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**MODELLING DRIVER RESPONSE UNDER
ROAD PRICING**

XIE LITIAN

SCHOOL OF CIVIL AND ENVIRONMENTAL ENGINEERING

2007

Modelling Driver Response under Road Pricing

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SUMMARY

Singapore's Electronic Road Pricing (ERP) system is an effective travel demand management tool which is constantly evolving. With a time-variable pricing method, the system charges for entering the city centre and using some expressways during the morning peak hours. New ERP gantry points are introduced on those roads where congestion becomes a serious problem. Meanwhile, the ERP charging rates for existing points are revised every three months to maintain traffic speeds within desirable bands. In planning these changes – for either introducing a new gantry or revising the existing charging rates – explicit models for predicting their effects on traffic would be useful. Responding to such a need, this study aims to propose a practical methodology for modelling and forecasting the short-term impacts of ERP changes on peak period traffic for a single charging point.

For planning an introduction of a new ERP gantry, an MNL-based model of motorist response is proposed. The choices considered include the time intervals of travel and re-routing to avoid the new toll. For both model calibration and application, only traffic volume data are used as they are much more readily available than data on travel behaviour of individual motorists. The proposed methodology was tested on one expressway and two arterial roads. The calibrated models reflected well the peak spreading effect of ERP on traffic and the penalties for rescheduling and re-routing of trips.

For planning of ERP rate adjustment, it is proposed to use transaction data automatically recorded by the system, because these data reflect the actual responses of individual motorists and are readily available from the ERP system itself. The overall modelling framework includes two key steps: (1) developing elasticity models to predict the impacts of rate adjustment on the total volume of

different vehicle types; and (2) developing scheduling decision models to predict the traffic distribution over time intervals under the new charging rates. Motorists using the ERP system are segmented into several categories based on elasticity analysis and application of data mining techniques to the ERP transaction dataset. Separate models are developed in accordance with this segmentation.

Modelling based on ERP transaction data presents some new challenges such as limited information on travel decision making, lack of social-economic data on travellers and unknown preferred arrival time (PAT). Several novel approaches are proposed to address these issues. A maximum likelihood method is developed to estimate individual motorists' PATs. Iterative procedures are proposed for both model calibration and application, since forecasting of individual motorist's scheduling decisions depends on the traffic speed which in turn is estimated based on traffic volume resulting from the aggregation of motorists' decisions.

The proposed modelling methodology was tested on a two-week transaction dataset recorded in 2003 before and after a rate adjustment at an ERP gantry located on the Central Expressway of Singapore. Another ERP rate adjustment in 2003 at the same site provided transaction data for model validation. The overall framework and the calibrated models were systematically evaluated and validated at both macro and micro levels. The results show that it is practical to apply the proposed methodology to an ERP system with peak period time-variable rates.

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LIST OF ABBREVIATIONS

ALS	Singapore's Area Licensing Scheme;
AYE	Ayer Rajah Expressway in Singapore;
BPR	Bureau of Public Roads;
CART	Classification and Regression Trees;
CBD	Central business district;
CHAID	Chi Square Automatic Interaction Detection;
CNL	Cross-nested logit model;
COV	Coefficient of variation;
CTE	Central Expressway in Singapore;
ERP	Electronic Road Pricing;
GEV	Generalised extreme value;
GPS	Global Positioning System;
HGV	Heavy goods vehicle;
HOT	High Occupancy Toll;
HOV	High Occupancy Vehicle;
HV	Heavy vehicle (including buses and heavy goods vehicles);
IIA	Independence of irrelevant alternatives;
IU	In-vehicle unit;
LGV	Light goods vehicle;
LTA	Land Transport Authority of Singapore;
MAT	Median arrival time;
MLPAT	Most likely preferred arrival time;

MNL	Multinomial logit model;
MPC	Marginal private cost;
MSC	Marginal social cost;
NL	Nested logit;
NLLS	Non-linear-least-squares;
OD	Origin-destination;
OGEV	Ordered generalised extreme value;
PAT	Preferred arrival time;
PCE	Passenger car equivalent;
RMSE	Root mean square error;
RP	Revealed preference;
RPS	Road Pricing Scheme;
RUM	Random utility maximization theory;
RZ	Restricted Zone in Singapore;
SDE	Schedule delay earlier;
SDL	Schedule delay later;
SP	Stated preference;
TDM	Travel demand management;
VPD	Vehicle presence detector;
WTF	Weekly travel frequency.

