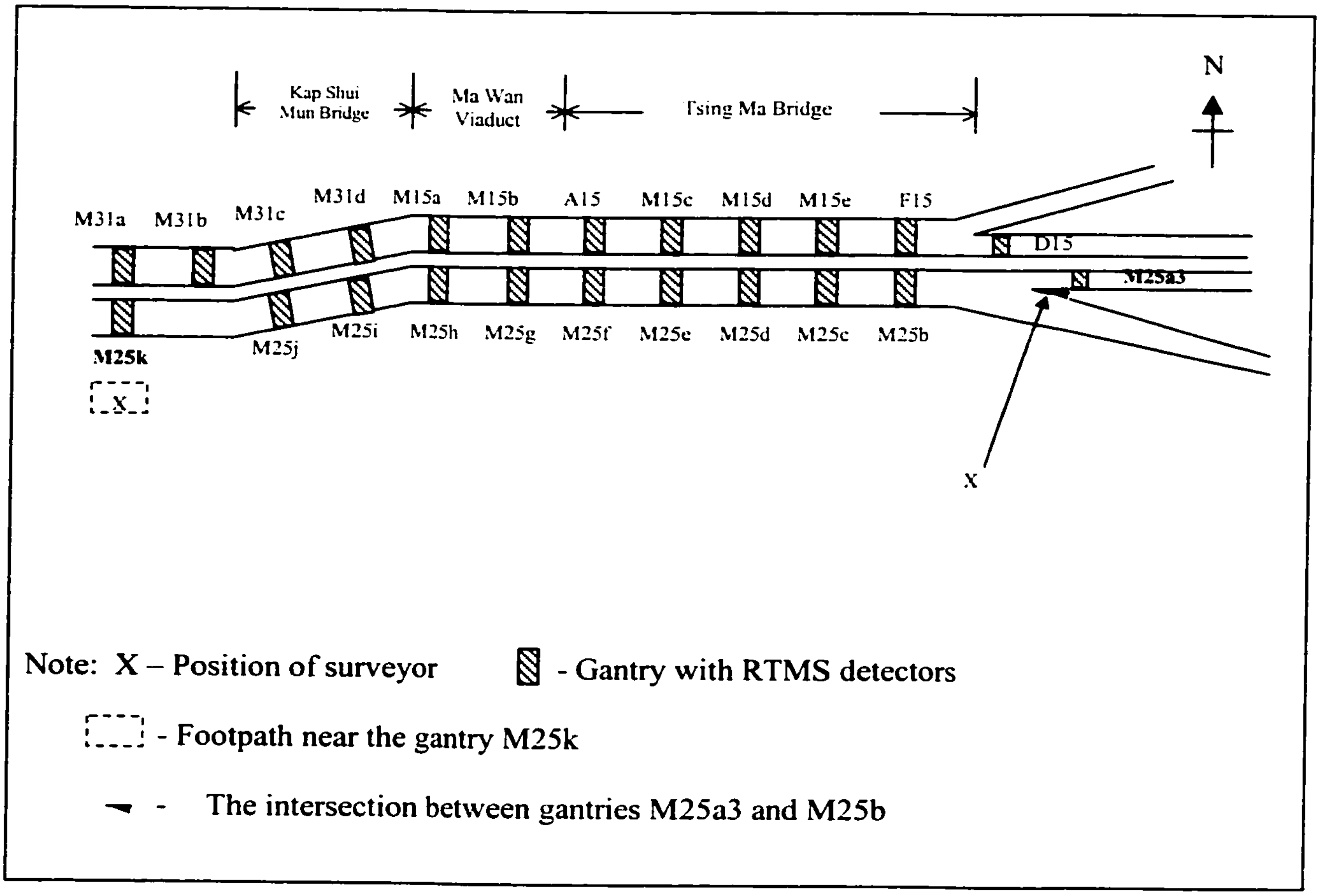

Figure 6.3. Location Map of the Surveyor and Detector

TMCA consists of the Tsing Ma Bridge, Ma Wan Viaduct and Kap Shui Mun Bridge. The road section in TMCA is a dual 3-lane carriageway. In order to manage and control traffic in real time, RTMS detectors are installed and their locations are shown in Figure 6.3. The distances between detector locations are given in Table 6.2.

Table 6.2 The Distances between each Detector Gantry

From	To	Distance(m)
M25a3	M25b	230
M25b	M25c	340
M25c	M25d	340
M25d	M25e	345
M25e	M25f	345
M25f	M25g	510
M25g	M25h	340
M25h	M25i	320
M25i	M25j	430
M25j	M25k	740
	Total	3940

During the survey period, the detectors in gantries M25b, M25c and M25d were not workable. However, a preliminary test on the accumulative flow data collected from various detectors had been done to check the consistency of detector data. The results of the preliminary test found that the output data of detectors in gantries M25f, M25g and M25j are not consistent. Therefore, only data from detectors at gantries M25a3, M25e, M25h, M25i and M25k are used in this study.

The data to be used for analysis have two main sources, the manual recording of vehicle license plate numbers, and the RTMS detectors. The former is a license plate survey conducted from 10:30 a.m. to 3:00 p.m. on 23-4-2000 and 24-4-2000. The survey sample targets are red and white vehicles and also buses going to the Hong Kong Chek Lap Kok (CLK) international airport. The sample size is 1656 that is about 20% of the population. The collected data from the RTMS detector is the detected travel speeds (point speeds) and number of vehicles, at 5-minute intervals. The observed link speed data are derived from the manual license plate survey.

It was decided to conduct the survey from 10:30 a.m. to 3:00 p.m. so as to collect data at the peak period for traffic going to the Hong Kong CLK international airport. The manual recording of vehicle license plate numbers was carried out at the entrance and exit of the study sections in the TMCA. The locations of the surveyors are shown in Figure 6.3. The intersection between gantries M25a3 and M25b was chosen for the manual license plate survey. Another location for the manual license plate survey was at the footpath near the gantry M25k. The positions of the surveyors are indicated in Figure 6.3. There were four surveyors at each of these two locations. The digital videos were also recorded in these two locations for independent checks of the observed travel time obtained by the manual license plate survey.

6.3.2 Data Screening

Girianna et al. (2000) carried out a data screening process of their collected traffic data. They stated that the collected traffic data after screening were more accurate and can reflect the real traffic conditions. In our case, the cumulative frequency of the speed detector data was firstly produced and then 5% at either end of the cumulative frequency was deleted. As a result, 10% of the collected data were rejected after the screening process. The resultant speeds are ranged from 69 to 102 kph.

6.3.3 Independent Check of the Survey Data

6.3.3.1 Independent check of the observed link travel time data

To investigate the error and accuracy of the manual license plate survey data, digital videos were recorded in the two survey locations. Define T_{man} be the travel time of the study link measured in the manual license plate survey, let T_{dvm} be the travel time of the study link obtained from the video survey. Denote the observed link travel time relative error % = $((T_{man} - T_{dvm})/T_{man})*100\%$. The study link is the link section from M25a3 to M25k. Figure 6.4 shows the frequency of various time relative error % at this study link. The time relative error is between -6% and 6%. The highest frequency occurs when the time relative error is 1%. Therefore, the manual license plate survey results look promising and reliable.

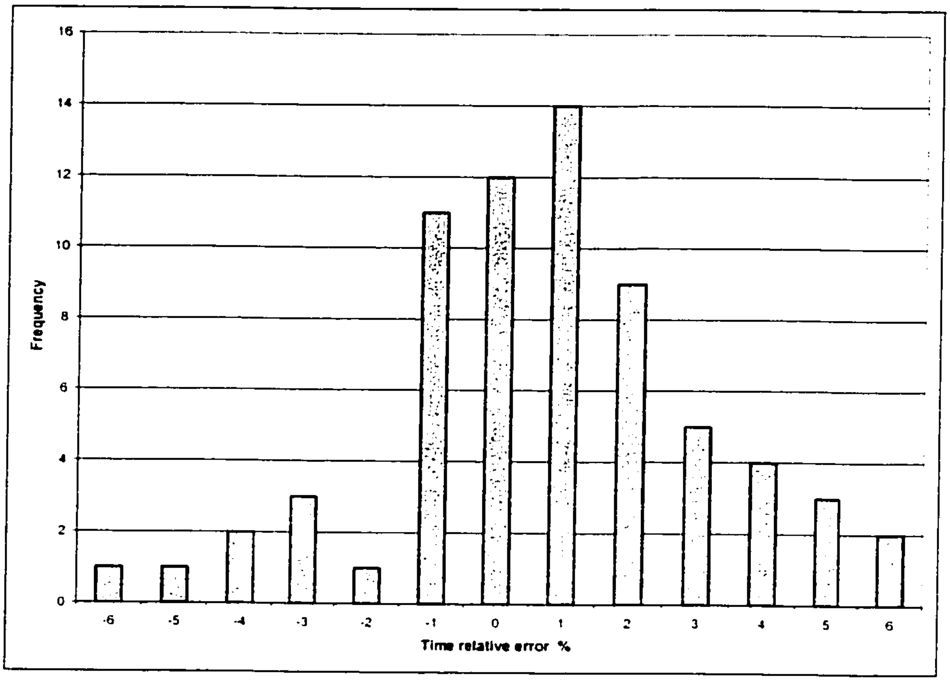

Figure 6.4 Frequency of Observed Link Travel Time Relative Error % at Study Link

6.3.3.2 Independent check of the observed link traffic flow data

To investigate the traffic flow differences between the manual license plate survey and the video survey, we define V_{man} as the traffic flow at M25a3 measured in the manual license plate survey, V_{vid} as the traffic flow at M25a3 obtained from the video survey. Denote the flow relative error % = $((V_{man}- V_{vid})/V_{man})*100\%$. Figure 6.5 shows the various flow relative error % of the study links in the survey period. The maximum flow relative error % is below 5%. Therefore, the observed traffic flow differences are small in the whole study period.

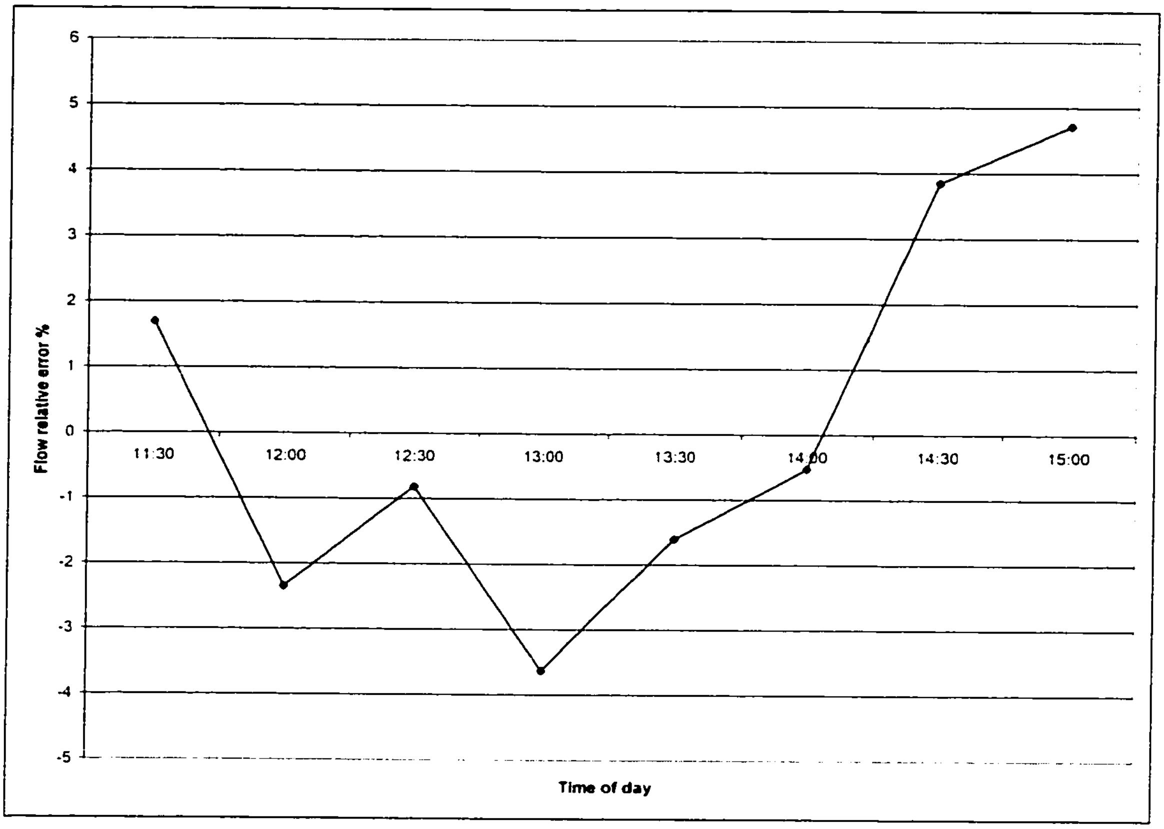

Figure 6.5 Observed Link Flow Relative Error % of the Study Link

6.3.4 BPR Function of the Survey Data

The calibrated BPR function for the observed traffic flow and link travel time data in TMCA is as follow:

$$T(q) = 136.21 + 339.96 * \left(\frac{q}{C}\right)^{1.41} \qquad (6.16)$$

where $T(q)$ is the average link travel time (sec) over a 5-minute period, q is the hourly link flow (veh/hr) over a 5-minute period, and C is the link capacity (veh/hr). The coefficient of determination R^2 is 0.6942. The time-flow relationship was calibrated using the observed data collected on 23-4-2000. The total number of observed samples is 817.

6.4 VALIDATION OF THE THREE METHODS

The link speeds estimated by the three methods are presented in Figure 6.6. The observed data on 24-4-2000 are used to validate the estimation results. The calibrated BPR function using the observed data collected on 23-4-2000 is adopted. However, it is known that the observed link flows are always not available in practice. Therefore, the detected traffic flows by 5-minute intervals on 24-4-2000 were input to the calibrated BPR function for estimating the link speeds accordingly.

Figure 6.6 shows that both of Dailey's and the proposed methods tend to overestimate the link speeds marginally. On the other hand, the resulting speeds estimated by the BPR function are slightly smaller than the observed link speeds in most of the study time period.

In general, their validation results are satisfactory. Their errors ranged from −11.21% to 6.14%.

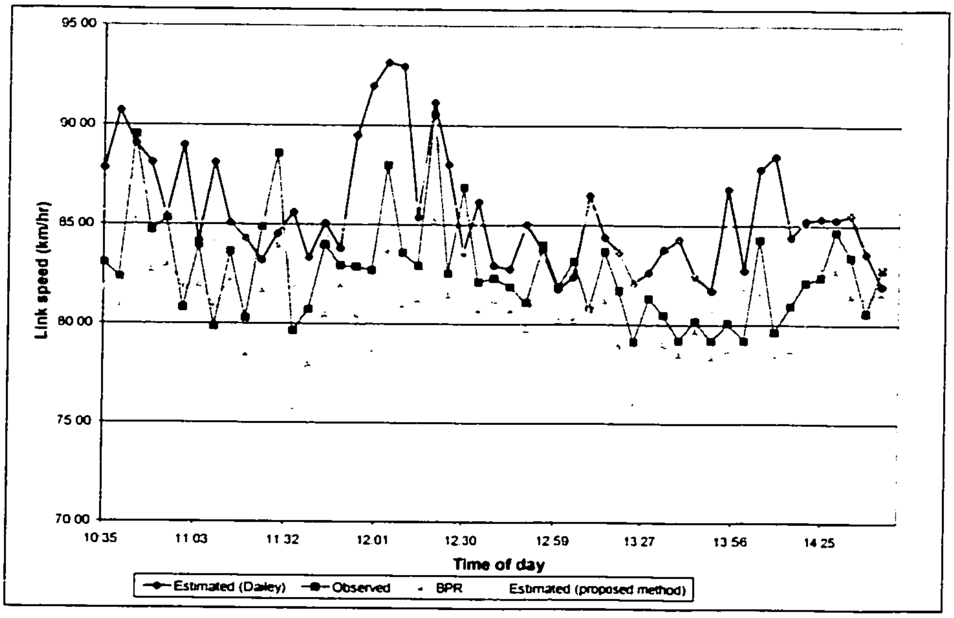

Figure 6.6 Comparison of the Estimated and Observed Link Speeds

In addition to the above comparison between the estimated and observed link speeds, validation test is carried out to evaluate the performance of the proposed method against the two existing methods for estimation of link travel times. Two error indices were computed as follows:

Average relative error,

$$ARE = \frac{1}{n}\sum_{k=1}^{n}\frac{T_{obs}(k) - T_{est}(k)}{T_{obs}(k)} \tag{6.17}$$

Square root of the mean square error,

$$RMSE = \sqrt{\frac{1}{n}\sum_{k=1}^{n}\left(T_{obs}(k) - T_{est}(k)\right)^2} \tag{6.18}$$

where $T_{obs}(k)$ and $T_{est}(k)$ are the observed and estimated travel times.

Table 6.3 presents the resulting link travel time estimation errors. The resulting *ARE* (%) and *RMSE* of the proposed method are only 1.92% and 2.24 seconds. These small values show that the estimated link travel times of the proposed method are close to the observed link travel times. The resulting *ARE* (%) and *RMSE* of the BPR function and Dailey's method are -4.62%, 6.52 seconds and 3.36%, 4.33 seconds respectively. Therefore, the estimated link travel times of these two methods are slightly different from the observed link travel time. It also implies that the link travel times estimated by the proposed method are more accurate than those estimated by the other two methods.

As shown in Table 6.3, the *ARE*(%) and *RMSE* values are not high for these three methods. However, the case study is carried out on a new highway without serious congestion. Thus, it can only be deduced that these three methods have satisfied estimation results for uncongested situation. When congestion occurs, the estimation errors may increase. Therefore, further data collection should be carried out to validate these three estimation methods for congested conditions. In addition, the variation of the link travel time estimation errors for different levels of service can also be investigated.

Table 6.3 Link Travel Time Estimation Errors

	ARE (%)	*RMSE* (seconds)
BPR function	-4.62	6.52
Dailey's method	3.36	4.33
Proposed method	1.92	2.24

6.5 SUMMARY

This chapter presents the proposed method, plus two existing methods for estimating link travel times by using RTMS detector data. This chapter also evaluates the link travel time estimation results against the observed data collected at the selected site on Tsing Ma Control Area (TMCA) in Hong Kong. The link travel time and link speed distributions have been investigated using data collected from the manual license plate number survey. The video and digital video data have been used for assessing the error and accuracy of the manual license plate number survey.

To validate the performance of the proposed method against the two existing methods, average relative error (*ARE*) and square root of the mean square error (*RMSE*) are adopted as the performance measures. The results indicate that the proposed method can provide better link travel time estimates than the other two existing methods. However, no congestion occurs at the survey location because it is a new highway. We can only conclude that the proposed method can provide good link travel time estimates for uncongested situations. Consequently, further study should be designed to evaluate the proposed method and the other two methods in congested situations. Further research should also be carried out to develop link travel time prediction methods that are capable of forecasting link travel time in advance.

7 DRIVER RESPONSES TO A DRIVER INFORMATION SYSTEM IN HONG KONG

In Chapter 6, the link travel times estimation method is developed by using the speed detector data at the selected site at the Tsing Ma Control Area (TMCA), Hong Kong. The license plate survey is conducted to collect the empirical data to validate the developed method.

The careful design of the driver information system (DIS) for varying travel time information is necessary. The question of how the DIS information affects driver behaviour must also be addressed. In Chapter 7, a stated preference (SP) survey is used to gauge driver reaction to the DIS information.

This chapter considers the responses of drivers to the proposed DIS on the expressway to the Chek Lap Kok (CLK) international airport in Hong Kong. Variable message signs (VMS) to be provided along the Lantau Link Corridor are new to Hong Kong drivers, and it is important to understand drivers' perceptions and responses to this.

Surveys were conducted using a questionnaire consisting of several hypothesized choice experiments. Travel time information on the expressway was provided and the respondents were asked to give their predicted travel times on two alternative routes. The variance of the drivers' perceived errors on link travel times were calibrated with the SP data. A binary logit model was calibrated for estimating the drivers' route choices under the DIS environment. The principal findings are that the perceived travel times of the drivers are strongly influenced by the travel time information provided by the DIS.

This chapter is organised as follows. Firstly, the background of this chapter is given in Section 7.1. Section 7.2 describes the stated preference survey design and data collection. Data analysis is considered in Section 7.3. Finally, a summary is given in Section 7.4.

7.1 BACKGROUND

It is well known that there are two types of stochastic user equilibrium (SUE) assignment models. In 1971, Dial proposed the logit assignment model in which the perceived travel cost errors are distributed using the Gumbel distribution. In the probit assignment model, suggested by Daganzo and Sheffi (1977), errors in the perceived travel time are normally distributed. However, the provided travel time information from the driver information systems (DIS) affects the perceived travel time. The relationship between the provided travel time and the perceived travel time is investigated in this chapter. The perceived travel time errors were firstly examined together with their distribution pattern. Following that, the calibration of the route choice model under the DIS environment was considered.