LIST OF COMMON SYMBOLS

C_k^0	Average rate charged before ERP rate adjustment for motorist category k ;
C_k	Average rate charged after rate adjustment for motorist category k ;
D	Number of days included in a transaction dataset;
D_n	Weekly travel frequency of motorist n ;
D_{in}^s	Number of days that motorist n chooses time interval i under ERP charging rates s ;
E_A	Arc elasticity of travel demand with respect to road pricing;
E_p	Point elasticity of travel demand with respect to road pricing;
ERP	ERP charging rate (S\$);
H	Binary variable indicating travelling in the preferred arrival time interval;
LS	Sum of squared differences between the estimated and observed traffic volumes;
M	Number of time options for a scheduling decision;
N_k	Number of motorists in category of k ;
Q_k^0	Number of passes for motorist category k before ERP rate adjustment;
Q_k	Number of passes for motorist category k after rate adjustment;
Q_{ik}	Number of passes for motorist category k within time interval i after rate adjustment;
Q_i	Total traffic volume in a time interval i ;
q	Traffic flow per lane (pcu/h/lane);
SDE	Variable of scheduling earlier than preferred arrival time (minutes);

SDL	Variable of scheduling later than preferred arrival time (minutes);
$TRTIME$	Travel time (minutes) on road segment affected by pricing;
$TTPK$	Congestion penalty variable – travel time per unit distance (min/km);
u	Average traffic speed (km/h);
V_i	Utility for travelling in time interval i ;
V_{ijk}	Utility for motorist belonging to category k with preferred arrival time in interval j to travel in interval i ;
X_{lij}	Explanatory variable l in the utility equation for a motorist with preferred arrival time in j to travel in interval i under ERP;
θ_l	Coefficient for the explanatory variable l in the utility equation;
α	Coefficient for variable of ERP ;
τ	Coefficient for the variable of travel time or congestion penalty;
β_1	Coefficient for the variable of scheduling earlier;
β_2	Coefficient for the variable of scheduling later;
γ	Coefficient for the variable of travelling at preferred arrival time;
ρ^2	The ρ^2 index;
ω^r	Convergence indicator estimated in the r^{th} iteration of a procedure.

CHAPTER ONE

INTRODUCTION

1.1. BACKGROUND

Traffic congestion has come to be a serious problem for large cities all over the world in the past 50 years. Travel demand management (TDM) attempts to relieve this problem by modifying existing travel patterns. As a part of TDM, road pricing has been proven to be one of the most effective measures. It is designed as an incentive to influence the travellers' demand on a particular stretch of road. The additional charge imposed by road pricing affects the travellers by changing the cost profiles of travel over modes, times of the day and routes through the network, and thus leads to a more efficient use of road capacity.

Singapore is unique in its long experience with road pricing schemes. It was the first country to implement road pricing in 1975 in a coupon-based form called the Area Licensing Scheme (ALS). The scheme was specifically designed to reduce peak period traffic flows, with a flat toll on vehicles entering the downtown area. In 1998, it was upgraded to an Electronic Road Pricing (ERP) system.

Under the electronic system, the charge is deducted automatically from a pre-paid smart card when a vehicle passes under an ERP gantry. A transaction record for each passage during the ERP operation hours is generated and stored in the system computer, including information about the time of entry, the fee charged and the unique identification code that corresponds to each passing vehicle. The ERP system makes it possible to vary charges by location, time of day and vehicle type, so that they can be related to the actual level of congestion. Unlike the ALS with its daily or monthly licences, the ERP is based on the different principle of "per pass"

charging and therefore its impact on travel behaviour is more direct. In urban transportation systems, motorists' scheduling decisions are central to the formation and dissipation of congestion during the peak hours. In order to encourage motorists to reschedule their trips, a method called "shoulder pricing" is used, which involves increasing the charging rate gradually before the peak and decreasing it after the peak. Consequently, this time-variable pricing policy leads to a more even distribution of traffic flows than schemes with a flat toll like the ALS.