A number of researchers have investigated drivers' responses to the DIS by using the stated preference (SP) approach and calibrated the route choice model using a logit model (Abdel-Aty et al., 1997; Lai and Wong, 2000; Wardman et al., 1997). Logit and probit models have been developed to predict whether commercial drivers or dispatchers would use an intelligent transportation system and also to quantify travelers' ratings of the importance of in-vehicle system attributes (Mannering et al., 1995; Ng L. et al., 1995). In this chapter, the logit model was chosen for calibrating the route choice model for the proposed DIS in Hong Kong.

A number of studies have been carried out to examine drivers' route choices. Previous researchers (Duffell and Kalombaris, 1988; Huchingson et al., 1977) have indicated that travel time is the most important factor affecting an individual's route choice. Some studies (Bonsall, 1992; Bonsall and Palma, 1998) have found that delay and congestion were also important determinants of route choice. Therefore, travel time and congestion conditions are considered in our SP hypothesized choice experiment design.

This chapter presents the results of surveys conducted at the Chek Lap Kok (CLK) international airport in Hong Kong. The data was collected using a SP survey. The main objective of the research described in this chapter is to investigate driver perception in response to travel time information. The proposed DIS on the Lantau Link Corridor (connecting to the Hong Kong CLK international airport) will utilize dedicated vehicle detectors to collect traffic data, with variable message signs (VMS) to display travel time information to drivers. As the VMS to be provided along the Lantau Link Corridor are new to Hong Kong drivers, it was necessary to conduct interview surveys to investigate the drivers' perceptions of the DIS. Due to their flexibility and low cost, SP surveys were conducted to collect data on drivers' responses.

By applying the fractional factorial design, several hypothesized choice experiments were adopted to test the drivers' decisions in the SP questionnaire. The SP questions are used to identify factors, which affect the drivers' perceived travel times and route choices if the current travel time is displayed on the VMS. Scenarios using combinations of different levels of factors were included in the questionnaire. Firstly, photographs of different scenarios were shown to the respondents, who were surveyed in the car parks of the Hong Kong CLK international airport. Secondly, modelled travel times of different scenarios were also given to the drivers. These travel times were obtained from the Bureau of Public Roads (BPR) functions. Finally, the perceived travel times of drivers for different scenarios were requested and recorded. In addition, drivers were asked to choose between two possible routes, the expressway and the urban road. The responses obtained were used to calibrate the route choice model.

7.2 SURVEY DESIGN AND DATA COLLECTION

7.2.1 Survey Design

Our SP study was related to drivers' route choices for the journey from the Hong Kong CLK international airport to Tsing Yi as depicted in Figure 7.1. This journey was chosen because it allowed the drivers to choose between an expressway and an urban road. The urban road in the reclamation area has not been constructed but is planned for future development. However, various travel times and number of signals on the urban road were stated in the questionnaire. During the interviews, respondents departing from the Hong Kong CLK international airport to the urban areas were told to assume that the urban road was open to traffic.

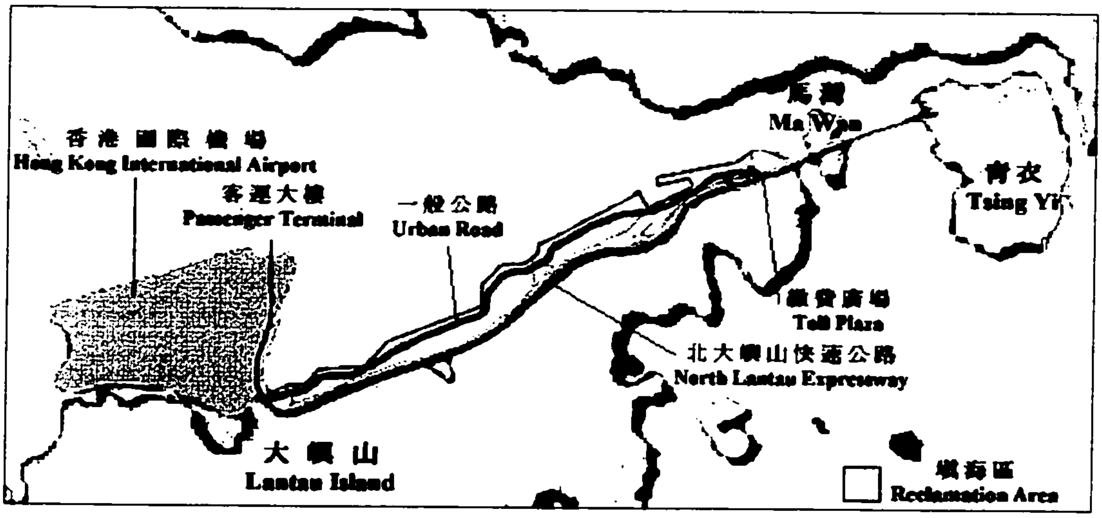

Figure 7.1 The Expressway and Urban Road in the Study Area

The target survey sample was comprised of individuals who drive a car to the Hong Kong CLK international airport. Two types of vehicles were considered: private car and taxi. The parking lots of the Hong Kong CLK international airport were chosen for conducting the questionnaire survey. The survey period was from 9:00 am to 9:00 pm on 1-11-98 (Sunday), 6-11-98 (Friday), 8-11-98 (Sunday) and 13-11-98 (Friday). Sunday and Friday were chosen because they are the peak travel days at the CLK international airport.

The SP questionnaire consists of two parts as shown below. The first part is to collect information on the characteristics of the drivers, which include sex, age, trip frequency, vehicle type, and their expected travel time. The second part is the SP experiments used for collecting the drivers' perceived travel times and their route choices under road traffic conditions with different levels of service (LOS). Pictorial representations of various road traffic conditions were generated. Figures 7.2–7.7 display the road traffic conditions ranging from LOS A to LOS F of the expressway. Two urban road attributes (or factors) are selected in this chapter. They are the normal travel times on the alternative routes and the number of signals on the urban road, which ranged from 1 to 5.

In the SP experiments, the drivers were asked about their expected travel times when no information has been provided for different LOS. Drivers were also asked their expected travel times when the estimated travel times have been provided. Respondents were also asked to choose between the urban road and expressway. In each experiment, the LOS on the urban road was fixed and the LOS on the expressway changed from LOS A to LOS F. The data obtained was used to calibrate the route choice model by using a logistic regression analysis approach. SPSS Logistic (using the method of maximum likelihood estimation) was then used to estimate the parameters of the model and produce the logistic regression model.

Figure 7.2 LOS A of the Expressway

Figure 7.3 LOS B of the Expressway

Figure 7.4 LOS C of the Expressway

Figure 7.5 LOS D of the Expressway

Figure 7.6 LOS E of the Expressway

Figure 7.7 LOS F of the Expressway

The following two SP questions were used to collect the drivers' perceived travel times and their route choices to establish different LOS. Firstly, Q1 aims to collect the driver's perceived travel time in response to a photograph corresponding to a particular LOS. Secondly, the estimated current travel time was given and the driver was asked again for the perceived travel time. Q2 is concerned with the route choices of the drivers. The expressway or urban road was chosen by drivers in response to a photograph and information relating to the two alternative routes, as shown in Table 7.1. The questionnaire is attached in Appendix A.

(Q1) (a) If the traffic conditions on the expressway are like Figure 7.5 now, what is your expected travel time on that expressway? _______minutes. (b) If the current travel time is _______minutes to arrive at Tsing Yi, what is your expected travel time?_______minutes

(Q2) If the traffic condition of the expressway is like Figure 7.6. which of the following routes will you choose?

Table 7.1 Information of Two Routes

	Route 1 (The existing route)	Route 2 (The assumed route)
Road type	Expressway	Urban road
Normal travel time	39 minutes	39 minutes
Estimated current travel time	43 minutes	--------------
No. of signal	---------------	5

[a] expressway

[b] urban road

7.2.2 Data Collection

The survey period was from 9:00 am to 9:00 pm in order to collect data from drivers during both peak and off-peak periods. Surveys were conducted in the multi-storey carpark at the Hong Kong CLK international airport, as shown in Figure 7.8. This location was selected because the number of cars parking in the multi-storey carpark is larger than the other two outdoor carparks.

For convenience, the two interviewers were positioned in the corridor near the shroff office of the multi-storey carpark, shown in Figure 7.9. Most vehicles using the multi-storey carpark were private cars. In order to avoid any bias in the survey results, taxi drivers in the taxi waiting area were also selected for the interview. Figure 7.10 shows the taxi waiting area in the Hong Kong CLK international airport.

Figure 7.8 Multi-storey Carpark

Figure 7.9 Shroff Office of Carpark

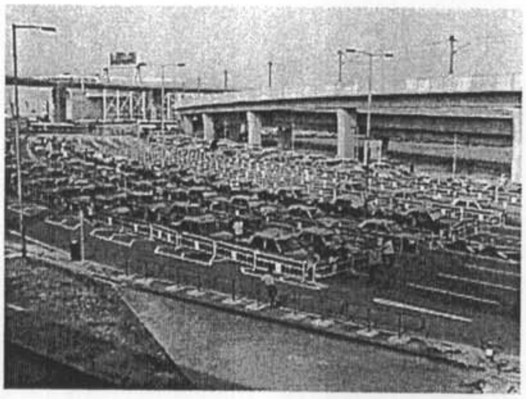

Figure 7.10 Taxi Waiting Area

A sample size of a minimum of 50 respondents per category is usually considered "sufficiently large" to ensure that the Central Limit Theorem can be applied to meet the requirement for normal distribution in later statistical analysis. There are six categories for six urban road LOS, therefore the total target sample size required should be larger than 300. A total of 465 valid samples were obtained. The population sizes of the private cars and taxi were around 600 and 950 respectively from 9:00 am to 9:00 pm on the days surveyed. The required sample size n' and the sample error can be expressed as (Walpole and Myers, 1993):

$$n' = (1.96s/\mu E)^2 \tag{7.1}$$

$$e = 1.96s/\mu\sqrt{n} \tag{7.2}$$

where 1.96 corresponds to the 95% confidence interval, s is the standard deviation of the sample, μ is the mean of the sample, E is the permitted error of the sample, e is the sample error and n is the sample size collected. By permitting 5% errors for each LOS, the resulting total sample size required was 319. The average sample error was 4.2%. Therefore, the sample size of the survey (465) is considered adequate.

7.3 DATA ANALYSIS

Similar to the SP questionnaire, the data analysis is divided into two parts. The first part includes the modelling issues and calibration of the perceived link travel time error variance. The second part is the methodological approach and calibration of the route choice model.

7.3.1 The Calibration of the Perceived Link Travel Time Error Variance

The perceived link travel time error variance is assumed to be the product of the provided link travel time and a perceived travel time error dispersion function. This perceived travel time error dispersion function $f^p(v_a/k_a)$ is due to the volume/capacity (v/c) ratio for the corresponding link.

The expected queuing and delay time for each driver is different. There is a large perceived travel time error variance among different drivers. For a static model, the overflow delay is incorporated into the BPR link travel time function (Ran et al., 1997). The large variation of the drivers' expected queuing and delay times refers to large link travel time. Larger link travel time results in greater perceived link travel time error variance. As a result, greater dispersion is also implied.

To justify the relationship between the perceived travel time error dispersion function and the v/c ratio, interview surveys were conducted using six LOS scenarios. One of the objective of this chapter was to investigate the perceived travel time error of the drivers under the six LOS scenarios. The perceived travel times of the drivers were compared with the modelled travel times.

The difference of the modelled travel time and perceived travel time is calculated as follows:

$$k=E(t_a)-E(t_p) \tag{7.3}$$

where $E(t_a)$ and $E(t_p)$ are the expected values of modelled travel time t_a and of perceived travel time t_p respectively. It is assumed that there is a constant difference between the actual and perceived travel times and that the modelled travel time provides an unbiased estimate of the actual travel time. Under these assumptions, the variance of the perceived travel time error, $var(e_p)$ can be derived as follow (Milton and Arnold, 1990):

$$var(e_p) \approx var(t_p - t_a) + k^2/n \tag{7.4}$$

where n is the sample size.

Therefore, the estimated variance of the perceived travel time error is obtained as follows,

$$EstVar(e_p) = var(t_p - t_a) + k^2/n \tag{7.5}$$

This estimated variance can then be calculated by the perceived travel times obtained from the survey together with the modelled travel times.

Figure 7.11 presents the $EstVar(e_p)/t_a$ for various v/c ratios. The dispersion of the perceived travel time error can be estimated by $EstVar(e_p)/t_a$. Consequently, Figure 7.11 shows that the dispersion of the perceived travel time error increases as v/c ratio increases.

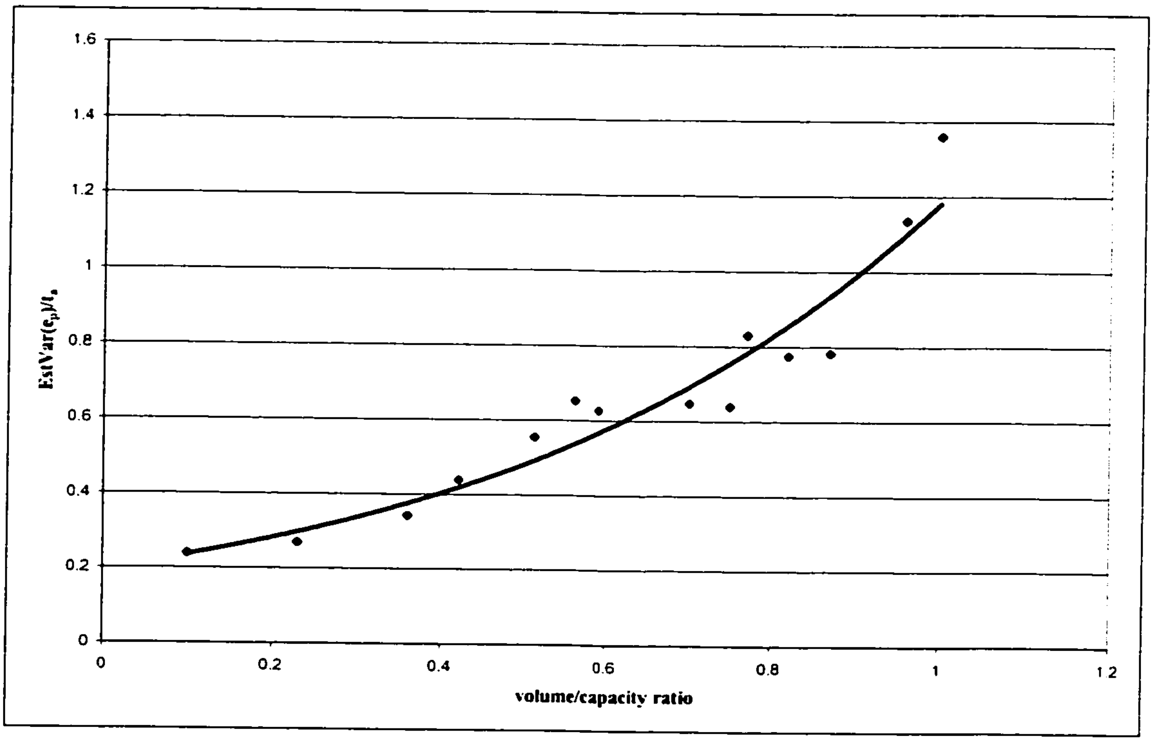

Figure 7.11 EstVar(e_p)/t_a for Different V/c Ratios

The perceived travel time error dispersion function is due to the v/c ratio for the corresponding link. When congestion occurs, it is more difficult for the drivers to perceive the travel time correctly. Therefore, the perceived travel time error variances of the drivers are larger as the v/c ratio increases. Consequently, the dispersion function of the perceived travel time errors of the drivers should be an increasing function of the v/c ratio.

In addition, Figure 7.12 presents the frequency of difference between the perceived travel time (T_p) and the estimated travel time (T_e) for various v/c ratios. It shows that the frequencies are higher only when frequency is zero for lower v/c ratio. The variation of the frequency is larger as the v/c ratio increases. This also implies that the travel time reliability decreases when v/c ratio increases.

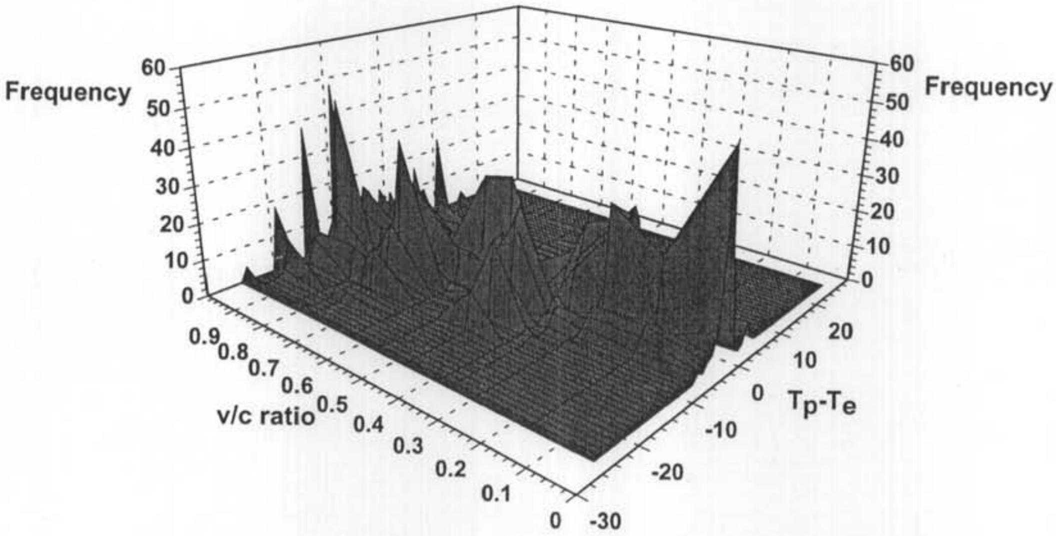

Figure 7.12 Frequency of (T_p-T_e) for Various V/c Ratios

7.3.2 Calibration of the Route Choice Model

The SP experiment offered choices between the two alternative routes. The data collected can be used to calibrate a binary logit model which expresses the probability that an individual *i* chooses the alternatives 0 (urban road) and 1 (expressway) as a function of the utilities (U).

The probabilities that individual *i* chooses the urban road and the expressway, P_0 and P_1, respectively, are:

$$P_0 = 1/(1+\exp U) \tag{7.6}$$

$$P_1 = \exp U/(1+\exp U) \tag{7.7}$$

where U is the utility function of the route choice.

$$U = \Sigma \beta_k X_k \tag{7.8}$$

where β_k is the coefficient for attribute k and X_k is the level of attribute k.

The collected survey data were used for calibrating the route choice model by applying logistic regression analysis. SPSS Logistic (using the method of maximum likelihood estimation) was used to estimate the model parameters and to produce the logistic regression model. The resulting model was specified with the following 4 variables:

- Normal travel time on expressway
- Estimated current travel time on expressway
- Normal travel time on the urban road
- Number of signals on the urban road

The estimated current travel time on expressway can be provided for the drivers because speed detectors are installed. However, both the normal travel times on expressway and the urban road can be given under various traffic conditions (i.e. different LOS). These normal travel times may not be accurate but can be used as references by the drivers. The resulting model attempts to simulate the drivers' decision making with respect to the drivers' responses to the provided travel time information on the expressway.

Table 7.2 presents the respective estimated coefficients. The resulting coefficients of variables X_1 and X_2 are -0.1485 and -0.1548, and reflect that the estimated current travel time on the expressway is slightly more important than the normal travel time on the expressway. The estimated coefficient of variable X_3 is 0.1532. As a result, the estimated current travel time on the expressway is marginally more important than the normal travel time on the urban road. The estimated coefficient of variable X_4 is only 0.0415, which shows that the number of signals on the urban road is less important in the drivers' route choice decisions.

Table 7.2 Coefficients Estimated for Binary Logit Model for Route Choice

Variable	Estimated coefficients (β_k; k=0, 1, 2, 3 4))	t-statistics
Constant (X_0)	3.0439	4.19**
Normal travel time of expressway (X_1)	-0.1485	-2.28*
Estimated current travel time of expressway (X_2)	-0.1548	-5.17**
Normal travel time of the urban road (X_3)	0.1532	6.18**
Number of signal of the urban road (X_4)	0.0415	2.21*

Notes: Values marked with an asterisk, * are statistically significantly at a 5% level
Values marked with an asterisk, ** are statistically significantly at a 1% level

According to the resulting t-statistics of the estimated coefficients in Table 7.2, variables X_1 and X_4 are statistically significant at 5%. However, variables X_2 and X_3 are statistically significant at 1%. Table 7.3 presents the calibration results for variables that are statistically significant at 1% level. The variables that are statistically significant at 5% level are rejected. It was found that the R-square of the retained model (1% level) and the rejected model (5% level model) are 0.75 and 0.69 respectively. Therefore, the model with two variables are chosen as the accuracy of the retained models is higher than the rejected models. The revised model is therefore recommended for modelling the route choices of the drivers. On the other hand, the resultant coefficients of the two travel time variables (X_2 and X_3) are close in magnitude to each other. Therefore, these two travel time variables are now combined to be one variable of travel time difference (X_2 - X_3). The resulting coefficient of variable (X_2 - X_3) is –0.141.

Table 7.3 Revised Coefficients Estimated for Binary Logit Model for Route Choice

Variable	Estimated coefficients (β_k; k=0, 2, 3))	t-statistics
Constant (X_0)	0.211	5.32**
Difference between estimated current travel time of expressway and normal travel time of the urban road (X_2 - X_3)	-0.141	-6.92**

Notes: Values marked with an asterisk, ** are statistically significantly at a 1% level

In order to investigate the difference between the route choices of taxi drivers and regular drivers, the SP logit models are calibrated for taxi drivers and regular drivers respectively. The resultant estimated coefficients of the SP logit models are presented in Tables 7.4 and 7.5. The revised model is therefore recommended for modelling the route choices of the drivers. The R-square of the binary logit model was 0.75. The resulting coefficient of variable (X_2 - X_3) for the taxi drivers' SP logit model is –0.136. For the regular drivers, the resulting coefficient of variable (X_2 - X_3) is –0.145. It can be observed that the resultant estimated coefficients for taxi drivers are smaller in magnitude than the regular drivers'. This implies that the regular drivers are more sensitive to the travel time information than the taxi drivers. This is because the taxi drivers are more familiar with the route so that the effect of the provided information are lower for them.

Table 7.4 Coefficients Estimated for Binary Logit Model for Taxi Drivers' Route Choices

Variable	Estimated coefficients (β_k; k=0, 2, 3))	t-statistics
Constant (X_0)	0.225	5.26**
Difference between estimated current travel time of expressway and normal travel time of the urban road (X_2 - X_3)	-0.136	-6.87**

Notes: Values marked with an asterisk, ** are statistically significantly at a 1% level

Table 7.5 Coefficients Estimated for Binary Logit Model for Regular Drivers' Route Choices

Variable	Estimated coefficients (β_k; k=0, 2, 3))	t-statistics
Constant (X_0)	0.216	5.29**
Difference between estimated current travel time of expressway and normal travel time of the urban road (X_2 - X_3)	-0.145	-6.89**

Notes: Values marked with an asterisk, ** are statistically significantly at a 1% level

7.4 SUMMARY

A stated preference (SP) survey was conducted to collect data regarding drivers' responses to road traffic information. The SP questionnaire consisted of several hypothesized choice experiments. The SP questions were used to identify factors, which affect the drivers' perceived travel times and route choices if the current travel time is given by the driver information system (DIS). Scenarios with combinations of different levels of factors were considered in the questionnaire.

The relationship between the provided travel time and the perceived travel time has been investigated in this chapter. The results show that the perceived travel time error variance of the drivers is larger as the v/c ratio increases. The travel time reliability is higher when the v/c ratio is smaller. The binary route choice models were calibrated using the SP data. The main finding is that the perceived travel times of the drivers are strongly influenced by the travel time information provided by the DIS. The estimation results are reliable as the sample error is only 4.2% and the R-square is 0.75. It is recommended that revealed preference surveys are conducted once the urban road is opened to traffic.

The calibrated perceived travel time error variance is useful for development of the proposed probit assignment model. In Chapter 8, a bilevel programming model is proposed for the network with travel time information provided by the DIS. The calibrated perceived travel time error variance can be adopted in the lower-level problem which is a probit assignment model. The application of the calibrated route choice model is described in Chapter 9 for validation of the results of the proposed probit assignment model.

8 OPTIMAL SPEED DETECTOR DENSITY FOR THE NETWORK WITH TRAVEL TIME INFORMATION

In Chapter 7, the perceived travel time error variance is calibrated for the probit assignment model. In Chapter 8, a bilevel programming model is proposed for the network with travel time information provided by the route guidance system (RGS). The calibrated perceived travel time error variance is adopted in the lower-level problem which is a probit assignment model.

In the expressway network, detectors are installed on the links for detecting the travel time information while the predicted travel time can be provided by the RGS. The speed detector density can be determined to influence flow distributions in such a way that the precision of the travel time information and the social cost of the speed detectors are optimized, provided that each driver chooses the minimum perceived travel time path in response to the predicted travel time information. In this chapter, a bilevel programming model is proposed for the network with travel time information provided by the RGS. The lower-level problem is a probit assignment model, while the upper-level problem is to determine the speed detector density that minimizes the measured travel time error variance as well as the social cost of the speed detectors. The sensitivity analysis based algorithm is proposed for the bilevel programming problem. Numerical examples are provided to illustrate the applications of the proposed model and of the solution algorithm.

8.1 INTRODUCTION

In view of the traffic congestion problem in most metropolitan areas around the world and recent developments in telecommunications and information processing technologies, there is growing opportunities for providing travel time information to the drivers. It is particularly important to gain more insight into the provision of route guidance system (RGS) information. Therefore, it is necessary to determine the speed detector density on the roads for the provision of the travel time information. The variance of the measured travel time error is inversely proportional to the speed detector density. The proposed bilevel programming model is used to optimize the appropriate speed detector density in order to maximize the precision of the travel time information but also to minimize the social costs of the speed detectors.

The advent of advanced transport telematics (ATT), also known as intelligent transportation systems (ITS), i.e. the application of information technology to transport, has opened up new possibilities to address the problem of providing driver information (Wall and Williams, 1991; Catling et al.; 1991; Makigami et al., 1996). ATT offers two broad categories of travel information which are the individual in-car information and roadside information. The individual in-car information technologies require the establishment of central control centre, communications network and the provision of a suitable in-vehicle units. Development of such systems is continuing at great speed.

For the RGS, some previous related works (Hounsell et al., 1991; Peeta et al., 1991; Al-deek and Kanafani, 1993; Bell et al., 1996) are based on the assumptions that trip-makers with different levels of network information can be classified and origin-destination (O-D) demands by user classes given; i.e. to introduce user classes to differentiate those trip-makers with access to on-line network information services from those without. In contrast, the simulation approach was proposed by Emmerink et al. (1995a, 1995b) using a boundedly rational principle with the assumption that drivers are seeking a satisfactory outcome, rather than a utility maximising.

For a traffic surveillance and information system with RGS, the value of the speed detector density used is very important because it affects the precision of the measurement of the travel time. In Hong Kong, the Transport Department has investigated the feasibility of implementing a driver information system covering the Tuen Mun Road (Delcan and Parsons Brinckerhoff, 1995), and the speed detectors are recommended with a speed detector density of 2 detectors/km. The speed detector density is 5 detectors/km in Tsing Ma control area near the Hong Kong Chek Lap Kok (CLK) international airport. In Japan, the expressway authorities are urging drivers to make more effective use of the expressway system by informing them of the sum of the present travel time (SPTT) of each expressway section (Makigami et al., 1996). The speed detectors are installed in each lane of the Meishin and the Tomei expressways at intervals of about 2 km. Therefore, the speed detector density is varied in different situations. It is important to determine an appropriate speed detector density for different purposes and under various situations. In fact, the choice of the speed detector density is related to the investment cost and the travel time measurement error. It is necessary to determine the optimal speed detector density which can minimize both the investment cost and the travel time measurement error.

The measured travel time errors which relate to the quality of information are not considered in the literature, but the route choice behaviour and the acceptance rate of the advice are closely correlated with the prediction precision and quality of the travel time information (Yang et al., 1993), also the un-informative and inaccurate information causes overreaction (Emmerink et al., 1995a). The optimal speed detector density which affects the measurement errors of the travel time and the cost of investment have not been considered and cannot be determined in the previous work. This chapter seeks to overcome such limitations.

In this chapter, a bilevel programming model is proposed for the network with travel time information provided by the RGS. The lower-level problem is a probit assignment model, while the upper-level problem is to determine the optimal speed detector density that minimize the measured travel time error, as well as the social cost of the speed detectors. Numerical examples are used to illustrate how to use the proposed model and solution algorithm for determining the optimal speed detector densities.

8.2 BASIC ASSUMPTIONS

Throughout this study, the following assumptions are made:

1. The origin-destination (O-D) demands are given and fixed.
2. Travel time on both expressway corridors and local urban roads are continuous and strictly increasing functions of traffic flows.

3. Drivers don't have sufficient knowledge of travel time for the network system if RGS are not provided and make routing decisions in a stochastic user optimal manner.
4. The stochastic network loading model is assumed as probit model where the perceived link travel time and measured link travel time are normally distributed.
5. The measured link travel time error variance is assumed as the product of the link travel time and a measured travel time error dispersion function. The measured travel time error dispersion function is assumed as a function of the speed detector density, volume/capacity (v/c) ratio and the scaling factor of the social cost for the installation and operation of the speed detectors. The measured travel time error dispersion function can be decomposed into three terms. The first term is the dispersion function due to various values of speed detector density. The second term is the dispersion function due to different speed detector technology which is a function of the scaling factor. The final term is the dispersion function due to the v/c ratio for the corresponding link.
6. If the number of speed detectors in a road increases, the speed detector measurement errors can be reduced. Thus, the variance of the measurement errors is smaller if the speed detector density is higher. We can assume that the dispersion function due to various values of speed detectors is an inversely proportional function to the speed detector density.
7. If the technology is more advanced, the precision of the speed detectors measurement will be higher. Generally, the price of the more advanced technology is high. Therefore, we assume that the price of the speed detectors is proportional to the precision of the speed detector measurement. Thus, if the scaling factor for the social cost of the speed detectors increases, the variance of

the measurement error decreases. Consequently, the dispersion function due to different speed detector technology is a decreasing function of the scaling factor.

8. The measurement travel time error dispersion function due to the v/c ratio for the corresponding link is assumed as an increasing function of the v/c ratio. If the v/c ratio increases, the variation of individual actual travel time in a road will be larger and the variance of the measurement errors increases.
9. The perceived link travel time error variance is assumed as the product of the measured link travel time and a perceived travel time error dispersion function. The perceived travel time error dispersion function is due to the v/c ratio for the corresponding link. It is more difficult for the drivers to perceive the travel time correctly as congestion occurs. Therefore, the perceived travel time error variance of the drivers is larger as the v/c ratio increases. Consequently, the dispersion function of the perceived travel time errors of the drivers should be an increasing function of the v/c ratio.

8.3 TRAFFIC CORRIDOR SYSTEM WITH SPEED DETECTORS

A traffic corridor system consists of both the expressway and local urban road. The expressway has a higher speed and capacity than a local urban road. The traffic flow of an expressway is also higher because of its higher level of service. However, the local urban road has limited speed and restricted capacity. The RGS and speed detectors system can be implemented to influence the drivers' choice of the expressway or the local urban road.

A successful RGS and speed detectors system should incorporate the evaluation of its effect such that an appropriate defined system performance measure is optimized. In this chapter, the variance of the measured travel time errors and the social cost of the speed detectors are optimized. For simplicity, the traffic corridor in Figure 8.1 which has an expressway and a local urban road is considered. The RGS is used to provide the travel time information of the expressway. The speed detectors are installed on the expressway as in Figure 8.1.

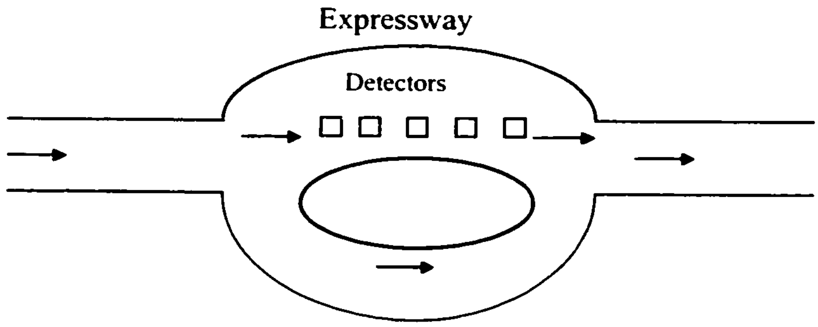

Figure 8.1 An Example of a Simple Corridor System

Figure 8.2 shows the equilibrium condition between the variance of measured travel time errors of the expressway and the social cost of the speed detectors with the speed detector density. The social cost of the speed detectors is assumed as the product of the number of speed detectors and the scaling factor. Thus, the social cost of speed detectors and speed detector density has a linear relationship with the slope equal to the product of the scaling factor and the distance of the expressway. The social cost is an increasing function of the speed detector density with intercept on the origin.

The variance of the measured travel time errors is assumed as a nonlinear decreasing function of the speed detector density since the variance of the measured travel time errors decrease as the value of the speed detector density increases. Therefore, the optimal speed detector density can be obtained by minimizing the sum of the variance of the measured travel time errors and the social cost of speed detectors in the feasible set of speed detector density.

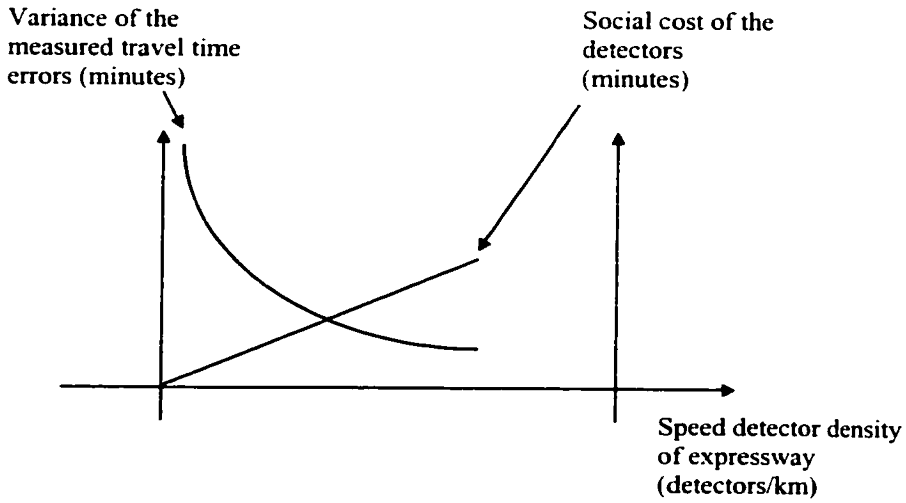

Figure 8.2 Equilibrium Condition: the Variance of Measured Travel Time Errors (minutes) and the Social Cost of the Speed Detectors (minutes) for the Expressway

8.4 TRAVEL TIME ERROR DISPERSION FUNCTION

The classical probit assignment model considers the perceived link travel time as normally distributed with mean equal to the link travel time and variance equal to the product of a dispersion parameter and the link travel time. This dispersion parameter is assumed as a constant in the literature (Sheffi, 1985; Maher and Hughes, 1997). However, the constant dispersion parameter is not suitable for a network with speed detectors and RGS. In this study, the perceived travel time error dispersion function and the measured travel time error dispersion function is assumed instead of using a constant dispersion parameter.

The measured link travel time error variance is assumed as the product of the link travel time and a measured travel time error dispersion function. The measured travel time error dispersion function is assumed as a function of the speed detector density, v/c ratio and the scaling factor of the social cost for the installation and operation of the speed detectors. The measured travel time error dispersion function is comprised of three functions $f^d(d_{da})$, $f^s(\theta_{da} d_{da})$ and $f^m(v_a/k_a)$.

The first function $f^d(d_{da})$ is the dispersion function where the variable is the speed detector density. Sen et al. (1997) reported that the variance of the mean of the travel times obtained from *n* probes for the same link over a fixed time period is shown to be inversely proportional to *n*. Sen et al. (1997) shows the standard error of the travel time for a different number of probes. According to Sen's results, the standard error of the travel time decreases as the number of probe vehicles increases.

The estimation of link speed by using probe vehicles and a speed detector is similar in principle as they both provide the sample link speed estimate on the road section concerned. Consequently, the effect of increasing the number of probe vehicles is more or less equivalent to that of increasing the number of speed detectors. Therefore, it can be implied that the measured travel time dispersion decreases as the number of speed detectors increases.

A survey has been carried out to collect the actual link travel time data by video recording at the entrance and exit of a road tunnel in Hong Kong. The survey results were compared against the detected travel speed by the speed detector system in the road tunnel. As a result, it was found in Figure 8.3 that the root mean square errors (RMSE) of the average link travel time estimate decreases as the number of speed detectors increase. This finding is similar to that of Sen et al. (1997) while the measured travel time errors are nonlinear inversely proportional to the number of probe vehicles or to the number of speed detectors.

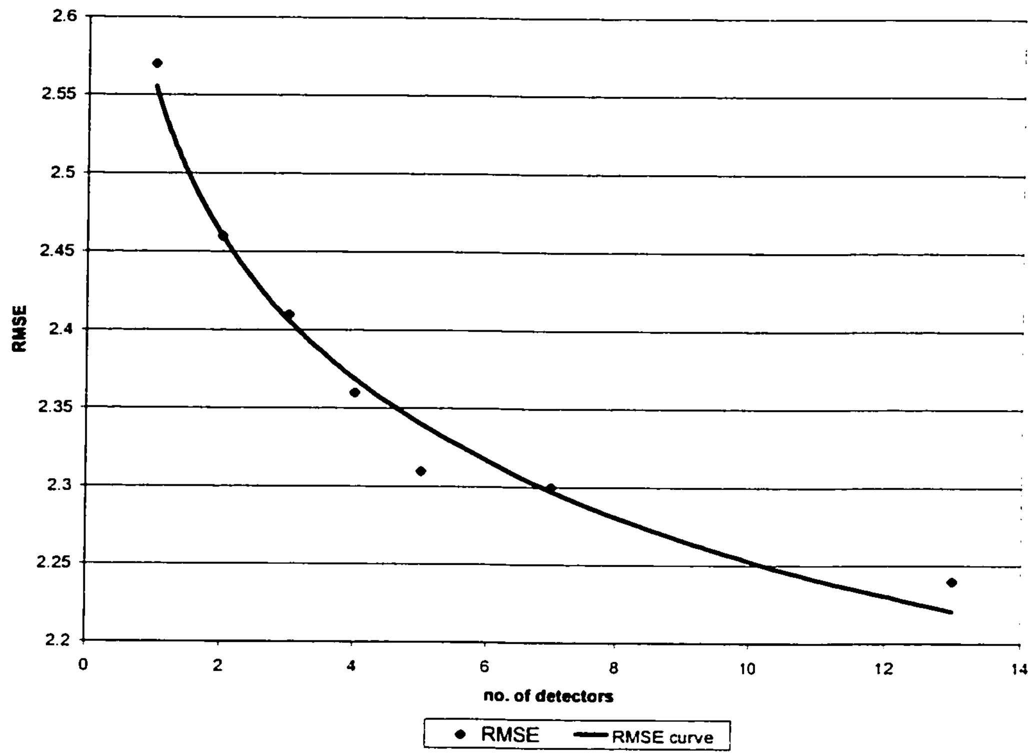

Figure 8.3 RMSE of Average Link Travel Time Estimate for Different Number of Speed Detectors

Sen et al. (1997) pointed out that their model is not only true for probes, but also for any method of measuring the travel times of vehicles. The measured travel time error dispersion in our model can also be applied for probe vehicles. This implies that the proposed model can be extended to determine the optimal probe sample size.

The second function $f'(\theta_{da}d_{da})$ is the dispersion function due to various speed detector technology which is a function of the scaling factor and speed detector density. The scaling factor is used to convert speed detector price units into units of hourly travel time. For example, a scaling factor was used to convert units of construction cost into units of daily travel cost for the network design problem (Davis, 1994).

The scaling factor can be calculated based on the life-cycle costs of the speed detector. The life-cycle cost includes the fixed cost, material cost, installation cost, maintenance cost and operations cost. The fixed cost is proportional to the equipment cost spread over the expected year of service. The material cost is the cost of non-reusable material. The installation, maintenance and operations costs are mainly labor costs.

For example, in Hong Kong, the yearly life-cycle cost of the loop detector and of air tube detector is US$2340 and US$5255 respectively. The yearly life-cycle cost can be converted to the daily cost by assuming 365 days per year. Similarly, the hourly life-cycle cost can be obtained. The scaling factor in this chapter refers to the hourly life-cycle cost. Consequently, the scaling factors should be 0.27 and 0.60 for the loop detector and air tube detector respectively.

We assume that the accuracy of detector measurement increases with price. This assumption is supported by the results shown in Table 8.1 in which Autoscope(video image processing) has higher accuracy than the RTMS(microwave) in the two testing periods. The price of Autoscope(US$36,600) is higher than that of RTMS (US$4,820). It shows that the speed detector with a higher price has better accuracy for these two types of speed detectors. We agree that sensing technology is undergoing a revolutionary change and better sensors may actually be cheaper in the long term. However, in general, the speed detector system with a higher price should be more accurate in the commercially competitive market.

Table 8.1 Comparison of Traffic Count between Manual Counts, and RTMS in Tuen Muen Road

	Price	04:00 to 05:00				10:00 to 11:00			
		V/c ratio	Count	Difference	%	V/c ratio	Count	Difference	%
Manual Counts		0.024	48	0	0.0%	0.331	662	0	0.0%
Autoscope	US$36,600	0.0255	51	3	6.3%	0.324	648	-14	-2.1%
RTMS	US$4,820	0.0175	35	-13	-27.1%	0.363	726	64	9.7%

The third function $f^m(v_a/k_a)$ is the dispersion function depends on the v/c ratio for the corresponding link. A survey has been conducted regarding the measured travel time error variance at the double loop detectors in a road tunnel in Hong Kong. The preliminary results show that the unstable flow (fluctuations of flow rate is large) occurs when the flow is at-capacity. For higher congestion levels, the forced flow (restriction of flow rate from downstream congestion) exists which causes the momentary car stoppage. Therefore, a higher congestion level will lead to larger measured travel time error dispersion.