The ERP system is an evolving TDM tool. Traffic situation on each road in Singapore is monitored and periodically evaluated by the Land Transport Authority of Singapore (LTA). New ERP gantry points will be introduced on those roads where congestion becomes a problem and where it is believed that the introduction of charging can relieve it. This electronic system has expanded from 28 gantries in 1998 to 48 gantries at present. The traffic speeds at existing ERP charging points are monitored by the LTA and the rates are revised quarterly to maintain the speeds within desirable bands, which are defined differently for different road categories. If the observed speed turns out to be less than the lower threshold, the rates will be increased whereas if the speed exceeds the upper threshold, the rates will be reduced.

In making these decisions, either introducing a new ERP gantry or revising the existing ERP charging rates, one of the difficulties is how to predict the effects of this change on traffic. For a simple pricing scheme involving a flat toll, an estimate of traffic impact can be calculated with known demand elasticities or even just based on expert experience. However, these methods become inadequate in the case of time-variable pricing as motorists have many options for rescheduling their trips to time periods with a lower or no charge.

This situation calls for an explicit model of motorists' decision making to forecast

the effects of road pricing change on traffic. As the ERP is an expanding system and the charging rates for existing gantries are revised every 3 months, for practical purposes the proposed modelling and forecasting should rely only on the current data from the site that are available from the ERP system itself.

1.2. PROBLEM STATEMENT

By capturing and recording information on each transaction, the ERP system provides a unique, ample and invaluable source of data on individual motorists' behaviour. How to make use of these data for modelling and forecasting the impacts of rate adjustment on motorists' scheduling decisions is a new and important research question.

Unlike theoretical network studies of road pricing and modelling based on stated preference (SP) surveys, modelling scheduling decision based on individual ERP transaction data faces four major challenges outlined below:

(1) Segmentation of motorists:

In developing a transportation model, certain homogeneity in the population segments considered is required (Ortúzar and Willumsen, 2001). To achieve this, one usually needs to segment the complex population and then develop separate models. How to segment the motorists into different categories based on their transaction records is one of the main issues in this research.

(2) Aggregate and disaggregate modelling:

A sophisticated disaggregate model is in general more reliable than an aggregate model. However, in the real world not all of the motorists' travels are subject to the impact of road pricing. For instance, arrival times of a particular taxi at a gantry may be decided by the various passengers rather than the driver. Modelling the change of travel demand at an aggregate level would be more

appropriate than at a disaggregate level to represent the impacts of pricing adjustment on taxis as a vehicle category. Therefore, the selection of disaggregate or aggregate models for different categories of motorists needs careful investigation.

(3) Model construction:

In modelling based on SP or network model derived data, the researcher is able to select variables to be included in the utility function and the related information can be collected from a survey or model run. However, modelling based on ERP transaction data has substantial constraints since the set of variables is limited by the system dataset. How can we model the motorists' decision making logically with these restrictions?

(4) Modelling techniques:

Several advanced modelling techniques have been employed and developed in modelling travel behaviour under road pricing. However, when a modeller faces a huge body of transaction data which contains various categories of motorists that require different modelling techniques, the situation becomes much more complex. Hence, the development of a comprehensive modelling framework that makes several modelling techniques work together is a major challenge in modelling motorists' decision making based on ERP transaction data.

In developing a model for forecasting the effects of a new charging point on traffic, there are other difficulties. Before the ERP is implemented on a site, traffic volume data are commonly available whereas individual behavioural data are difficult to capture and assemble. Under this situation, the main challenge is how to develop a reliable model which can use traffic volume data to forecast the traffic flows after ERP introduction.

1.3. OBJECTIVES AND SCOPE OF THE RESEARCH

This research responds to the above challenges by proposing a practical

methodology for modelling and forecasting the effects of new charging points and rate adjustment on motorists' scheduling decisions and then on traffic flows.

Specifically, the main objectives of this research are as follows:

- (1) To investigate the travellers' sensitivity to road pricing in Singapore and compare it with overseas experience;
- (2) To develop a methodology for using traffic volume data to model the travel response to the introduction of a single ERP gantry;
- (3) To analyse the ERP transaction database and segment the motorists based on their daily transaction records;
- (4) To propose an overall methodological framework for using ERP transaction data to model the effects of road pricing adjustment on motorists' scheduling decisions during the peak period hours;
- (5) To develop separate scheduling decision models for each category of motorists under the overall modelling framework and investigate the impacts of road pricing on different segments of the motorist population.