The perceived link travel time error variance is assumed as the product of the measured link travel time and a perceived travel time error dispersion function. The perceived travel time error dispersion function $f^p(v_a/k_a)$ is due to the v/c ratio for the corresponding link.

The expected queue and delay for each driver is different. As a result, there is large perceived travel time error variance. However, the proposed model is basically a static model in which the overflow delay is incorporated into the BPR link travel time function (Ran et al., 1997). The large variation of the drivers' expected queues and delay would refer to large link travel time. Larger link travel time will result in a greater perceived link travel time error variance. As a result, greater dispersion is also implied.

To justify the relationship between the perceived travel time error dispersion function and the v/c ratio, an interview survey has been carried out at the Hong Kong CLK international airport in November, 1998. There are six scenarios in the questionnaire referring the six levels of service (LOS). The objective of the survey is to investigate the perceived travel time errors of the drivers for the various scenarios. Firstly, the photo of different scenarios will be shown to the respondents (i.e. selected drivers at the car parks of the Hong Kong CLK international airport). Secondly, the modelled travel times of different scenarios will be given to the drivers. Finally, the perceived travel times of drivers for different scenarios will be asked and recorded. The perceived travel times of the drivers will be compared with the modelled travel times.

The calculation for the difference of the modelled travel time and perceived travel time is shown below:

$$k=E(t_a)-E(t_p) \tag{8.1}$$

where $E(t_a)$ and $E(t_p)$ are the expected values of modelled travel time t_a and of perceived travel time t_p respectively. We assume that there is a constant difference between the actual and perceived travel time and that the modelled travel time provides an unbiased estimate of actual travel time. Under this assumption, the variance of the perceived travel time error, $var(e_p)$ can be derived as follow:

$$var(e_p) \approx var(t_p - t_a) + k^2/n \qquad (8.2)$$

where n is the sample size.

Therefore, the estimated variance of the perceived travel time error is obtained as below,

$$EstVar(e_p) = var(t_p - t_a) + k^2/n \qquad (8.3)$$

This estimated variance can then be calculated by the perceived travel times obtained from the survey and the modelled travel times.

Figure 8.4 shows the $EstVar(e_p)/t_a$ for various v/c ratios. The dispersion of the perceived travel time error can be estimated by $EstVar(e_p)/t_a$. Consequently, Figure 8.4 shows that the dispersion of the perceived travel time error increases as v/c ratio increases. These empirical results justify the assertion #9.

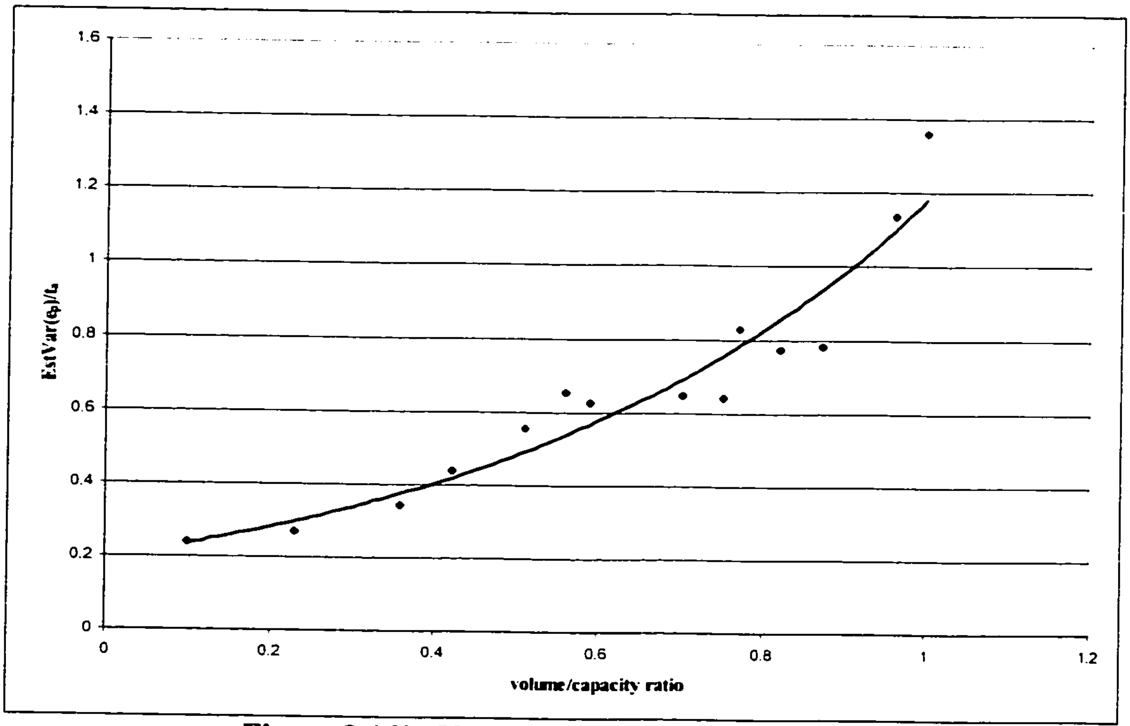

Figure 8.4 EstVar(e_p)/t_a for Different V/c Ratios

Table 8.2 summarizes the above mentioned travel time error dispersion functions. The properties of the functions are also stated.

Table 8.2 Travel Time Error Dispersion Functions

Dispersion function	Description	Properties
$f^d(d_{da})$	Measured travel time error dispersion function due to the speed detector density value	Decreasing
$f^r(\theta_{da}d_{da})$	Measured travel time error dispersion function due to the scaling factor and the speed detector density value	Decreasing
$f^m(v_a/k_a)$	Measured travel time error dispersion function due to the v/c ratio	Increasing
$f^p(v_a/k_a)$	Perceived travel time error dispersion function due to the v/c ratio	Increasing

Table 8.3 shows the examples of the functional forms for each of the dispersion functions. In practice, the forms and the parameters of each dispersion function

should be calibrated by the survey data. In Hong Kong, the vehicle speed detectors are recommended with speed detector density of 2 detectors/km in Tuen Mun Road (Delcan and Parsons Brinckerhoff, 1995) while the speed detector density is 5 detectors/km in Tsing Ma control area near the Hong Kong CLK international airport. In Japan, the speed detectors are installed in each lane of the Meishin and the Tomei expressways at intervals of about 2 km (Makigami et al., 1996). It is not reasonable and sensible to have a very large value of the speed detector density in practice. Therefore, the maximum speed detector density d_{max} is assumed to be 5 detectors/km in our study. Since the price of the speed detector technology must has a lower bound, θ_{min} is assumed as the minimum required scaling factor. The dispersion function due to the different speed detector technology depends on the ratio of the scaling factor θ_{da} and θ_{min}.

Table 8.3 Examples of the Travel Time Error Dispersion Function Form

Dispersion function	Examples of the function form	Parameters
$f^d(d_{da})$	$\boldsymbol{a} + \boldsymbol{b}/d_{da}$. $\alpha_{da}\exp(-\beta_{da}d_{da}/d_{max})$,	α_{da}:dispersion due to zero speed detector density $\boldsymbol{a}$, $\boldsymbol{b}$, β_{da}:calibration parameter d_{max}: Maximum speed detector density (detectors/km)
$f^t(\theta_{da}d_{da})$	$\alpha_{ta}\ \exp(-\beta_{ta}\ \theta_{da}\ d_{da}\ /\theta_{min}\ d_{max})$	α_{ta}:dispersion due to speed detector technology for zero speed detector density β_{ta}: calibration parameter (detectors/mins)
$f^m(v_a/k_a)$	$\alpha_{ma}(\ v_a/k_a)^{\beta_{ma}}$	α_{ma}: measurement error dispersion due to v/c ratio for at-capacity flow β_{ma}: calibration parameter
$f^p(v_a/k_a)$	$\alpha_{pa}\exp(\beta_{pa}\ v_a/k_a)$	α_{pa}: perceived error dispersion due to v/c ratio for zero flow β_{pa}: calibration parameter

8.5 MODEL FORMULATION

Upper-level problem

The objective of the upper-level problem is to maximize the precision of the travel time information provided and to minimize the construction and social cost of the speed detectors. The speed detector density is determined for given flow distributions so that the optimal measured travel time error variance of the travel time information and the social cost of the speed detectors are obtained. Consequently, the upper-level problem P(U-L) can be written as follows:

P(U-L): $$\underset{\mathbf{d}}{\text{Minimize}}\ Z(\mathbf{d}) = \sum_a C_{va}(\mathbf{v},\mathbf{d}) + \sum_a \theta_{da} d_{da} D_a$$

subject to

$$\sum_a \theta_{da} d_{da} D_a \le B \tag{8.4a}$$

$$d_{da} D_a \in I^+,\ a \in A_d \tag{8.4b}$$

$$0 \le d_{da} \le d_{max},\ a \in A_d \tag{8.4c}$$

where I^+ is the positive integer set and B is the budget for the social cost of the speed detectors.

The terms $C_{va}(\mathbf{v},\mathbf{d})$ in the objective function is the sum of the variances of the measured and perceived travel time errors for link a. It can be defined as follow,

$$C_{va}(\mathbf{v},\mathbf{d}) = [f^d(d_{da}) + f^t(\theta_{da} d_{da}) + f^m(v_a/k_a) + f^p(v_a/k_a)]C_a(v_a) \tag{8.5}$$

where the function $f^d(d_{da})$, $f^t(\theta_{da} d_{da})$ and $f^m(v_a/k_a)$ are the measured travel time error variances due to the speed detector density, speed detector technology and v/c ratio respectively. As the speed detector density increases, the measured error variance $f^d(d_{da})$ decreases. When the v/c ratio increases, the function value of $f^m(v_a/k_a)$ will increase. The function $f^p(v_a/k_a)$ is the perceived travel time error variance for modelling the congestion effect. Since the perceived error of the drivers is larger as the v/c ratio increases. Therefore, $f^p(v_a/k_a)$ increases as the value of the v/c ratio v_a/k_a increases.

In this chapter, the measured travel time error ε_{ma} and perceived travel time error ε_{pa} are assumed as normally distributed. The relationship between the measured travel time C_{ma} and travel time of link a is as follows,

$$C_{ma} = C_a + \varepsilon_{ma} \tag{8.6}$$

The perceived travel time for link a C_{pa} can be expressed as the sum of the perceived travel time error and the measured travel time as below,

$$C_{pa} = C_{ma} + \varepsilon_{pa} \tag{8.7}$$

Therefore, the perceived travel time C_{pa}, the link travel time C_a, the perceived travel time error ε_{pa}, the measured travel time error ε_{ma} and the total travel time error variance for link a $C_{va}(\mathbf{v},\mathbf{d})$ are related as eqn. (8.8), (8.9) and (8.10).

$$C_{pa} = C_a + \varepsilon_{pa} + \varepsilon_{ma} \tag{8.8}$$

$$\varepsilon_{pa} + \varepsilon_{ma} \sim N(0,\ C_{va}(\mathbf{v},\mathbf{d})) \tag{8.9}$$

$$C_{pa} \sim N(C_a,\ C_{va}(\mathbf{v},\mathbf{d})) \tag{8.10}$$

The second term in the upper-level objective function is the social cost of the speed detectors. The social cost of the speed detectors is the product of the number of speed detectors and the scaling factor. When the speed detector density is zero, the social cost is also equal to zero. The social cost is an increasing function of the speed detector density with intercept on the origin.

Lower-level problem

In the proposed model, the lower-level problem is a stochastic network equilibrium model. For the stochastic network equilibrium, each driver chooses the minimum perceived travel time path in response to the given speed detector density. The lower-level problem is a probit assignment model if the travel time error is assumed as a normal variate. The steady-state traffic assignment on the network for a given set of speed detectors, **d**, is equivalent to the following minimization problem (Sheffi and Powell, 1982).

P(L-L): $$\underset{v \geq 0}{\text{Minimize}} \; z(\mathbf{v}) = -\sum_a \int_0^{v_a} C_a(x)dx + \sum_a C_a(v_a)v_a - \sum_w T_w S_w(\mathbf{v}, \mathbf{d})$$

where S_w is the expected perceived minimum time (the satisfaction function between O-D pair $w \in W$) which depends on link travel time, speed detector density.

8.5.1 Sensitivity Analysis

Sensitivity analysis methods have been widely used for network equilibrium problems recently. A heuristic algorithm was proposed by Tobin and Friesz (1988) for sensitivity analysis which makes use of the derivatives of the equilibrium link flows with respect to perturbation parameters. The sensitivity analysis is applied to solve the network design problems by Friesz (1990). A heuristic method for the inflow control problem is developed (Yang et al., 1994). A sensitivity analysis is performed for the queuing equilibrium network assignment problems while the derivatives of equilibrium link flows and equilibrium queuing times with respect to traffic control parameters are derived (Yang, 1995).

It is necessary to derive the derivatives of the decision variables with respect to the perturbation parameters for the sensitivity analysis approach developed by Tobin and Friesz (1988). This derivatives information is adopted for solving the bilevel programming model. In our proposed problem, the derivatives of equilibrium link flows with respect to the speed detector density needs to be calculated. These derivatives are then used to obtain the linear approximation of the objective function value for the upper-level problem.

Now, the perturbed equilibrium problem can be written as

$$P(\varepsilon): \quad Z(\mathbf{v}, \varepsilon) = -\sum_a \int_0^{v_a} C_a(x)dx + \sum_a C_a(v_a)v_a - \sum_w T_w S_w(\mathbf{v}, \varepsilon)$$

where ε is the perturbation parameter.

It can be observed easily that the necessary conditions for the perturbed equilibrium assignment problem at $\varepsilon = 0$ is that:

$$\nabla_v Z(\mathbf{v}^*, 0) = 0 \tag{8.11}$$

The Jacobian matrix of the above system with respect to $\mathbf{v}$ is

$$J_v = \nabla_v \nabla_v Z(\mathbf{v}^*,0) \tag{8.12a}$$

$$= \nabla_v^2 Z(\mathbf{v}^*,0) \tag{8.12b}$$

It can be proved that

$$\nabla_v^2 Z(\mathbf{v}^*, 0) = \sum_w T_w[(\nabla_v \mathbf{C}\, \Delta^w)(-\nabla_C \mathbf{P}^w)(\nabla_v \mathbf{C}\, \Delta^w)^T] + \nabla_v \mathbf{C} + \nabla_v^2 \mathbf{C}\, \mathbf{R} \tag{8.13}$$

where $\mathbf{R}$ is a diagonal matrix, the ath element of which is $-\sum_w \sum_k T_w P_k^w \delta_{ak}^w + v_a$

and $\delta_{ak}^w = \begin{cases} = 1 \text{ if link a is on path k between OD pair w} \\ = 0, \text{ otherwise} \end{cases}$

$$[J_v]^{-1} = [\nabla_v^2 Z(\mathbf{v}^*,0)]^{-1} \tag{8.14}$$

The Jacobian matrix with respect to ε is

$$J_\varepsilon = \nabla_\varepsilon \nabla_v Z(\mathbf{v}^*,0) \tag{8.15}$$

where $\nabla \;\; \nabla_v Z(\mathbf{v}^*,0) = \nabla_\varepsilon [(-T_w \mathbf{P}^w \Delta^{w\,T} + \mathbf{v}) \cdot \nabla_v \mathbf{C}]$ (8.16a)

$$= -\nabla_\varepsilon [(T_w \mathbf{P}^w \Delta^{w\,T}) \cdot \nabla_v \mathbf{C}] \tag{8.16b}$$

Since

$$\nabla_\varepsilon \mathbf{v} = [J_v]^{-1} [-J_\varepsilon] \tag{8.17a}$$

$$= -[\nabla_v^2 Z(\mathbf{v}^*,0)]^{-1} [\nabla_\varepsilon \nabla_v Z(\mathbf{v}^*,0)] \tag{8.17b}$$

Let **ε** = δ **d**, representing a small variation in speed detector density

$$\nabla_\varepsilon \mathbf{v} = \nabla_{\mathbf{d}} \mathbf{v} \tag{8.18}$$

Therefore,

$$\nabla_{\mathbf{d}} \mathbf{v} = -[\nabla_v^2 Z(\mathbf{v}^*,0)]^{-1} [\nabla_{\mathbf{d}} \nabla_v Z(\mathbf{v}^*,0)] \tag{8.19}$$

where $\nabla_v^2 Z(\mathbf{v}^*,0)$ is expressed in eqn. (8.13)

and $\nabla_{\mathbf{d}} \nabla_v Z(\mathbf{v}^*,0) = -\; \nabla_{\mathbf{d}} [(T_w \mathbf{P}^w \Delta^{w\,T}) \cdot \nabla_v \mathbf{C}]\cdot$ (8.20)

The derivative information in eqn. (8.19) will be used for obtaining the linear approximation of the original nonlinear upper-level objective function.

8.5.2 Solution Algorithm

It is difficult to evaluate the upper-level objective function directly because it involves the nonlinear function and implicit function of the speed detector density. We use the linearized objective function based on the derivative information instead of the original objective function. The well-known simplex method can then be adopted for solving the linear programming problem obtained.

Linear approximation of the terms $C_{va}(\mathbf{v},\mathbf{d})$ (in eqn. (8.5)) can be derived by using the derivative information in eqn. (8.19).

$$C_{va}(\mathbf{v},\mathbf{d})=C_{va}(\mathbf{v}^*,\mathbf{d}^*)+\frac{\partial C_{va}(v_a)}{\partial v_a}\{\sum_b[\frac{\partial v_a(\mathbf{d})}{\partial d_{db}}]_{\mathbf{d}=\mathbf{d}^*}(d_{db}-d_{db}^*)\}$$

$$+\left.\frac{\partial C_{va}(\mathbf{d})}{\partial d_{da}}\right|_{\mathbf{d}=\mathbf{d}^*}(d_{da}-d_{da}^*) \tag{8.21}$$

After substituting eqn. (8.21) into the problem P(U-L) and omitting the constant terms, the linear approximation upper-level problem P'(U-L) can then be obtained as follows:

$$\text{P'(U-L): Minimize}_{\mathbf{d}} \quad Z(\mathbf{d})=\sum_a\left(\sum_b\frac{\partial C_{vb}(v_b)}{\partial v_b}[\frac{\partial v_b(\mathbf{d})}{\partial d_{da}}]_{\mathbf{d}=\mathbf{d}^*}+\left.\frac{\partial C_{va}(\mathbf{d})}{\partial d_{da}}\right|_{\mathbf{d}=\mathbf{d}^*}+\theta_{da}D_a\right)d_{da}$$

subject to (8.4a), (8.4b) and (8.4c)

A solution algorithm is proposed for solving the proposed bilevel mathematical problem in this section. The mechanism of the solution algorithm is an iterative process between the upper-level and lower-level problem. The method of successive average (MSA) is adopted to update the speed detector density value. Clark's approximation or the simulation algorithm can be used to solve the lower-level probit assignment problem. Recently, a new heuristic probit assignment method (Maher and Hughes, 1997) which does not require Monte-Carlo simulations but suffers from the cycle problems and needs to adopt the Clark's approximation while scanning the network from origin to destination was proposed.

In this chapter, the simulation assignment is used for computing the link flow. One of the advantages of the simulation approach is that the random errors can be any types of distribution. The column generation algorithm proposed by Bell et al. (1993) is adopted to identify the set of feasible paths. By applying the Monte-Carlo simulation to solve the SUE problem, the solution algorithm is proposed as below,

Step 0: Determine an initial speed detector density $\mathbf{d}^0$. Set N=0.

Step 1: Solve the SUE problem and get the link flow pattern $\mathbf{v}^N$.

Step 2: Find derivative $\nabla_{\mathbf{d}}\mathbf{v}$.

Step 3: Solve the linear programming of upper-level problem and obtain the auxiliary vector of speed detector density $\mathbf{y}$.

Step 4: Compute $\mathbf{d}^{N+1}=\mathbf{d}^N+(\mathbf{y}-\mathbf{d}^N)/(N+1)$

Step 5: If $\max|\mathbf{d}^{N+1}-\mathbf{d}^N| \leq K$ or N=M then stop.

Otherwise, let N=N+1 and goto Step 1. M= maximum number of iterations.

K is a stopping parameter with small value.

8.6 NUMERICAL EXAMPLE

The example network shown in Figure 8.5 consists of 1 origin zone, 1 destination zone, 4 nodes and 4 links. In the network, the speed detectors are introduced on links 2 and 3. The example is designed for three purposes, namely (a) to demonstrate the effects of the travel time information via RGS, (b) to test the feasibility of providing travel time information by minimizing the measured travel time error variance, (c) to illustrate the convergence of the solution algorithm. To demonstrate the effects of RGS, the RGS results will be compared with the probit assignment results, the dispersion parameter (β) is adopted in the numerical example. In an urban traffic network, local urban roads with the relatively low speed and restricted capacity are always connected to expressways with higher speed and greater capacity. Therefore, a road corridor with one expressway and one local urban road is used as the example network and is shown in Figure 8.5. Link 2 is an expressway which is designed for a higher level of service, faster travel and higher capacity. Link 3 is a local urban road, its speed is lower and its capacity is limited.

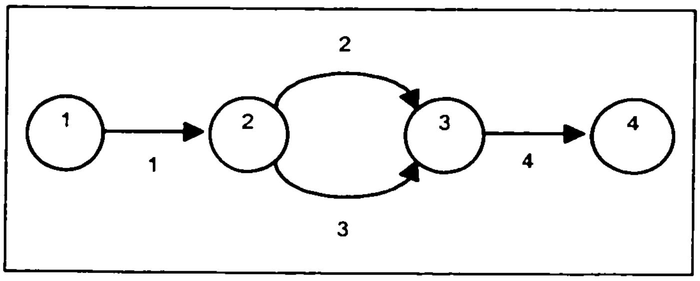

Figure 8.5 Example Network

Suppose the travel time error dispersion functions are assumed as follows and θ_{min} = 0.01 and d_{max} =5.0:

$$f^p(v_a/k_a) = \beta_a \exp(v_a/k_a) \quad (8.22)$$

$$f^d(d_{da}) = 0.11 + \lambda/(d_{da} + \varphi) \quad (8.23)$$

$$f^t(d_{da}) = 0.15\exp(-4(\theta_{da} d_{da}/\theta_{min} d_{max})) \quad (8.24)$$

$$f^m(v_a/k_a) = 0.01(v_a/k_a)^2 \quad (8.25)$$

The following link travel time functions with respect to link flows are adopted:

$$C_a = \gamma_a + \alpha_a (v_a / k_a)^{\rho_a} . \tag{8.26}$$

where k_a is the capacity of link a and a=1,2,3,4, γ_a is the free flow time, α_a and ρ_a are the calibration parameters of link a. φ is a very small value.

Table 8.4. The Link Data of the Network

Link no.	γ_a (hrs)	k_a (pcu/hr)	parameter ρ_a	α_a
1	0.1500	6000	4	0.1500
2	0.1250	5400	4	0.2083
3	0.2000	1000	4	0.1333
4	0.1500	6000	4	0.1500

Four scenarios are tested for the convergence of the solution algorithm by using different O-D demands which are assumed to be 4,000 pcu/hr, 6,000 pcu/hr, 8,000 pcu/hr and 10,000 pcu/hr. The distance of the links is 10 km. The scaling factor θ_{da} is supposed to be 1.0. The stopping parameter K is 0.005. The computational results are shown in Figure 8.6, Tables 5, 6, 7 and 8. The upper-level objective values for different number of iteration are presented in Figure 8.6.

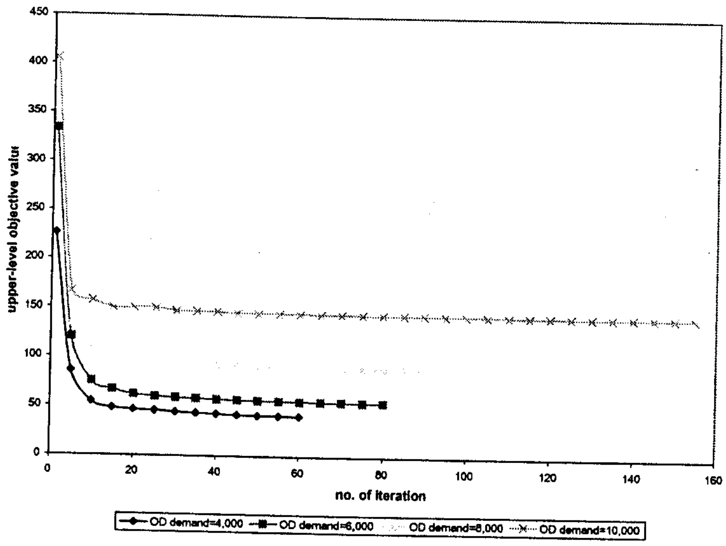

Figure 8.6 The Upper-level Objective Values for Different No. of Iteration

The fluctuation of the objective value becomes small as the iteration proceeds which demonstrates that the solution algorithm converges for this example. It can be observed that the proposed algorithm has a faster convergence for smaller O-D demand. For larger O-D demand, more iterations are needed because large O-D demand leads to more traffic flow and higher travel time which results in the significant change for the upper-level objective function as the value of the speed detector density varies.

By fixing the O-D demand to be 6,000pcu/hr, measurement error parameter λ=0.1 and the stochastic user equilibrium (SUE) parameters for equipped cars β_a =0.3, Table 8.5 shows the obtained optimal speed detector density for different network characteristics. If both links 2 and 3 are expressways, the travel time will be smaller which leads to a smaller travel time error variance and a smaller speed detector density required to reduce the variance. However, in order to reduce the travel time error variance due to higher traffic flow on the urban road, the higher speed detector density is adopted if both links 2 and 3 are urban roads.

Table 8.5 Speed Detector Density (detectors/km) for Different Network Characteristics (O-D demand=6,000pcu/hr)

Network	Both links 2 and 3 are expressway	1 expressway and 1 urban road	Both links 2 and 3 are urban road
Link 2	2.1	2.4	3.8
Link 3	2.1	2.9	3.8

The network with one expressway and one urban road is now adopted. The measurement error parameters λ=0.1 and SUE parameters for equipped cars β_a =0.3. Table 8.6 presents the changes of the total network travel times for various O-D demands. The total network travel time in the network without RGS is also shown.

Table 8.6 indicates that the total network travel times are smaller for networks with RGS than without RGS for various O-D demands.

Table 8.6 Total Network Travel Time (pcu-hr) for Various O-D Demands

O-D demand(pcu/hr)	4,000	6,000	8,000	10,000
(a)Without RGS	718	1,800	5,004	13,525
(b)With RGS	667	1,727	4,884	12,920
% of time saving with RGS = (b-a)/b * 100%	7.65	4.06	2.40	4.47

The speed detector density of links 2 and 3 are shown in Table 8.7 for different O-D demands and measurement error parameter λ. The larger the measurement error parameter λ, the larger the measured travel time error variance. Table 8.7 indicates that the speed detector density increases when the O-D demand increases. It is because larger O-D demand leads to the larger link flow and link travel time. Therefore, it is necessary to use higher speed detector density for minimizing the variance of the measured travel time errors.

Table 8.7 Speed Detector Density (detectors/km) for Various O-D Demands and Measurement Error Parameters λ

		O-D demand (pcu/hr)			
Measurement error parameter λ	Link no.	4,000	6,000	8,000	10,000
0.05	2	1.2	1.8	3.0	5.0
	3	1.5	2.3	4.2	5.0
0.10	2	1.6	2.4	4.1	5.0
	3	2.1	2.9	4.8	5.0
0.15	2	2.4	3.1	5.0	5.0
	3	3.0	4.1	5.0	5.0
0.20	2	2.7	3.6	5.0	5.0
	3	3.6	4.6	5.0	5.0

It can be seen in Table 8.7 that the required speed detector density increases as the measurement error parameter λ increases. This is due to the increase of λ results in larger measured travel time error variance and speed detector density should be increased to reduce this error variance. The speed detector density for link 3 is relatively large compared to link 2's for various O-D demands. This is because the large travel time of link 3 results in greater measured travel time error variance and a higher speed detector density needs to be used for reducing its variance.

It is assumed in the following sensitivity test that the difference between the SUE parameters for equipped cars (β_a) and that for unequipped cars (β) is 0.3. The larger the SUE parameters for equipped and unequipped cars are, the larger the corresponding perceived travel time error variances are. The ratio of the perceived travel time error variance for equipped cars and unequipped cars is β_a/β. In other words, it is implied that SUE perceived error of those equipped cars is less than that for unequipped cars. Table 8.8 presents the changes of the total network travel times for various scaling factors when the O-D demand is 6,000 pcu/hr.

It can be observed from Table 8.8 that total network travel time with RGS is less than that without RGS. Table 8.8 shows that the total network travel time increases when the scaling factor increases. This is because larger scaling factors imply higher speed detector costs. Higher speed detector costs in the upper-level objective problem will lead to lower speed detector density values. This results in larger total network travel time. The total network travel time also increases as the SUE parameters for equipped and unequipped cars increase.

Table 8.8 Total Network Travel Time (pcu-hr) for Various Scaling Factors θ (O-D demand=6,000 pcu/hr)

SUE parameter for equipped cars (β_a)	Scaling factor θ					SUE parameter for unequipped cars (β)	Without RGS (pcu-hr)
	0.1	0.5	1.0	1.5	2.0		
	Total network travel time (pcu-hr) with RGS						
0.2	1723.9	1724.1	1727.4	1737.6	1744.4	0.5	1799.7
0.3	1734.1	1737.6	1742.9	1746.5	1748.7	0.6	1859.6
0.4	1747.9	1752.9	1758.6	1761.8	1763.7	0.7	1897.5
0.5	1776.9	1782.8	1793.1	1806.5	1827.1	0.8	1990.8
0.6	1857.9	1864.3	1868.5	1883.1	1897.6	0.9	2046.9

8.7 CASE STUDY

Figure 8.7 shows the example network of the Tuen Mun Road Corridor which connects Tuen Mun and Kowloon urban areas in Hong Kong. The network consists of 3 zones and 10 links.

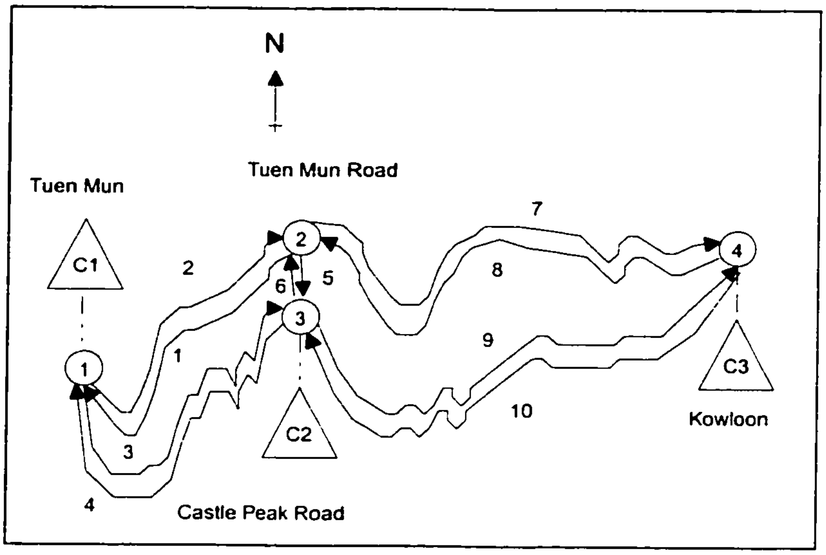

Figure 8.7 Tuen Mun Road Corridor Network

The link travel time function with respect to link flow is given as follow:

$$C_l = \gamma_l + \alpha_l \, (V_l / s_l)^{\rho_l} \tag{8.27}$$

where s_l is the capacity of link l and l=1,2,..10, γ_l is the free flow time, α_l and ρ_l are the calibration parameters of link l. The O-D matrix and the link data for the example network are given in Tables 9 and 10 respectively. The scaling factor θ is 1.0. This example is designed for demonstrating the effects of the travel time information via RGS in the real situation, and to test the feasibility of providing travel time information and obtaining the optimal speed detector density in real network.

Table 8.9 The Link Data of the Network

Link no.	γ_l (hrs)	s_l (pcu/hr)	Parameter	
			ρ_l	α_l
1,2	0.090	5175	3.5	0.1050
3,4	0.1843	850	3.6	0.1843
5	0.0093	730	3.6	0.0093
6	0.0093	950	3.6	0.0093
7,8	0.0335	4800	3.6	0.0335
9,10	0.1533	1000	3.6	0.1533

Table 8.10 O-D matrix (passenger car units per hour)

		Destination	zones		pcu/hr
		C1	C2	C3	Total
Origin	C1	-	27	4774	4801
zones	C2	135	-	305	440
	C3	4299	271	-	4570
	Total	4434	298	5079	9811

The speed detectors are installed on the expressway which are links 2 and 7. By using the dispersion functions in eqn. (8.22)-(8.24), the resultant optimal speed detector density is 2.3 detectors/km. The obtained optimal detector density is close to the value recommended which is 2.0 detectors/km (Delcan and Parsons Brinckerhoff, 1995). The resultant link flows and travel times for the system with and without RGS are presented in Table 8.11. It can be observed that the flows of links 1, 2, 7 and 8 are larger for the system with RGS. However, the increases of link travel times of those links are not large, but the decreases of link travel times of other links are larger. Therefore, the total network travel times can be reduced for the system with RGS. The total network travel times are 2022.5 pcu-hr and 2425.6 pcu-hr for the system with and without RGS respectively.

Table 8.11 The Resultant Link Flows and Times for the System with and without RGS

	Link	1	2	3	4	5	6	7	8	9	10
With RGS	Link Flow (pcu/hr)	3964	4319	482	470	696	831	4947	4457	132	113
	Travel Time (minutes)	7.86	8.72	12.6	12.47	1.05	0.92	4.25	3.55	9.21	9.20
Without RGS	Link Flow (pcu/hr)	3771	3947	868	847	1203	1442	4105	3690	841	818
	Travel Time (minutes)	7.48	7.84	18.55	17.55	3.93	3.06	3.15	2.79	14.13	13.65

8.8 SUMMARY

In this chapter, a bilevel programming model is proposed to determine the speed detector density for networks with travel time information via route guidance systems. Explicit expressions of the derivative of equilibrium link flows with respect to speed detector density is derived. A mathematical formulation and its solution algorithm are also presented for the model. The numerical example drawn from road network with expressway and local urban road is adopted to illustrate the convergence of the proposed solution algorithm. The results of sensitivity tests for the optimal speed detector density are presented using various O-D demands. As O-D demand increases, the speed detector density required increases because larger O-D demand results in larger link travel time and larger measured travel time error variance. The case study in Tuen Mun road corridor was used to test the proposed model and solution algorithm with real data.

The proposed solution algorithm is limited to medium size network at this stage. The alternative method is the logit assignment approach instead of the probit assignment approach. Therefore, the path flow estimation (Bell et al., 1997) can in practice be incorporated in large network application. The advantage of using probit assignment approach instead of the logit assignment approach is that the IIA problem can be removed. Another advantage is that the use of a simulation method for solving the probit assignment approach is flexible if the travel time error distribution is varied. However, the logit assignment approach is more practical for large network problems. For application of the probit assignment model in large network problems, Clark and Watling (2001) stated that additional effort is approximately 10 to 20 times for the Sioux Falls network. The developments on efficient algorithms (Clark and Watling, 2001) and quasi-simulation approach (Bhat, 2000) for solving the probit assignment model are ongoing. The new algorithms have the potential to increase the efficiency for practical applications of the probit assignment model.

The measured travel time error dispersion in the proposed probit assignment model can also be adopted for other methods of measuring vehicles travel times (for example, probe vehicles). Therefore, the proposed bilevel progamming model can be extended for determining the optimal probe sample size (Lam et al., 2000).

In Chapter 9, a case study is carried out to calibrate and validate the dispersion parameters of the time-dependent stochastic probit assignment model proposed in Chapter 5. The SP route choice model in Chapter 7 is used to adjust and validate the dispersion parameters.

9 CASE STUDY

In Chapter 5, a time-dependent stochastic traffic assignment model was proposed for determining the link flows and drivers' route choices. For simplicity, the proposed time-dependent stochastic traffic assignment model herewith is referred to as the probit assignment model in the remaining of this chapter.

A route choice model was calibrated by using stated preference (SP) survey data reported in Chapter 7. The purpose of SP survey is used to gauge driver reaction to the driver information system (DIS) information. In the SP survey, the expressway and urban road are given to the drivers to choose the travel from the Hong Kong Chek Lap Kok (CLK) international airport to urban areas. Firstly, the photographs of different levels of service (LOS) on the expressway were shown to the drivers. Secondly, the modelled travel times of different scenarios were given to the drivers. Finally, the expected travel times of drivers for different scenarios were asked and recorded. As a result, the dispersion parameters (β_{pl}) of the drivers' perceived travel time errors can be calibrated by the difference between the expected travel times of drivers and the modelled travel times for different scenarios (or various LOS). The β_{pl} becomes large when the perceived travel time errors are larger particularly under congested condition. The SP survey results in Chapter 7 show that the values of β_{pl} (Figure 7.11) are varied for different LOS. The collected drivers' responses are used to calibrate the drivers' route choice model (i.e. the SP logit model in the rest of this chapter).

In Chapter 9, a case study is carried out at a selected location in Hong Kong to illustrate the application of the probit assignment model in practice. The dispersion parameters (β_{pl}) calibrated from SP survey in Chapter 7 are adopted in the probit assignment model. The SP logit model is calibrated from the collected data in the same survey. The data are collected from the same set of samples at the Hong Kong CLK international airport for similar scenarios. In order to compare the results of the two models, the probit assignment model simulates the same set of scenarios with different LOS which are consistent with the SP logit model. Therefore, the probit assignment model results can be calibrated by the SP logit model results. The SP logit model is used for calibrating the probit model's dispersion parameters because the calibrated SP logit model generally cannot be adopted for estimating traffic flows in the whole network. This is because the output of this SP logit model is only the route choices of the drivers for two or few alternative routes. However, the calibrated probit assignment model can be used to estimate the route choices and link flows within the whole network. The purpose of the case study is to calibrate and validate the probit assignment model in Chapter 5 and compare its results against the SP results. The steps in the case study are as follows:

i. selection of study area;

ii. collection of road network data;

iii. estimation of drivers' route choice decisions by probit assignment (Algorithm A5.2);

iv. SP logit model (eqn. (7.6)-(7.8) and Table 7.3) and calibration of perception adjustment parameters. These perception adjustment parameters (Δ) are defined for adjusting the probit assignment results to match the SP logit model results (replace β_{pl} by β_{pl} $-\Delta$ in Step 1 of Algorithm A5.1). These perception adjustment parameters (Δ) varied with the LOS because origin-destination (O-D) demands are adjusted from LOS A to LOS E in the 2-hour study period so as to simulate the various scenarios in the SP survey. The purpose of varying the LOS refers to scenarios adopted in the SP survey for collecting the drivers' route choices in response to different LOS on alternative routes;

v. The findings in the case study are summarized.

In the following sections, the results of the case study are presented and discussed. This chapter is organised as follows. Firstly, the selection of the study area is shown in Section 9.1. Section 9.2 describes the data collection. It is followed by the estimation of the drivers' route choices by the probit assignment model (Algorithm A5.2) in Section 9.3. In Section 9.4, SP logit model (eqn. (7.6)-(7.8) and Table 7.3) is used for the estimation of drivers' route choices. Also, the perception adjustment parameters (Δ) are calibrated. Finally, a summary of the findings in the case study is given in Section 9.5.

9.1 SELECTION OF STUDY AREA

A study road network in the Lantau Link in Hong Kong, as shown in Figure 9.1, is used for calibrating and validating the probit assignment model. This study area was chosen because the variable message signs (VMS) provided along the Lantau Link are new to Hong Kong drivers.

The study road network consists of 3 zones, 7 nodes and 16 links. The layout of the study network is shown in Figure 9.2. Links 9,10,11 and 12 correspond to the Lantau Link. The Lantau Link is a dual-3 expressway which is designed for a higher level of service, faster travel and higher capacity. Links 2,3,6 and 7 refer to a proposed dual-2 urban road, its speed is lower and its capacity is affected by the signalized intersections.

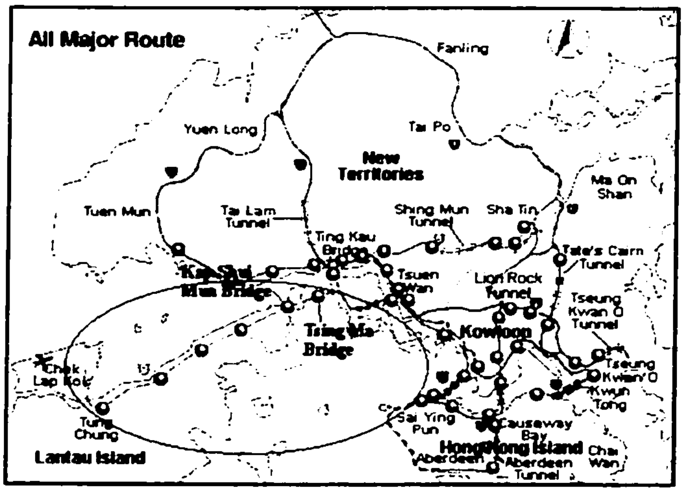

Figure 9.1 Location of the Selected Study Area

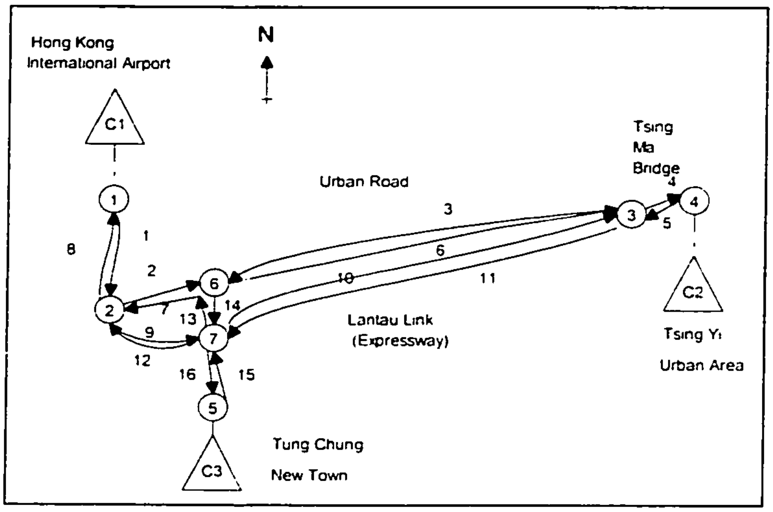

Figure 9.2 Study Network for the Case Study

9.2 DATA COLLECTION

The purpose of the case study is to estimate the traffic flows and to calibrate the perception adjustment parameters (Δ). It should be borne in mind that the collected data are mainly used in the probit assignment model for determining the drivers' route choices in the study network so as to compare the results with the SP logit model. The relevant data collected consists of:

i. link distance;

ii. link capacity;

iii. link free flow speed; and

iv. origin-destination (O-D) matrix by time interval.