This research focuses on modelling the short-term impacts of road pricing on peak period traffic at a single charging point. In developing the model for the effects of a new ERP gantry, only traffic volume data will be used. For modelling the impacts of ERP rate adjustment on motorists, it is assumed that the only available data sources are the ERP transaction records. The models proposed are to be practical traffic forecasting tools that can be applied in ERP system planning.

This research will not be concerned with road pricing fundamentals, such as theories of second-best marginal cost pricing, Pareto pricing and revenue refunding schemes, environmental issues of road congestion and pricing, social equity, and so on. These issues have been addressed by a large body of literature, most of which is

within the general network equilibrium context of optimization and economic theories (e.g. Goodwin, 1989; Hau, 1992a; Small and Yan, 2001; Yang and Zhang, 2002; Verhoef and Small, 2004; Ho et al., 2005).

There is a considerable number of studies modelling scheduling decisions based on multiple origins and destinations in a network (e.g. Arnott et al., 1990; Chen and Hsueh, 1998; Gentile et al., 2005; De Palma et al., 2005; De Palma and Lindsey, 2006), based on detailed information about travellers' origins and destinations and their preferences for these choices. This kind of modelling, which usually is based on a simulated network, is not within the scope of this research.

Several studies have focused on the issues of the relationship between drivers' socio-economic characteristics and their responses under road pricing (e.g. O'Mahony et al., 2000; Burris and Pendyala, 2002; Saleh and Farrell, 2005), which will not be considered in this study.

1.4. ORGANISATION OF THE DISSERTATION

The remainder of this thesis consists of eight chapters.

Chapter 2 reviews some of the existing literature on road pricing, scheduling decision models and related modelling techniques. The state of art and the knowledge gap in the selected studies are summarised.

Chapter 3 discusses the research methodologies proposed for the development of models based on traffic volume data and individual ERP transaction data.

Chapter 4 examines the motorists' sensitivity to road pricing in Singapore. It provides empirical estimates of travel demand elasticities for different vehicle types, time periods and road categories. The results are compared with the overseas experience.

Chapter 5 develops an aggregate model of travel response to pricing for a single toll point. This methodology is applicable to planning a new ERP gantry point.

Chapters 6 – 8 develop a methodology for using the ERP transaction data to model the short-term impacts of rate adjustment on peak period traffic flows:

- Chapter 6 introduces data collection through the ERP system and describes statistical analyses of the transaction data. It also discusses the segmentation of motorists.
- Chapter 7 describes the development of the overall modelling framework for using ERP transaction data to forecast traffic, as well as the development of separate scheduling models for different categories of motorists.
- Chapter 8 provides validation of the modelling approach, both of the overall framework and of the separate models.

Finally, Chapter 9 presents conclusions and recommendations for further research.

CHAPTER TWO

LITERATURE REVIEW

2.1. INTRODUCTION

In accordance with the study objectives presented in Chapter 1, this chapter reviews the status quo of road pricing systems as well as the research on the impacts of road pricing. This part of literature review leads to a summary of issues that need to be carefully considered in investigating a road pricing system and an assessment of the necessity of this research. After that, a few important studies on scheduling decision modelling are reviewed, as they provide a basic perspective and the theoretical fundamentals for this study. Discrete choice modelling techniques are examined as they are the common modelling tool employed by most of the studies. The different types of data that have been used in previous studies are also compared and discussed.

2.2. ROAD PRICING

2.2.1. Objectives and Types of Road Pricing Systems

Road pricing was initially proposed with an economic objective related to the efficiency with which congested roads are used (Vickrey, 1955). On a road without additional charge, the marginal social cost (MSC) caused by a motorised trip is greater than the marginal private cost (MPC) which the motorist incurs, because each journey contributes to congestion the burden of which is carried by all the road users. The difference between MSC and MPC caused by a trip is larger when traffic congestion on a road is heavier. Road pricing, by charging such cost difference for a journey, was designed to ensure that the only drivers who travel are those whose benefits from travelling exceed the cost that they impose both on themselves and on

the others. As a result, traffic flows would be lower, and speeds and reliability of journey times higher. Therefore, road pricing has also been seen as an economic measure to reduce congestion. Systematic analyses of the economic fundamentals of road pricing can be found in Hau (1992a, 2005a, 2005b), Small (1992) and Rouwendal and Verhoef (2006).