Table 9.1 shows the link data of the road network. Table 9.2 gives the parameters of the BPR link travel time function.

Table 9.1 The Link Data of the Study Network

Link no.	Link type	Distance (km)	Capacity (veh/hr)	Free flow speed (km/hr)
1,4,5,8	Expressway	4	5,600	100
2,7	Urban road	15.3	2,400	65
3,6	Urban road	0.6	2,400	65
9,12	Expressway	0.5	4,200	100
10,11	Expressway	15	4,200	100
13,14,15,16	Urban road	1	2,400	65

The BPR link travel time function by link type is:

$$C_a = \gamma_a + \alpha_a (v_a / k_a)^{\beta_a} . \tag{9.1}$$

where C_a is the link travel time, v_a is the link flow, k_a is the capacity of link a and $a=1,2,3,...16$, γ_a is the free flow travel time, α_a and ρ_a are the calibration parameters of link a.

Table 9.2. The Parameters of the BPR Link Travel Time Function

Link no.	γ_a (hrs)	k_a (pcu/hr)	parameter ρ_a	α_a
1,4,5,8	0.04	5,600	2.9	0.0933
2,7	0.0092	2,400	3.7	0.0108
3,6	0.2354	2,400	3.7	0.2746
9,12	0.005	4,200	2.9	0.0117
10,11	0.15	4,200	2.9	0.35
13,14,15,16	0.0154	2,400	3.4	0.0179

The study period is designed to be 2 hours. The initial O-D demands OD_0 in eqn. (9.1) are obtained in the observation survey reported in Chapter 7. The O-D demands increase such that the LOS of the expressway is varied from LOS A to LOS E. The purpose for varying the LOS refers to the scenarios adopted in the SP survey for collecting drivers' route choices in response to different LOS on alternative routes. The concept of LOS was introduced by the Highway Capacity Manual (Transportation Research Board, 1985) as a qualitative measure of the degree on congestion of a road (Table 5.2).

The time-dependent O-D demand functions are given on the basis of incremental time period T (with each time interval of 5 minutes) as below in eqn. (9.2):

$$OD(T)[Ci \rightarrow Cj] = OD_0 + OD_f\,(T/120) \qquad (9.2)$$

where $0 \leq T \leq 120$ (in minutes). Table 9.3 shows the parameters of the O-D demand functions in eqn. (9.2). Note that the initial O-D demands are observed on site during the survey period from 1:00 p.m. to 2:00 p.m on 24-4-2000.

Table 9.3 The Parameters of the O-D Demand Functions

C_i	C_j	OD_0	OD_f
C1	C2	660	2,400
C1	C3	180	400
C2	C1	660	2,400
C2	C3	170	3,200
C3	C1	200	400
C3	C2	190	3,200

9.3 ESTIMATION OF DRIVERS' ROUTE CHOICES

In order to estimate drivers' route choices under the DIS environment, a probit assignment model was proposed in Chapter 5. A route choice model is calibrated by using the SP data reported in Chapter 7. Figure 9.3 shows the proposed approach of determining the drivers' route choices estimated by the probit assignment model and the SP logit model. The perception adjustment parameters (Δ) are calibrated for each time interval due to the variation of LOS on the alternative routes.

The duration of the study period is 2 hours. The O-D demand increases during the study period. The probit assignment is used to obtain the resultant link flows and the drivers' route choice proportions for each O-D pair. The resultant route travel times are inputted into the logit model calibrated by the SP data in Chapter 7. As shown in

Figure 9.3, the percentages of users diverted to the expressway estimated by the probit assignment model ($\%Exp^{P}$) and the percentages of users diverted to expressway estimated by the probit assignment model ($\%Exp^{L}$) are obtained. The resultant $\%Exp^{P}$ is compared with the resultant $\%Exp^{L}$.

The dispersion parameter of the drivers' perceived travel time errors (β_{pl}) of the probit assignment model are adjusted in the proposed approach. The perceived link travel time can be generated by $C_{pl} \sim N(C_{ml}, \beta_{pl} C_{ml})$. When the β_{pl} (Step 1 of Algorithm A5.1) are large, the perceived travel time errors are also large. Consequently, the drivers are more sensitive to the actual travel times when β_{pl} are small. The SP survey result presented in Chapter 7 shows that the values of β_{pl} (Figure 7.11) are varied for different LOS. If the difference (ς) between $\%Exp^{P}$ and $\%Exp^{L}$ is large, the value β_{pl} should be reduced by a value delta (Δ). Define adj $\beta_{pl} = \beta_{pl} - \Delta$, where the adj β_{pl} is the resultant adjusted dispersion parameter. The preliminary tests indicated that the adj β_{pl} should be smaller than the β_{pl} so that β_{pl} are reduced by Δ in the proposed approach. This is because more drivers will choose the expressway when their sensitivity to the actual travel times is higher. Higher sensitivity corresponds to lower β_{pl}. The probit assignment will be repeated until the tolerance (ς=0.001) is satisfied, so that the resultant Δ will be obtained.

The SP logit model is used to obtain $\%Exp^{L}$ as below:

$$\%Exp^{L} = \exp U/(1+\exp U) \qquad (9.2)$$

U= 0.206-0.1412 (Estimated current travel time of expressway)+ 0.1395 (Normal travel time of the urban road) (9.3)

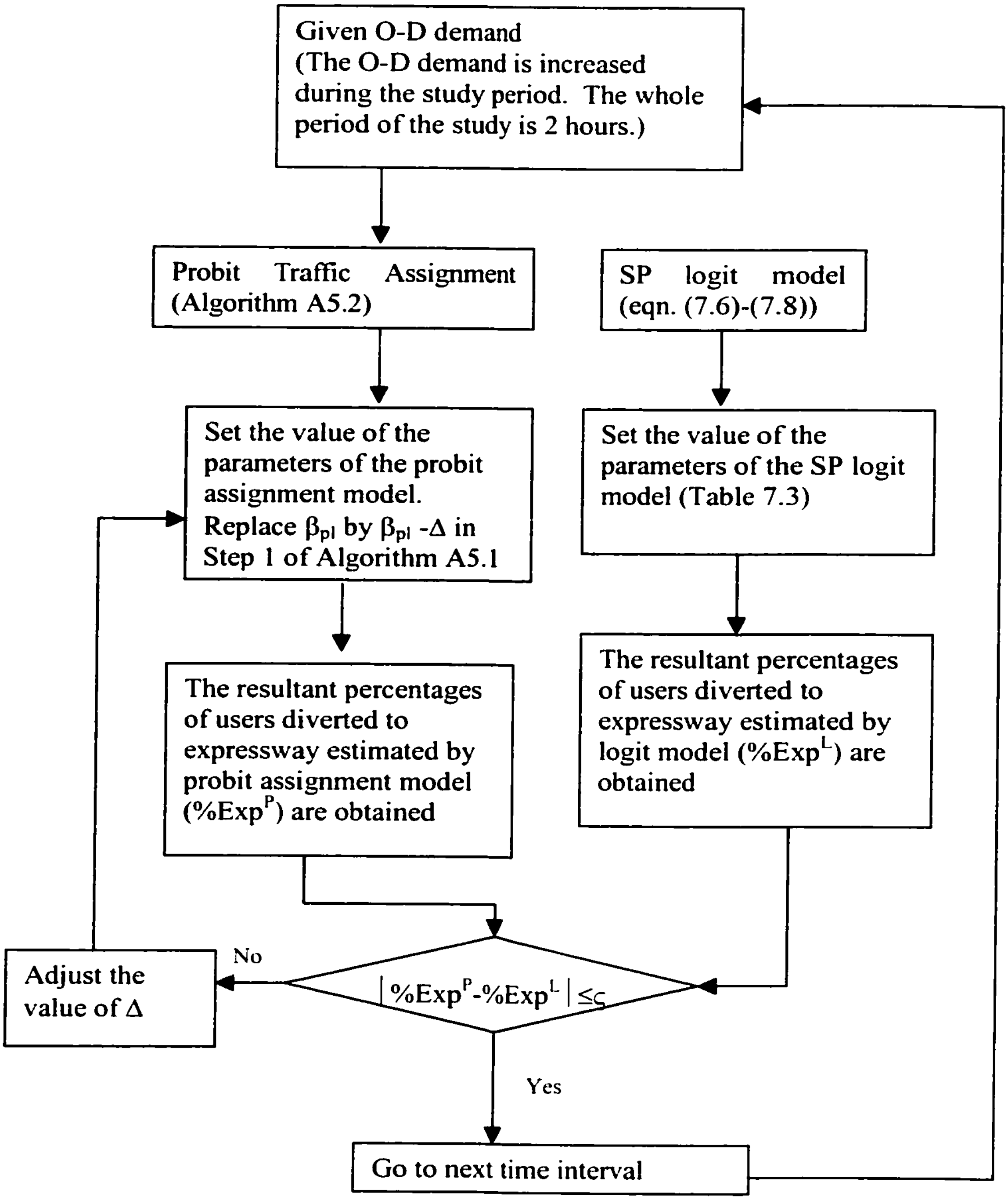

Figure 9.3 Flow Chart of the Proposed Approach

Figure 9.4 compares the percentages of users diverted to expressway (%Exp) estimated by the probit assignment model and SP logit model for various volume/capacity (v/c) ratios or LOS.

It can be observed from Figure 9.4 that %Exp decreases as the v/c ratio increases. Those %Exp obtained by the SP logit model are larger than those obtained by the probit assignment model. The differences of these percentages estimated by the two models become larger as the v/c ratios increases, and vice versa.

The differences of %Exp estimated by the probit assignment model and SP logit model show that their results are not close to each other. This may be partly due to the fact that in the SP survey the drivers were asked to provide their expected travel times on the expressway. Their expected travel times were used for calibrating the dispersion parameter (β_{pl}) adopted in the probit assignment model. The estimated current travel time information on the expressway and the urban road are provided in the SP questions. The drivers are then asked to choose among the expressway and the urban road. However, there is discrepancy between the expected travel times of the drivers collected from the SP survey and the estimated current travel times. This discrepancy may also be due to the difference of the drivers' value of time on the expected travel times and estimated current travel times. The drivers' values of time on the expected travel times and estimated current travel times may vary under different LOS conditions. This discrepancy should be taken into account in the probit assignment model by using the following perception parameters (Δ).

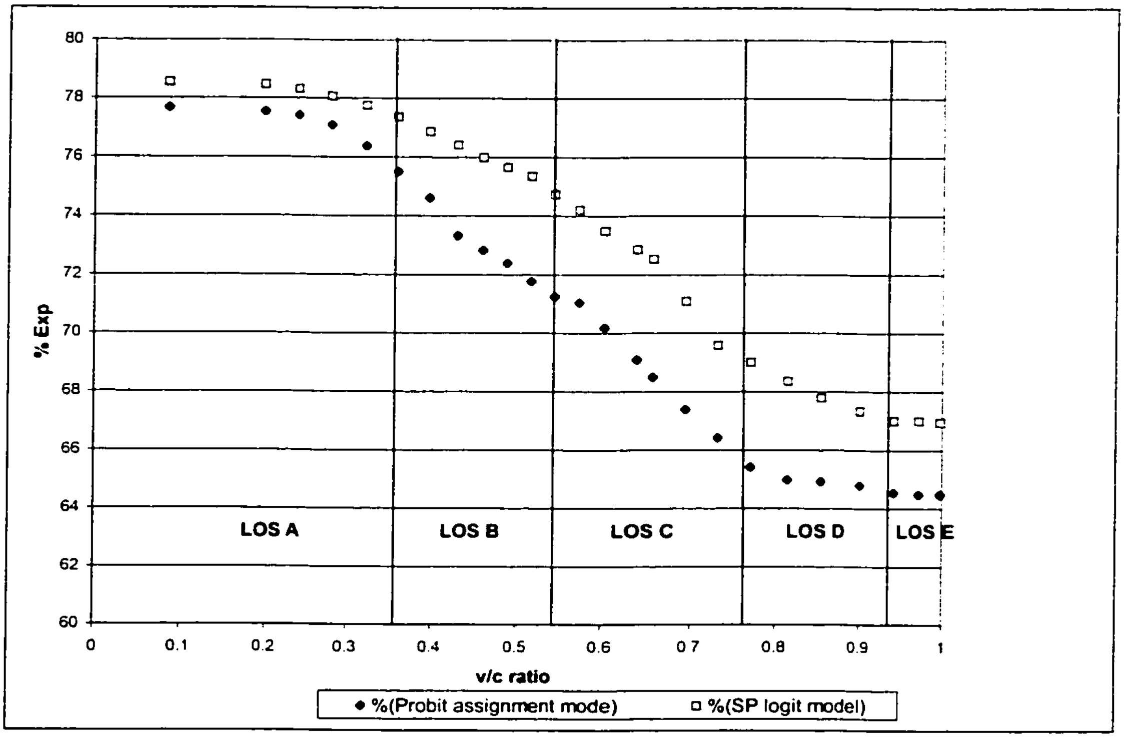

Figure 9.4 %Exp Estimated by the Probit Assignment Model and SP Logit Model for Various V/c Ratios.

9.4 CALIBRATION OF PERCEPTION ADJUSTMENT PARAMETERS

As shown in Section 9.3, the differences between the results of the probit assignment and SP logit model are significant and are varied by v/c ratio (or LOS) on the expressway. Therefore, the perception adjustment parameters (Δ) are calibrated in this section for minimizing the differences between %Exp between the SP logit model and probit assignment model. The adjusted percentages of users diverted to expressway estimated by the probit assignment model (adj $\%Exp^{P}$) are obtained from the proposed approach. Also, the adjusted percentages of users diverted to the expressway estimated by the SP logit model (adj $\%Exp^{L}$) are obtained accordingly.

Both %Exp^P and %Exp^L are adjusted because link flows and link travel times are also changed due to the change of the perception adjustment parameters (Δ).

Figure 9.5 compares the differences between the adj %Exp^P and adj %Exp^L. It can be seen that the derivation from the 45 degree line (adj %Exp^P=adj %Exp^L) is very small. The resultant R-square is 0.99 which is close to 1.0. Therefore, the adj %Exp^P can be best fitting the adj %Exp^L.

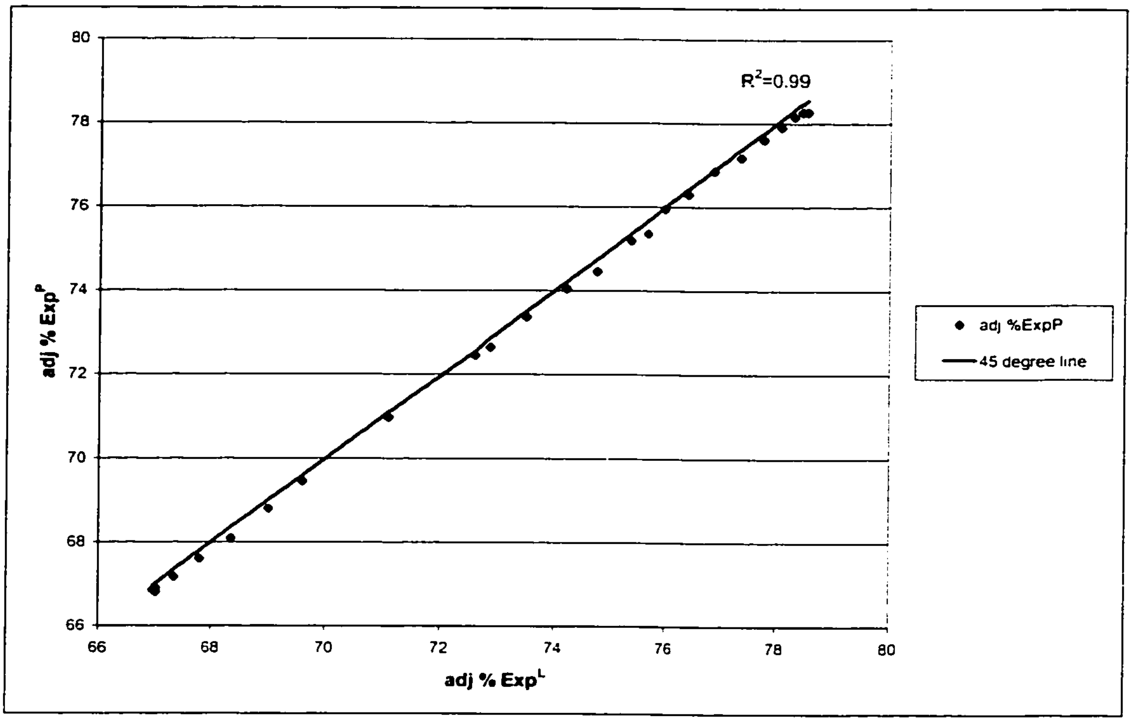

Figure 9.5 Validation of the adj %Exp^P

Figure 9.6 displays the resultant perception adjustment parameters Δ and the adjusted dispersion parameters for various v/c ratios. It shows that both the perception adjustment parameters and the the adjusted dispersion parameters increase nonlinearly as the v/c ratios increase. Therefore, the perception adjustment parameters are also larger when the v/c ratios are larger. Therefore, the modelling errors of the probit assignment model increase as the value of Δ increases. The value of Δ can be used for correcting the errors on the dispersion parameters (β_{pl}) adopted in the probit assignment model. The value of Δ also reflects the discrepancy between the expected travel times of the drivers collected from the SP survey and the estimated current travel times. This discrepancy is more serious when congestion occurs. The derivation of the adjusted dispersion parameter (β_{pl}-Δ) is more significant than that of perception adjustment parameters (Δ). It implies that it is more difficult for drivers to predict the accurate travel times when congestion occurs on the expressway.

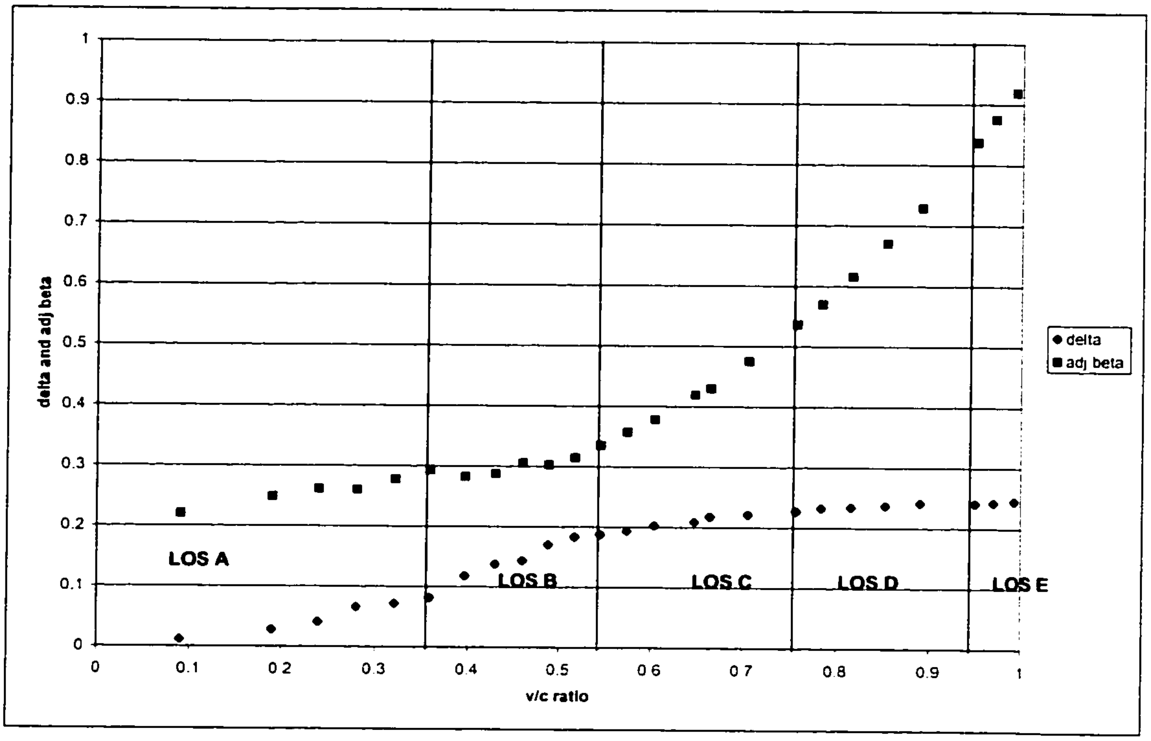

Figure 9.6 Perception Adjustment Parameters (delta) and Adjusted Dispersion Parameters (adj beta) vs LOS on the Expressway

9.5 SUMMARY

This Chapter presents a case study at a selected study area in Hong Kong. Based on the results of the probit assignment model and SP logit model in Chapters 5 and 7, the drivers' route choice proportions were calculated. It was found in the case study that the percentages of users diverted to the expressway decrease as the v/c ratios increase. Also, the differences between the resultant percentages for the two models tend to increase when the v/c ratios increase. These differences can be examined by the proposed perception adjustment parameters (Δ).