Over the years, the objectives of road pricing have expanded. It has come to be seen as a way of reducing the environmental impacts of traffic. Those pollution components related to the level of congestion, such as noise, carbon monoxide emissions and carbon dioxide production will be more effectively reduced by road pricing systems which tackle congestion directly than by conventional traffic management tools (Hau, 1992b, 2006a, 2006b; Small, 1997).

Raising revenue is another important objective. Road pricing is potentially a source of very substantial revenues (Jones and Hervik, 1992; May and Milne, 2000; Richards, 2006). For example, the three Norwegian toll rings have been designed specifically to generate revenue to help finance transport infrastructure. Traditional toll roads, which have a history of more than 100 years, usually are not considered as road pricing facilities, as the tolls are collected purely to raise revenue for the purpose of road financing. The Norwegian toll rings have been classified as road pricing schemes because they were designed as revenue sources for transportation development, not only for the construction of the roads covered by the toll rings themselves. High Occupancy Toll (HOT) or High Occupancy Vehicle (HOV) discount schemes sometimes are also seen as road pricing, as they aim to encourage carpooling as well as to collect tolls from road users.

More recently these different objectives have been combined, by seeing road pricing as part of an integrated strategy, in which it contributes to the objectives of relieving congestion, reducing environmental pollution and providing finance for

transportation improvements (May and Roberts, 1995).

According to the method of charging, four kinds of road pricing systems that have been implemented so far (Hau, 1992b):

- (1) Point charging – this involves charging motorists at a particular site.
- (2) Cordon ring – every entering trip into a restricted zone will be charged.
- (3) Area-wide congestion charging – this means charging travellers who use cars inside a zone, no matter whether the trip is internal, through, inbound or outbound.
- (4) Travel distance-based charging – this involves charging a fee according to the distance a user has travelled on the tolled road.

Some other possible charging methods have been proposed. For instance, May and Milne (2000) tested cordon ring, travel distance-based charging, and two new proposals: charging based on time spent in travel and time spent in congestion.

Another approach is to classify the road pricing schemes into uniform rate systems, variable pricing systems, dynamic charging systems and HOT (or HOV). Paulley (2002) highly recommended variable pricing system as an effective travel demand management strategy for shifting travel from peak to off-peak periods.

Table 2.1 presents some well-known road pricing systems, with their primary objectives and charging methods. These systems have been successfully implemented, except the Hong Kong ERP trial scheme which was terminated for political reasons. Generally, the discrepancy in objectives and charging manners lead to differences in system design and performance (May, 1992; Small, 1997; May et al., 1998; Marcurri, 2001). This can partly explain why the price elasticities for the Norwegian toll rings have been so different to those in Singapore. This issue will be discussed further in Chapter 4.

Table 2.1: Examples of road pricing systems

Name and Location	Primary objective (starting date)	Description of charging	Source
Area Licensing Scheme (ALS), Singapore	Congestion alleviation (1975)	Cordon ring and uniform rate	Menon and Chin (1998)
Hong Kong Electronic Road Pricing (ERP) Trial Scheme, Hong Kong	Congestion alleviation (1983)	Cordon ring and variable pricing	Hau (1990)
Bergen Toll Ring, Norway	Finance for transport investments (1986)	Cordon ring and uniform rate	Larsen (1988)
Oslo Toll Ring, Norway	Finance for transport investments (1990)	Cordon ring and uniform rate	Ramjerdi (1994)
Trondheim Toll Ring, Norway	Finance for transport investments (1991)	Cordon ring and uniform rate (with off-peak discount)	Polak and Meland (1994)
Autoroute A1, expressway connecting Senlis to Paris, and Paris to Lille, France	Traffic demand management (1992)	Point charging and variable pricing	Small (1997)
SR 91, Express Lanes on California State Route 91, US	Road financing (1995)	Point charging and variable pricing with HOT discount	Lam and Small (2001)
I-15 Congestion Pricing Project in San Diego, US	Congestion alleviation (1996)	Point charging and dynamic charging (since 1998), with HOT discount	Ghosh (2001)
LeeWay (Cape Coral and Midpoint Bridges) in Lee County, Florida, US	Road financing (1998)	Point charging and variable pricing	Burris and Pendyala (2002)
Electronic Road Pricing (ERP), Singapore	Traffic demand management (1998)	Point charging, cordon ring and variable pricing	Menon (2000)
Congestion Charging Scheme in central London, UK	Congestion alleviation (2003)	Area-wide congestion charging and uniform rate	TfL (2003)
Stockholm Toll Collection System, Sweden	Congestion alleviation (2006)	Cordon ring and variable pricing	ITDP (2006)

2.2.2. Road Pricing in Singapore

Area Licensing Scheme (ALS, 1975-1998)

Singapore's ALS was part of a stringent set of policies designed to restrict automobile ownership and use in this crowded island city-state. The national government chose the ALS over conventional road tolls and higher parking fees because space for toll stations was lacking in the city centre and it was thought that higher parking fees would be ineffective in the face of heavy through traffic and numerous cars (Holland and Watson, 1978; Wilson, 1988).

The size of the charging area (called the central area Restricted Zone, abbreviated as RZ) and charging structure of the ALS have varied over the years. When first implemented in July 1975, the fee was imposed only on vehicles entering the downtown area during the morning peak period (Monday – Saturday). Initially, the morning peak was defined as 7:30–9:30 AM but soon after it was extended to 10:15 AM due to a heavy surge of traffic between 9:30 and 10:15 AM. During that period cars and taxis entering the RZ were required to display paper licenses, which were available on either daily (S\$3) or monthly (S\$60) basis. Goods vehicles, buses, motorcycles and passenger cars carrying at least four people were exempted from the licence requirement. The fees for passenger cars were increased to S\$4 in 1976 and then to S\$5 in 1980. Reviewing the historical changes of the volumes of passenger car traffic entering the RZ corresponding to the changes in charging levels, Menon et al. (1993) observed that the initial introduction of the ALS in 1975 had the most dramatic effect on inbound car traffic. Detailed discussions of the early historical development of the ALS and its impacts are also given by Small (1997) and Li (1999).

In 1989, the hours during which the fee applied were extended to include the afternoon peak. The afternoon peak was first defined as 4:30–7:00 PM (Monday – Friday) and the charging was extended to include all types of motor vehicles, with

the exception of scheduled buses. Later, the period was shortened in 1990 to 4:30–6:30 PM (Monday – Friday). This inclusion of PM peak charging produced the desired effect on through traffic. For administrative and practical reasons, it was decided that charging in the PM period would also apply to the inbound (rather than outbound) flows and that the same coupon licence would be used. Although this arrangement meant that the PM ALS was of limited relevance to commuters, it created a significant disincentive to through traffic, shoppers and other casual visitors to the RZ. At the same time as the PM ALS was introduced, the price of a Daily Licence for passenger cars was reduced from S\$5 to S\$3. The effects of the 1989 modification on traffic flows in the RZ have been described by Menon and Seddon (1991), Olszewski and Tan (1991), Polak et al. (1994) and Li (1999).

One side effect of the introduction of the PM restricted period was to induce a “mid-day peak”, caused by some journeys being re-timed earlier or later to avoid the two restricted periods. To even out this peak, in January 1994 the ALS was extended to cover the whole day. However, a degree of time-variable pricing was retained by introducing a Part-Day Licence (at a reduced price of S\$2 for passenger cars), which was only valid for entering the RZ during the inter-peak period (10:15 AM–4:30 PM). The effects of this change have been discussed by Olszewski et al. (1996).

Although the ALS served its purpose of controlling traffic congestion for over two decades, the paper licence scheme has been considered inconvenient and inflexible. The most important drawbacks were:

- (1) Inconvenience – additional effort, time and pre-planning were required for buying licences.
- (2) Complexity – although simple in principle, the system became too complex with 12 different licence types (daily, monthly, whole-day and part-day for 3 vehicle types).

- (3) Traffic surges – which were occurring immediately before and after the restricted hours.
- (4) Lack of flexibility – it was practically impossible to adjust the fees precisely according to the level of congestion on the road.

Due to the above problems, the Singapore authorities decided in 1993 to upgrade the system.

Electronic Road Pricing System (ERP, 1998-present)

After an extensive evaluation of alternative technologies (Menon and Chin, 1998), in September 1998 the manual ALS scheme was converted to a fully automated state-of-the-art Electronic Road Pricing system (Luk, 1999).