The perception adjustment parameters are calibrated by the probit assignment and SP logit model results. The perception adjustment parameters are larger as the v/c ratios become larger. The perception adjustment parameters can be an index for the discrepancy between the expected travel times of the drivers collected from the SP survey and the estimated current travel times. This discrepancy is higher when the v/c ratios increase. As a result, it can be concluded that it is more difficult for drivers to predict the accurate travel times when congestion occurs on the expressway.

10 CONCLUSIONS AND RECOMMENDATIONS

10.1 SUMMARY AND CONCLUSIONS

In view of the serious traffic congestion on most of the Hong Kong expressways and recent improvement of information technology, there is a growing aspiration to relieve traffic congestion by the applications of electronic information and communication technology. Providing drivers with travel time information, such as estimated journey times on major routes, should help drivers to select better routes and guide them to utilise existing expressway network. Under this perspective, the investigation of the drivers' responses to the driver information system (DIS) and the evaluation of effects of providing the proposed DIS are significant research topics in the field of transport planning.

This study introduces a new stochastic traffic assignment model for estimating drivers' route choices under the DIS environment, while taking account of both the measured link travel time error variances and the perceived link travel time error variances. Most previous traffic assignment models have only considered the perceived link travel time error variances. The measured link travel time error variances can be a function of speed detector density. This research brings a new concept of incorporating the speed detector density in the proposed time-dependent stochastic traffic assignment model for the DIS. It is hoped that the concept proposed can provide better insights for future transport planning of the DIS.

There are three significant contributions of this study. The first one is a new approach of time-dependent stochastic probit assignment models for estimating drivers' route choices under the DIS environment, in which both the measured link travel time error variances and the perceived link travel time error variances are considered. The second contribution is the first bilevel programming model for determining the optimal speed detector density under the DIS environment. The third contribution is the model calibration and validation for predicting the effects of the DIS in Hong Kong.

In summary, this study has achieved the following. A link-based alternative to Bell's node-based logit assignment method is proposed in Chapter 3. A probit assignment model is presented for estimating the link flows and their variances in Chapter 4. The probit assignment model described in Chapter 4 is extended to a time-dependent stochastic traffic assignment model for estimating drivers' route choices under the DIS environment in Chapter 5. A link travel time estimation method by using speed detector data is proposed in Chapter 6 and is compared with two existing methods. A stated preference (SP) survey is used to gauge driver reaction to the DIS information and a SP logit model for route choice is calibrated and described in Chapter 7. A bilevel programming model for determining the optimal speed detector density is proposed in Chapter 8. A case study is used to calibrate and validate the time-dependent stochastic traffic assignment model in Chapter 9.

In Chapter 3, a link-based alternative to Bell's node-based logit assignment method is proposed to progressively eliminate the cycles existing in Bell's method. The absence of any efficiency constraint on the set of feasible paths makes the link-based logit assignment method attractive for use in the stochastic user equilibrium (SUE) method or in the approximation of user equilibrium (UE) through SUE. By extending the approach to exclude cycles with a greater number of nodes, sub-paths and/or complete paths without cycles will progressively be generated but the indicator matrices and/or path-node matrix will be very large. However, this may not be practical for a large network. Numerical examples are used to illustrate the applications of the link-based logit assignment method and demonstrate the convergence of the link-based assignment algorithm.

Chapter 4 presents a probit assignment model for estimating the link flows and their variances. The effectiveness of the probit assignment model and the simulation method are illustrated in the numerical example. The root mean square (RMS) differences and the total network costs are adopted for demonstrating the convergence of the solution. The resulting RMS and average relative error (ARE) of the probit assignment model are lower than that obtained by the C-logit model and the logit assignment model in Chapter 3. This probit assignment model is extended to time-dependent dimension in Chapter 5 for assessing the effects of the DIS.

Chapter 5 aims to investigate the effects and benefits of providing the DIS. In order to assess the effects of the DIS, a time-dependent traffic assignment model is proposed. A numerical example is used to illustrate the effects of the DIS. The measured link travel time error variances and the perceived link travel time error variances are taken into account in the proposed model. The simulation technique, shortest path algorithm and method of successive average (MSA) are adopted in the proposed model. By applying the time-dependent traffic assignment algorithm to the Tuen Mun Road Corridor, the total network times can be computed and compared for the non-recurrent and recurrent congestion situations. The effects of providing the

DIS in the situation of non-recurrent congestion are more significant because the reduction of the total network time is much greater than the one for the recurrent congestion.

In Chapter 6, link travel times have been estimated by a proposed method, plus two existing methods by using speed detector data. The link travel time estimation results are evaluated by the observed data collected at the selected site on Tsing Ma Control Area (TMCA) in Hong Kong. The link travel time and link speed distributions have been investigated using data collected from the manual license plate number survey. The results indicate that the proposed method can provide better link travel time estimates than the other two existing methods. However, no congestion occurred at the survey location because it is a new highway. It can be concluded that the proposed method is demonstrated with empirical data to produce reliable travel time estimates for uncongested situations.

In Chapter 7, a SP survey is conducted to collect data regarding drivers' responses to road traffic information. The relationship between the provided travel times and the drivers' perceived travel times are investigated. The results show that the perceived travel time error variances of the drivers are larger as the volume/capacity (v/c) ratios increase. The travel time reliability is higher when the v/c ratio is smaller. In the SP survey, the expressway and urban road are given to the drivers to choose for the travel from the Hong Kong Chek Lap Kok (CLK) international airport to the urban area. The SP logit model for route choice is calibrated by using the SP data. The main findings are that the perceived travel times of the drivers are strongly influenced by the travel time information provided by the DIS.

In Chapter 8, a bilevel programming model is proposed for determining the optimal speed detector density. The lower-level problem is a probit traffic assignment model, while the upper-level problem is to determine the speed detector density that minimizes the measured travel time error variances as well as the social costs of the speed detectors. A sensitivity based solution algorithm has been derived in Chapter 8 for solving the proposed bilevel programming model for determining the optimal speed detector density. Numerical examples have demonstrated the applicability of the proposed model and the solution algorithm.

The contributions of the study in Chapter 8 are summarized as follows. Firstly, it is the first bilevel programming model for determining the optimal speed detector density under the DIS environment. Secondly, the measured travel time error variances are incorporated in the model. The relationship between the measured travel time error variances and the speed detector density are studied and established. Finally, the measured travel time error dispersion in our model can also be adopted for other methods of measuring travel times of vehicles (for example, probe vehicles). Therefore, the proposed model can be easily extended for determining the optimal probe sample size.

In Chapter 9, a case study validates the proposed time-dependent stochastic traffic assignment model with the SP logit model. It was found in the case study that the percentages of users diverted to the expressway decrease as the v/c ratios increase. Also, the differences between the resultant percentages for the two models tend to increase when the v/c ratios increase. The perception adjustment parameters (Δ) are calibrated by the probit assignment model and SP logit model results. The values of Δ are larger as the v/c ratios become larger. The values of Δ can be an index for the discrepancy between the expected travel times of the drivers collected from the SP survey and the estimated current travel times. This discrepancy is higher when the v/c ratios increase. Therefore, it is more difficult for drivers to predict accurately their travel times when congestion occurs on the expressway.

10.2 RECOMMENDATIONS

Based on this research work, several limitations of the study are listed as follows:

1. In Chapter 6, the proposed link travel time estimation method is demonstrated with empirical data to produce reliable travel time estimates for uncongested situations only.
2. In Chapter 7, a SP survey is conducted. It is necessary to evaluate the SP results when the urban road is opened to traffic.
3. In Chapter 8, a sensitivity based solution algorithm has been derived for solving the proposed bilevel programming model in this study. However, the sensitivity based solution algorithm may not be able to give the solution when the inverse matrix does not exist during the computation.
4. The solution algorithm for solving the probit assignment model is cumbersome particularly in large networks.
5. The proposed bilevel programming model can determine the optimal detector density, but it is also important to determine the optimal deployment of the VMS.
6. The formulation of the proposed time-dependent stochastic traffic assignment

model and the bilevel programming model are dependent on certain assumptions (e.g. the form and parameters of the measurement travel time error dispersion function).

According to the above limitations, further study is recommended:

1. It is suggested to evaluate the proposed link travel time estimation method and the other two existing methods in a congested road corridor.
2. It is recommended that a revealed preference (RP) survey should also be conducted in the Hong Kong CLK international airport once the urban road is opened to traffic.
3. If the sensitivity based solution algorithm is not workable in so of the example network, some other optimization techniques such as a genetic algorithm can also be considered for solving the proposed bilevel programming problem.
4. The development of an efficient algorithm for solving the probit assignment model particularly in large network is recommended. It is suggested to solve the proposed bilevel problem by some other optimization techniques such as a genetic algorithm.
5. It is necessary to develop a model for determining the optimal deployment of the VMS (in terms of number and location).
6. It is suggested to conduct a survey to collect the road network data and the detector data for validating the model assumptions.

REFERENCES

Aashtiani H. (1979) The multi-modal traffic assignment problem. PhD Thesis, Operations Research Center, MIT, Cambridge, M.A.

Abdel-Aty M.A., Kitamura R. and Jovanis P.P. (1997) Using stated preference data for studying the effect of advanced traffic information on drivers' route choice. *Transportation Research*, Vol. 5C, pp. 39-50.

Abours S. (1986) Estimation of travel time from occupancy on an urban network: an experiment in Paris, France. *Proceedings of the Second International Conference on Road Traffic Control,* Institution of Engineers, London, U.K, pp. 191-198.

Adler J.L. (2001) Investigating the learning effects of route guidance and traffic advisories on route choice behavior. *Transportation Research*, Vol. 9C, pp. 1-14.

Akamatsu T. (1996) Cyclic flows, markov process and stochastic traffic assignment. *Transportation Research*, Vol. 30B, pp. 369-386.

Al-deek H. and Kanafani A. (1993) Modeling the benefits of advanced traveler information systems in corridors with incidents. *Transportation Research*, Vol. 1C, pp. 303-324.

Al-Deek H.M., Khattak A.J. and Thananjeyan P. (1998) A combined traveler behavior and system performance model with advanced traveler information systems. *Transportation Research*, Vol. 32A, pp. 479-493.

Asakura Y. (1999) Evaluation of network reliability using stochastic user equilibrium. *Journal of Advanced Transportation*, Vol. 33, pp. 147-158.

Asmuth (1978) Traffic Network Equilibria. PhD Thesis, Department of Operations Research, Stanford University, Stanford, CA.

Bell M.G.H. (1995) Alternatives to Dial's logit assignment algorithm. *Transportation Research*, Vol. 29B, pp. 287-295.

Bell M.G.H., Lam W.H.K. and Iida Y. (1996) A time-dependent multi-class path flow estimator. *Proceedings of the 13th International Symposium on Transportation and Traffic Theory*, Lyon, France, pp. 173-194.

Bell M.G.H., Lam W.H.K., Ploss G. and Inaudi D. (1993) Stochastic user equilibrium assignment and iterative balancing. *Transportation and Traffic Theory*, pp. 427-439.

Bell M.G.H., Shield C.M., Busch F. and Kruse G. (1997) A stochastic user equilibrium path flow estimator. *Transportation Research*, Vol. 5C, pp. 197-210.

Benekohala R.F. and Zhaob W. (2000) Delay-based passenger car equivalents for trucks at signalized intersections. *Transportation Research*, Vol. 34A, pp. 437-457.

Bhat C.R. (2000) A multi-level cross-classified model for discrete response variables. *Transportation Research*, Vol. 34B, pp. 567-582.

Biesterbos J.W.M. and Zijderhand F. (1995) Socrates – a dynamic car navigation, driver information and fleet management-system. *Philips Journal of Research*, Vol. 48, pp. 299-313.

Bonsall P.W. (1992) The influence of route guidance advice on route choice in urban networks. *Transportation*, Vol. 19, pp. 51-73.

Bonsall P.W. and Merrall A.C. (1995) Analysing and modelling the influence of road side variable message displays on drivers' route choice. *Proceedings of the 7th World Conference on Transport Research* 1, Sydney, Australia, pp. 11-25.

Bonsall P.W. and Palma I.A. (1998) VMS signs-the important phrasing the message. *Behavioural and Network Impacts of Driver Information Systems.*

Boyce D.E., Lee D., Janson B.N. and Berka S. (1997) Dynamic route choice model of large-scale traffic network. *Journal of Transportation Engineering*, Vol. 123, pp. 276-282.

Bureau of Public Roads (1964) Traffic Assignment Manual. U.S. Department of commerce, Urban Planning Division, Washington D.C.

Cascetta E., Nuzzolo A., Russo F.and Vitetta A. (1996) A new route choice logit model overcoming IIA problems: Specification and some calibration results for interurban networks. *Proceeding of the 13th International Symposium on Transportation and Traffic Theory*, pp. 691-711, Lyon, France, 24-26 th July.

Cascetta E., Russo F. and Vitetta A. (1997) Stochastic user equilibrium assignment with explicit path enumeration: comparison of models and algorithm. *Proceedings of 8th IFAC Symposium on Transportation Systems*, pp. 1078-1084.

Catchpole J., Hancock A. and Cairney P. (1995) Driver comprehension of formats for presenting traffic information on dynamic signs. *ARRB Transport Research*, ARR269, September.

Catling I., Op De Beek F., Casimir C., Mannings R., Zijderhand F., Zechnall W. and Hellaker J. (1991) Socrates: System of cellular radio for traffic efficiency and safety. . *Proceedings of the DRIVE Conference*, pp. 28-43.

Chan K.S. and Lam W.H.K. (1997) Estimation of link flow variance by stochastic traffic assignment. *Proceeding of the 8th IFAC Symposium on Transportation Systems*, Vol. 3, Chania, Greece, 16-18 th June.

Chang G.L. and Mahmassani H. (1988) Travel time prediction and departure time adjustment behavior dynamics in a congested traffic system. *Transportation Research*, Vol. 22B, pp. 217-232.

Chatterjee K. and McDonald M. (1999) The network safety effects of dynamic route guidance. *ITS Journal*, Vol. 4, pp. 161-185.

Chen M. and Alfa A.S. (1991) Algorithms for solving Fisk's stochastic traffic assignment model. *Transportation Research*, Vol. 25B, pp. 405-412.

Chen T.Y., Chang H.L. and Tzeng G.H. (2001) Using a weight-assessing model to identify route choice criteria and information effects. *Transportation Research*, Vol. 35A, pp. 197-224.

Choi Y.L. (1986) Land Use Transport Optimization (LUTO) model for strategic planning in Hong Kong. *Asian Geographer*, Vol. 5, pp. 155-176.

Clark S.D. and Watling D.P. (2001) Sensitivity analysis of the probit-based stochastic user equilibrium assignment problem. *Transportation Research B, forthcoming.*

Cremer M. (1995) On calculation of individual travel times by microscopic models. *Proceedings of the IEEE-IEE Vehicle Navigation and Information Systems Conference*, Seattle, Washington, USA, pp. 187-193.

Daganzo C.F. (1979) Multinomial probit: The theory and its application to demand forecasting, Academic Press, New York.

Daganzo C.F. and Sheffi Y. (1977) On stochastic models of traffic assignment. *Transportation Science*, Vol. 11, pp. 253-274.

Dailey D.J. (1993) Travel-time estimation using cross-correlation techniques. *Transportation Research*, Vol. 27B, pp. 97-107.

Dailey D.J. (1997) Travel time estimates using a series of single loop volume and occupancy measurements. Paper No. 970378 presented in the 76th Annual Meeting of Transportation Research Board, Washington D.C.

Damberg O., Lundgren J.T. and Patriksson M. (1996) An algorithm for the stochastic user equilibrium problem. *Transportation Research*, Vol. 30B, pp. 115-131.

Davis G. A. (1994) Exact local solution of the continuous network design problem via stochastic user equilibrium assignment. *Transportation Research*, Vol. 28B, pp. 61-75.

Delcan International Corporation and Parsons Brinckerchoff (Asia) Ltd (1995) Traffic Surveillance and Information System for Tuen Mun Road. Prepared for Hong Kong Transport Department, Traffic Control and Surveillance Division.

Dial R.B. (1971) A probabilistic multipath traffic assignment model which obviates path enumeration. *Transportation Research*, Vol. 5, pp. 83-111.

Duffell J. and Kalombaris A. (1988) Empirical studies of car driver route choice in Hertfordshire. *Traffic Engineering and Control*, Vol. 29, pp. 398-408.

Dutch Ministry of Transport (1992) Dynamic traffic management in the Netherlands. *Report of the Transportation and Traffic Research Division*, Ministry of Transport, Public Works and Water Management, Rotterdam.

Emmerink R.H.M., Axhausen K.W., Nijkamp P. and Rietveld P. (1995a) Effects of information in road transport networks with recurrent congestion. *Transportation*, Vol. 22, pp. 21-53.

Emmerink R.H.M., Axhausen K.W., Nijkamp P. and Rietveld P. (1995b) The potential of information provision in a simulated road transport network with non-recurrent congestion. *Transportation Research*, Vol. 3C, 293-309.

Emmerink R.H.M., Nijkamp P., Rietveld P. and Ommeren J.N.V. (1996) Variable message signs and radio traffic information: An integrated empirical analysis of drivers' route choice behaviour. *Transportation Research*, Vol. 30A, pp. 135-153.

Fisk C. (1980) Some developments in equilibrium traffic assignment. *Transportation Research*, Vol. 14B, pp. 243-255.

Floyd R.W. (1962) Algorithm 97, shortest path. *Comm. ACM*, Vol. 5, pp. 345.

Friesz T.L., Bernstein T., Smith R. and Tobin B.W. (1993) A variational inequality formulation of the dynamic network user equilibrium problem. *Operations Research*, Vol. 41, pp. 179-191.

Friesz T.L., Tobin R.L., Cho H.J. and Mehta N.J. (1990) Sensitivity analysis based heuristic algorithms for mathematical programs with variational inequality constraints. *Mathematical Programming*, Vol. 48, pp. 265-284.

Fu L.P. (1998) Expected shortest paths in dynamic and stochastic traffic networks *Transportation Research*, Vol. 32B, pp. 499-516.

Garrido R.A. and Mahmassani H.S. (2000) Forecasting freight transportation demand with the space-time multinomial probit model. *Transportation Research*, Vol. 34B, pp. 403-418.

Gerlough D.L. and Huber M.J. (1975) Traffic Flow Theory. Transportation Research Board Special Report 165, National Research Council, Washington D.C.

Girianna M., Butzek A., Benekohal B.F. and Hicks J.H. (2000) Algorithms for delay and speed estimation using AVI and ETC. Paper presented in the *6th International Conference on Applications of Advanced Technologies in Transportation Engineering*, Singapore.

Hong Kong Transport Department and Wilbur Smith Associates (1999) Third Comprehensive Transport Study (CTS-3)- final report. Hong Kong Government.

Hounsell N., McDonald M., Breheret L. (1991) The modelling of dynamic route guidance. *Proceedings of the DRIVE Conference*, pp. 89-98.

Huang H.J. (1995) A combined algorithm for solving and calibrating the stochastic traffic assignment model. *Journal of Operation Research society*, Vol. 46, pp. 977-987.

Huang H.J. and Bell M.G.H. (1998) A study on logit assignment which excludes all cyclic flows. *Transportation Research*, Vol. 32B, pp.: 401-412.

Huchingson R., McNees R. and Dudek C. (1977) Survey of motorist route-selection criteria. *Transportation Research Record*, Vol. 643, pp. 45-48.

Jha M., Madanat M. and Peeta S. (1998) Perception updating and day-to-day travel choice dynamics in traffic networks with information provision. *Transportation Research*, Vol. 6C, pp.: 189-212.

Khattak A.J., Schofer J. and Koppelman F.S. (1993) Commuters' enroute diversion and return decisions: Analysis and implications for advanced traveler information systems. *Transportation Research*, Vol. 27A, pp. 101-111.

Khattak A.J. (1998) Comparative analysis of spatial knowledge and en route diversion behavior in Chicago and San Francisco - Implications for advanced traveler information systems. *Transportation Research Record*, Vol. 1621, pp. 27-35.

Kyte M. and Marek J. (1989) Estimating capacity and delay at a single-lane approach, all-way stop-controlled intersection. *Transportation Research Record*, Vol. 1225, pp. 73-82.

Lai K.H. and Wong W.G. (2000) SP approach toward driver comprehension of message formats on VMS. *ASCE Journal of Transportation Engineering*, Vol. 126, pp. 221-227.

Lam W.H.K. (1988) Effects of road pricing on system performance. *Traffic Engineering and control*, Vol. 29, pp. 631-635.

Lam W.H.K. and Chan K.S. (1998) A link-based alternative to Bell's logit assignment algorithm. *HKIE Transactions*, Vol. 5, pp.11-18.

Lam W.H.K., Chan K.S. and Bell M.G.H. (1996) The treatment of cycles in stochastic user equilibrium assignment. Paper presented at the *4th meeting of the EURO working group on transportation*, University of Newcastle, upon Tyne, 9-11 th September.