Unlike the ALS with a daily or monthly licence, the ERP is based on a different principle for charging – per pass charging and therefore its impact on travel behaviour is more direct. Under the electronic system, the charge is deducted automatically when a vehicle passes under an ERP gantry. This makes it possible to emphasise the link between road pricing and congestion – by varying the charges by location, time of day and vehicle type. The rates for different types of vehicles are set to be approximately proportional to their passenger car equivalent (PCE) values (Menon, 2000). A method called “shoulder pricing” was introduced, which involves increasing the rate in steps every half an hour before the peak and decreasing it after the peak. Table 2.2 shows a typical example of peak period ERP rates on an expressway. This charging method has effectively eliminated the traffic surges, which were occurring immediately before and after the restricted hours under the ALS. The traffic conditions at the gantry points are monitored by LTA and the rates are revised on a quarterly basis to maintain the speeds within desirable bands. The target speed range was defined as 45–65 km/h for expressways and 20–30 km/h for arterials and roads crossing the RZ cordon (Menon, 2000). If the observed speed turns out to be less than the lower threshold, the rates will be increased whereas if

the speed exceeds the upper threshold, the rates will be reduced. Drivers respond to every change of the rates by re-timing or re-routing their trips.

Table 2.2: Time-variable ERP rates for Central Expressway (S\$) — June 2002

Time period	Vehicle type			
	Cars, taxis, and LGVs	Motorcycles	HGV and small buses	Very HGV and big buses
7:30–8:00	1.00	0.50	1.50	2.00
8:00–8:30	2.50	1.25	3.75	5.00
8:30–9:00	3.00	1.50	4.50	6.00
9:00–9:30	1.00	0.50	1.50	2.00

In the first phase of ERP implementation, all the ALS gantries around the RZ were converted to ERP gantries. The charges around the RZ apply on working days during most of the daytime hours: 7:30 AM–7:00 PM, with a free entry period from 10:00 AM to 12:00 noon. In addition, ERP was also started at three expressway locations, which were subject to coupon pricing (called RPS) before. The expressway pricing involved only the AM peak period (7:30–9:30) and amounted to point charging (as opposed to cordon charging in RZ). Usually, the operating hours for a particular gantry are fixed, but may be adjusted during the June and December school holidays.

A significant drop in the inbound traffic volume was observed after the introduction of ERP, amounting to about 15% (Menon, 2000), even though the ERP rates were set lower than the previous ALS rates. This decrease was attributed to a different method of charging (per trip rather than per day) which affected those making multiple trips. As the inbound traffic volume dropped below the expected level, the rates were revised in November 1998, two months after the ERP introduction. The effects of ERP on traffic flows are described by Menon (2000), Chin (2002) and Santos et al. (2004).

Since the year 2000, northbound Central Expressway (CTE) has been experiencing severe traffic congestion during the evening peak hours. To alleviate the situation, ERP was introduced in August 2005, on the northbound CTE during the PM peak period (6:00–8:00) on weekdays. Two new ERP gantries, located near Handy Road and after the YMCA Building, were introduced to demarcate the Orchard Road cordon from the rest of the central area RZ in October 2005. The ERP operating hours for the Orchard Road area were also extended to 8.00 PM on weekdays, and from 12.00 noon to 8.00 PM on Saturdays (LTA, 2005).

At present there are 48 ERP gantries: 30 form a cordon around the central area RZ (including the demarcated Orchard Road cordon), 13 are located on selected expressway segments and five on radial arterial roads. The gantry locations are listed and shown on maps in Appendix A.

2.2.3. Travel Demand Elasticity

In order to know how the motorist will respond to road charging, knowledge of travel demand elasticity with respect to the pricing level is very important. According to TRACE (1998a), the elasticity concept was originally put forward by the British economist Alfred Marshall, as a dimensionless measure of the sensitivity of a dependent variable to change in an independent variable.

Oum (1989) as well as Luk and Hepburn (1993) provided useful reviews of the elasticity concepts and formulae. Demand elasticity is defined as the ratio of percentage change in the quantity demanded (Q) to the percentage change in the variable postulated to be inducing that change, e.g. the price (C). In general, elasticity is not constant but depends on the value of C . At any point, the point elasticity (E_p) is the product of the slope of the demand function $Q(C)$ and the ratio of price (C) to quantity or demand (Q) at that point.

$$E_p = \frac{\partial Q}{\partial C} \frac{C}{Q} \quad [2.1]$$

When a change in demand caused by a change in price occurs in practice, two values of price (C^0 , C) and demand (Q^0 , Q) are observed. A problem arises in deciding whether the percentage change should be calculated using initial values, or some average as the base. In such cases, an arc elasticity (E_A) definition is the most appropriate. This formula uses an arithmetic average of the values of C and Q before and after the change as the bases for percentage change calculation.