Lam W.H.K., Gao Z.Y., Chan K.S. and Yang H (1999) A stochastic user equilibrium assignment model for congested transit networks. *Transportation Research*, Vol. 33B, pp. 351-368.

Lam W.H.K., Lo H.P., Chan K.S. (2000) Optimal sample size of probe vehicles for advanced traveler information systems. *Proceedings of the 6th International Conference on Applications of Advanced Technologies in Transportation Engineering*, 28-30 June, 2000, Singapore .

Lam W.H.K. and Yin Y. (2001) An activity-based time-dependent traffic assignment model. *Transportation Research*, Vol. 35B, pp. 549-574.

Lim Y. and Lee S. (1997) An integrated dynamic traffic assignment model for responsive signal control and variable message sign. *Journal of Eastern Asia Society for Transportation Studies*, Vol. 2, pp. 753-763.

Lo H.K. (1999) A dynamic traffic assignment formulation that encapsulates the cell-transmission model. *Proceedings of the 14th International Symposium on Transportation and Traffic Theory*, Haifa, Israel, pp. 327-350.

Lo H.P., Zhang N. and Lam W.H.K. (1996) Estimation of an origin-destination matrix with random link choice proportions: A statistical approach. *Transportation Research*, Vol. 30B, pp. 309-324.

Lotan T. and Koutsopoulos H.N. (1993) Models for route choice behaviour in the presence of information using fuzzy set theory and approximate reasoning. *Transportation*, Vol. 20, pp. 129-155.

Luce R.D. and Suppes P. (1965) Preference, utility and subjective probability. Handbook of Mathematical Psychology. John Wiley & Sons, New York.

Maher M.J. (1992) SAM-A stochastic assignment model. In: Mathematics in Transport Planning and Control (edited by J.D. Griffiths.) pp. 121-132. Oxford University Press, Oxford.

Maher M.J. (1998) Algorithms for logit-based stochastic user equilibrium assignment. *Transportation Research*, Vol. 32B, pp. 539-549.

Maher M.J. and Hughes P.C. (1997) A probit-based stochastic user equilibrium assignment model. *Transportation Research*, 31B, pp. 341-355.

Mahmassani H.S. and Jayakrishnan R. (1991) System performance and user response under real-time information in a congested traffic corridor. *Transportation Research*, Vol. 25A, pp. 293-307.

Makigami Y., Taguro K. and Yamashita M. (1996) A basic study of expressway travel time estimation using a bottleneck simulation model. *Proceedings of the 13th International Symposium on Transportation and Traffic Theory*, Lyon, France, pp. 55-78.

Mammar S., Messmer A., Jensen P., Papageorgiou M., Haj-salem H, and Jensen L. (1996) Automatic control of variable message signs in Aalborg. *Transportation Research*, Vol. 4C: 131-150.

Mannering F., Kim S.G., Ng L. and Barfield W. (1995) Travelers' references for in-vehicle information systems: an exploratory analysis. *Transportation Research*, Vol. 3C, pp. 339-351.

Menjeguzzer C. (1995) An equilibrium route choice model with explicit treatment of the effect of intersection. *Transportation Research*, Vol. 29B, pp. 329-356.

Messmer A., Papageorgiou M. and Mackenzie N. (1998) Automatic control of variable message signs in the interurban Scottish highway network *Transportation Research*, Vol. 6C, pp. 173-187.

Milton J.S. and Arnold J.C. (1990) Introduction to probability and statistics. McGraw-Hill Publishing Company.

Nam D. H. and Drew R. D. (1996) Traffic dynamics: Model for estimation freeway travel time in real time from flow measurements. *ASCE Journal of Transportation Engineering*, Vol. 122, pp. 185-191.

Nam D.H. and Drew D.R. (1999) Automatic measurement of traffic variables for intelligent transportation systems applications. *Transportation Research*, Vol. 33B, pp. 437–457.

Ng L., Wessels R., Do D., Mannering F. and Barfield W. (1995) Statistical analysis of commercial driver and dispatcher requirements for advanced traveler information systems. *Transportation Research*, Vol. 3C, pp. 353-369.

Nielsen A. (2000) A stochastic transit assignment model considering differences in passengers utility functions. *Transportation Research*, Vol. 34B, pp. 377-402.

Nihan N., Hamed M. and Davis G. (1995) Interactions between driver information, route choice, and optimal signal timing on a simple network. *Journal of Advanced Transportation*, Vol. 29, pp. 163-182.

Nijkamp P., Pepping G. and Banister D. (1996) Telematics and transport behaviour. Berlin, Heidelberg: Springer-Verlag.

Ortúzar J. de D. and Willumsen L.G. (1994) Modelling transport. John Wiley & Sons Ltd..

Peeta S., Mahmassani H.S., Rothery R. and Herman R. (1991) Effectiveness of real-time information strategies in situations of non-recurrent congestion. *Proceedings of the 2nd International Conference, Applications of Advanced Technologies in Transportation Engineering*, Minneapolis, Minnesota, August.

Peeta S. and Mahmassani H.S. (1995) Multiple user classes real-time traffic assignment for online operations: a rolling horizon solution framework. *Transportation Research*, Vol. 3C, pp. 83-98.

Petty K. F., Bickel P., Ostland M., Rice J., Schoenberg F., Jiang J. and Ritov Y. (1998) Accurate estimation of travel times from single-loop detectors. *Transportation Research*, Vol. 32A, pp. 1-17.

Pfefer R.C. and Raub R.A. (1998) Effects of urban roadway lane blockage on capacity. *ITE Journal*, Vol. 68, pp. 46-51.

Polak J. and Jones P. (1993) The acquisition of pre-trip information: A stated preference approach. *Transportation*, Vol. 20, pp. 179-198.

Powell, W.B. and Sheffi, Y. (1982) The convergence of equilibrium algorithms with predetermined step sizes. *Transportation Science*, Vol. 16, pp. 45-55.

Prashker J.N. and Bekhor S. (1998) Investigation of stochastic network loading procedures. *Transportation Research Record*, Vol. 1645, pp. 94-102.

Pushkar A., Hall F. L. and Acha-Daza J. A. (1995) Estimation of speeds from single-loop freeway flow and occupancy data using cusp catastrophe theory model. *Transportation Research Record*, Vol. 1457, pp. 149 - 157.

Ramsay E.D., Catchpole J.E. and Luk J.Y.K. (1997) An evaluation of VicRoads' drive time system. *ARRB Transport Research*, ARR305, June.

Ran B., Lo H.K. and Boyce D.E. (1996) A formulation and solution algorithm for a multi-class dynamic traffic assignment. *Proceedings of the 13th International Symposium on Transportation and Traffic Theory*, Lyon, France, pp. 195-216.

Ran B., Rouphail N.M., Tarko A. and Boyce D.E. (1997) Toward a class of link travel time functions for dynamic assignment models on signalized networks. *Transportation Research*, Vol. 31B, pp. 277-290.

Richards A., McDonald M. and Lyons G. D. (1996) Urban congestion reduction using variable message signs. *Proceedings of 24th PTRC European Transport Forum*, Seminar E, Part 2, Brunel University, England.

Sen A., Thakuriah P., Zhu X. and Karr A. (1997) Frequency of probe reports and variance of travel time estimates. *ASCE Journal of Transportation Engineering*, Vol. 123, pp. 290-297.

Sheffi Y. (1985) Urban Transportation Networks: Equilibrium Analysis with Mathematical Programming Methods. Englewood Cliffs, NJ: Prentice Hall.

Sheffi Y. and Powell W.B. (1982) An algorithm for the equilibrium assignment problem with random link times. *Networks*, Vol. 12, pp. 191-207.

Sisiopiku V. P. and Rouphail N. M. (1995) Towards the use of detector output for arterial link travel time estimation: a literature review. *Transportation Research Record*, Vol. 1457, pp. 158 - 165.

Tobin R.L. and Friesz T.L. (1988) Sensitivity analysis for equilibrium network flows. *Transportation Science*, Vol. 22, pp. 242-250.

Transportation Research Board (1985) Highway Capacity Manual. Transportation Research Board, Special Report 209.

Tsugawa S., Aoki M., Hosaka A. and Seki K. (1997) A survey of present IVHS activities in Japan. *Control Engineering Practice*, Vol. 5, pp. 1591-1597.

Van Aerde M. (1994) Integration: a model for simulating integrated traffic networks. User's guide for model version 1.5g. M, Van Aerde and associates, Ltd. and Transportation systems research group, Queen's University, Kingston, Canada.

Van Vliet D. (1981) Selected node-pair analysis in Dial's assignment algorithm. *Transportation Research*, Vol. 15B, pp. 65-68.

Van Vuren T. and Watling T. (1991) Multiple user class assignment model for route guidance. *Transportation Research Record*, Vol. 1306, pp. 22-32.

Vovsha P. and Bekhor S. (1998) Link-nested logit model of route choice - Overcoming route overlapping problem. *Transportation Research Record*, Vol. 1645, pp. 133-142.

Wall N.D.C. and Williams D.H. (1991) Drive integrated communications infrastructure. *Proceedings of the DRIVE Conference*, pp. 3-12.

Walpole R.E. and Myers R.H. (1993) Probability and Statistics for Engineers and Scientists. Maxwell Macmillan International Publishing Company.

Wardman M., Bonsall P.W. and Shires J.D. (1997) Driver response to variable message signs: a stated preference investigation. *Transportation Research*, Vol. 5C, pp. 389-405.

Wardrop J.G. (1952) Some theoretical aspects of road traffic research. *Proceedings of Institution of Civil Engineers*, II, pp. 325-378.

Warshall S. (1962) A Theorem on Boolean Matrices. *Journal of ACM*, Vol. 9, pp. 11-12.

Wong W.G. and Lai K.H. (1999) Driver attitudes towards display formats of real-time traffic information systems. *Transportation Planning and Technology*, Vol. 23, pp. 1-19.

Yang C.Y.D., Fricker J.D. and Kuczek T. (1998) Designing advanced traveler information systems from a driver's perspective - Results of a driving simulation study. *Transportation Research Record*, Vol. 1621, pp. 20-26.

Yang H. (1995) Sensitivity analysis for queuing equilibrium network flow and its application to traffic control. *Mathl. Comput. Modelling*, Vol. 22, pp. 247-258.

Yang H. (1998) Multiple equilibrium behaviors and advanced traveler information systems with endogenous market penetration. *Transportation Research, Vol.* 32B, pp. 205-218.

Yang H. (1999) System optimum, stochastic user equilibrium, and optimal link tolls. *Transportation Science*, Vol. 33, pp. 354-360.

Yang H., Kitamura R., Jovanis P.P., Vaughn K.M. and Abdel-Aty M.A. (1993) Exploration of route choice behaviour with advanced traveler information using neural network concepts. *Transportation*, Vol. 20, pp. 199-223.

Yang H., Ma O.S. and Wong S.C. (1999) New observations on the benefit evaluation of advanced traveler information systems. *ITS Journal*, Vol. 5, pp. 251-274.

Yang H., Yagar S., Iida Y. and Asakura Y. (1994) An algorithm for the inflow control problem on urban freeway networks with user-optimal flows. *Transportation Research*, Vol. 28B, pp. 123-139.

Zhao S., Harata N. and Ohta K. (1996) Assessing driver benefits from information provision: A logit model incorporating perception band of travel time information. *Proceedings of 24th PTRC European Transport Forum*, Seminar E, Part 1, Brunel University, England.

APPENDIX A SURVEY QUESTIONNAIRE

The Hong Kong Polytechnic University
Department of Civil & Structural Engineering

Questionnaire Survey for drivers using Lantau Link

Reference No.____________ Time:__________ Investigator__________

(I) Personal Data

(Q1) How many round trips have you made on the Lantau Link last week?

[a] >5 [b] 5 [c] 4
[d] 3 [e] 2 [f] 1
[g] 0, how many round trips have you made on the Lantau Link before?

(Q2) What is your current trip purpose?

[a] Travelling to and from work?
[b] Business trips or driving as part of your work?
[c] Recreation?
[d] To greet or farewell somebody?
[e] Others : ________

(Q3) What type of vehicle did you use for this trip?

[a] Private car [b] Taxi
[c] Others: ________

(Q4) When did you arrive at the new airport today?

____

(Q5) When do you leave the new airport today?

____

Official use

A) ☐
B) ____
C) ☐
D) ____
E) ☐
F) ____
G) ____
H) ____

(II) SP questions

The travel time mentioned below refers to the time from the airport (passenger terminal) to Tsing Yi (Tsing Yi end of the Tsing Ma Bridge). Firstly, there are six questions which correspond to the six LOS of the expressway, consisting of the North Lantau Expressway and the Lantau Link. Each question has two parts:

(i) asking the drivers their expected travel time when no information is provided;

(ii) asking the drivers' expected travel time when the current travel time is provided.

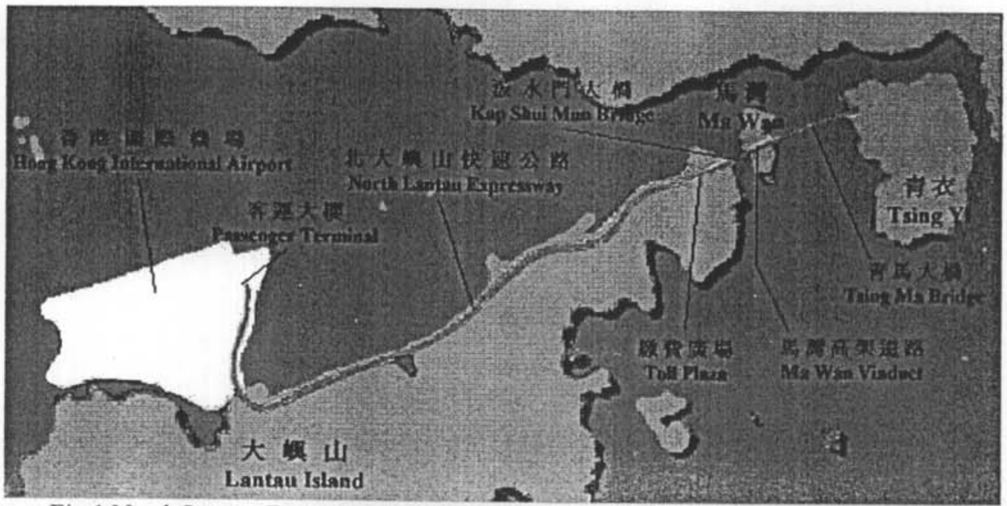

Fig.1 North Lantau Expressway and the Lantau Link

Fig. 2 Variable message sign in Japan

Official use

(Q6) If the traffic condition of the expressway is like Fig. 3 now, what is your expected travel time of the expressway? _______minutes. If the current travel time is _______minutes to arrive at Tsing Yi, what is your expected travel time?_______minutes

I) ____

J) ____

Fig. 3 LOS A

(Q7) If the traffic condition of expressway is like Fig. 4 now, what is your expected travel time of the expressway? _______minutes. If the current travel time is _______minutes to arrive at Tsing Yi, what is your expected travel time?_______minutes

K) ____

L) ____

Fig. 4 LOS B

(Q8) If the traffic condition of expressway is like Fig. 5 now, what is your expected travel time of the expressway? _______minutes. If the current travel time is _______minutes to arrive at Tsing Yi, what is your expected travel time?_______minutes

Official use

M) ____

N) ____

Fig. 5 LOS C

(Q9) If the traffic condition of expressway is like Fig. 6 now, what is your expected travel time of the expressway? _______minutes. If the current travel time is _______minutes to arrive at Tsing Yi, what is your expected travel time?_______minutes

O) ____

P) ____

Fig. 6 LOS D

Official use

(Q10) If the traffic condition of expressway is like Fig. 7 now, what is your expected travel time of the expressway? _______minutes. If the current travel time is _______minutes to arrive at Tsing Yi, what is your expected travel time?_______minutes

Q) ____

R) ____

Fig. 7 LOS E

(Q11) If the traffic condition of expressway is like Fig. 8 now, what is your expected travel time of the expressway? _______minutes. If the current travel time is _______minutes to arrive at Tsing Yi, what is your expected travel time?_______minutes

S) ____

T) ____

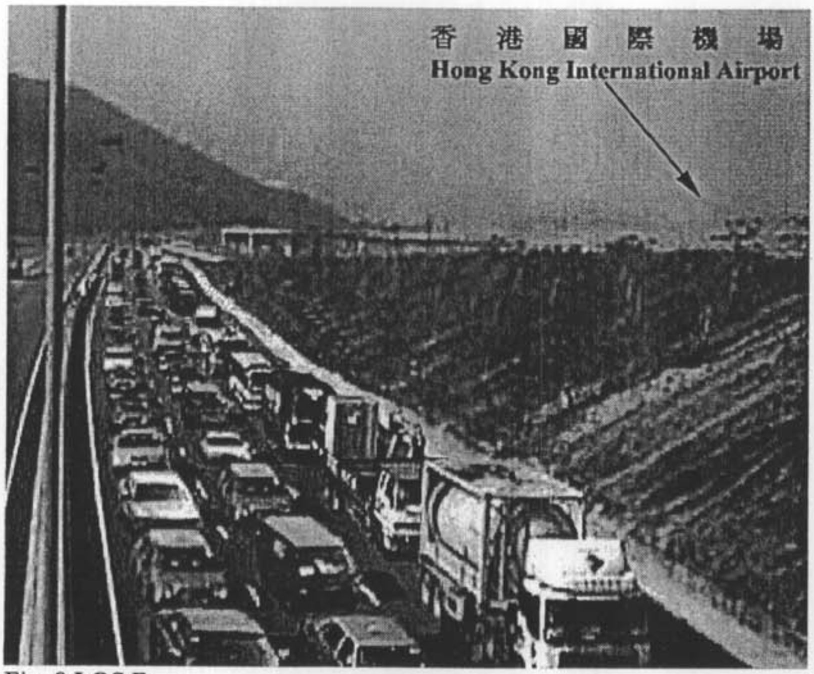

Fig. 8 LOS F

Secondly, the SP questions are for investigating the dirvers' route choice. Two alternatives are provided for the respondent to choose:

(i) expressway which consists of the North Lantau Expressway and the Lantau Link;

(ii) urban road which includes an assumed urban road and the Lantau Link. The assumed urban road is parallel with North Lantau Expressway, starting at the airport and ending at Toll Plaza of Lantau Link.

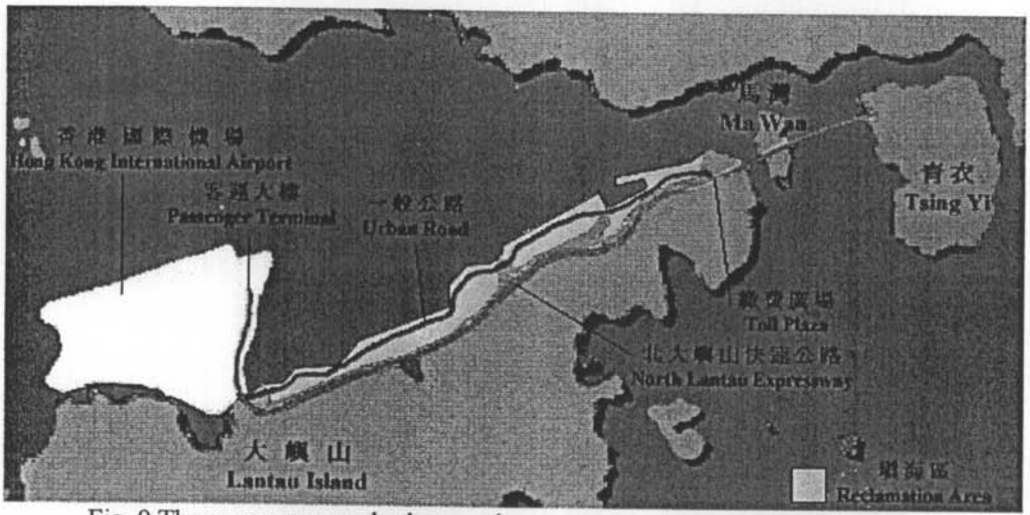

Fig. 9 The expressway and urban road

(Q12) If the traffic condition of the expressway is like Fig. 10, which of the following route will you choose?

Fig. 10

	Route 1 (The existing route)	Route 2 (The assumed route)
Road type	Expressway	Urban road
Normal travel time	30 minutes	25 minutes
Estimated current travel time	33 minutes	--------------
No. of signal	---------------	10

[a] expressway
[b] urban road

(Q13) If the traffic condition of the expressway is like Fig. 11. which of the following route will you choose?

Fig. 11

	Route 1 (The existing route)	Route 2 (The assumed route)
Road type	Expressway	Urban road
Normal travel time	39 minutes	39 minutes
Estimated current travel time	43 minutes	--------------
No. of signal	---------------	20

[a] expressway
[b] urban road

Official use

U) ☐

V) ☐

(Q14) If the traffic condition of the expressway is like Fig. 12, which of the following route will you choose?

W) ☐

Fig. 12

	Route 1 (The existing route)	Route 2 (The assumed route)
Road type	Expressway	Urban road
Normal travel time	53 minutes	60 minutes
Estimated current travel time	58 minutes	--------------
No. of signal	--------------	10

[a] expressway
[b] urban road