$$E_A = \frac{Q - Q^0}{C - C^0} \frac{0.5(C^0 + C)}{0.5(Q^0 + Q)} = \frac{(Q - Q^0)(C^0 + C)}{(C - C^0)(Q^0 + Q)} \quad [2.2]$$

Luk and Hepburn (1993) also reviewed the concepts of own- and cross-price elasticity of demand. The demand for a good or service is influenced both by its own-price and the price of competing goods. The demand elasticity for a good with respect to its own price is the own-price elasticity of demand. The demand elasticity for a good with respect to the price of another good is the cross-price elasticity of demand.

Elasticities were commonly assumed to be fixed. However, it has been found that the assumption of fixed elasticities in simple models is likely to be unreliable for changes of more than about 10 to 30 percent in the independent variables. Recent evidence suggests that elasticity varies depending on the direction of change and the pattern of past movements in the independent variable (Luk and Hepburn, 1993). This is consistent with the conclusion of Dargay (1992), who found that the relationship between demand and price might be irreversible.

There is a considerable body of literature on travel demand elasticity with respect to petrol prices, parking fees and the cost of driving in general, for example, Goodwin

(1992), Oum et al. (1992), TRACE (1998b) and De Jong and Gunn (2001). For most of these studies, travel demand elasticities are found to be in the range of -1 to 0 and the long-term values are always higher than the short-term ones.

Harvey (1994) found the lowest values of demand elasticities with respect to tolls were usually observed for bridges with a uniform toll in highly congested metropolitan areas in the US. He explained that this was because of the relative low level of toll compared with other components of the total costs, such as parking fees. However, the author ignored the fact that usually there are no other alternatives to avoid the bridge tolls and that could be the main reason for the low elasticity values. To estimate the impact on traffic and toll revenue when tolls are increased in the future, URS (2001) developed a set of elasticities for New York area bridges and tunnels and found that toll elasticity of traffic was between -0.085 and -0.386 , which was around the average value of -0.1 for cars reported earlier by Hirschman et al. (1995). Gifford and Talkington (1996) studied the Golden Gate Bridge in San Francisco and found a toll elasticity from -0.05 to -0.19 . The authors also found that increases in tolls on one day tended to dampen traffic on other days of the week. Cain et al. (2001) showed the travellers' responses to off-peak toll discount implemented at two county bridges in Florida. They found that demand elasticities calculated across different off-peak periods varied considerably. These results suggest that the implementation of variable pricing schemes can encourage a more efficient use of roads compared with a uniform toll throughout the day.

Ramjerdi (1994) provided some evidence on the impact of the opening of the toll ring in Oslo. A two-wave panel survey was conducted to evaluate the introduction of the toll scheme. The author found that at the level of tour frequency and trip generation, the toll elasticity of the number of car tours was -0.026 or -0.038 , depending on the model form. At the level of mode choice the toll elasticity was -0.04 for all work tours. Jones and Hervik (1992) estimated the elasticity of cars in Alesund and Oslo

and found a higher value than Ramjerdi's study. This may be partially due to the difference in the toll application method (point toll for Alesund and toll ring for Oslo). For the toll ring of Trondheim, another city in Norway, Polak and Meland (1994) found the elasticity of car traffic to be -0.30 for the morning peak period.

Matas and Raymond (2002) studied the elasticities of demand on tolled motorways in Spain with respect to the main variables influencing it. They found that the toll elasticities varied across motorway sections and the values were in the range from -0.21 for the most inelastic to -0.83 for the most elastic. They analysed the factors causing such differences and concluded that the quality of the alternative road and the length of the priced section were the main factors.

Luk (1999) provided some empirical own- and cross-price elasticities with respect to charging changes in Singapore and found that the values ranged from -0.19 to -0.58 . Using the values provided by Goodwin (1992) as a reference, Luk found that the short-term elasticity due to congestion pricing in Singapore appears to be effective in reducing car travel. The results also suggested that the effect of congestion tolls on modal split would be similar to that of petrol price increases.

2.2.4. Behavioural Responses to Road Pricing

Polak and Meland (1994) presented results of a before-and-after study monitoring the effect on travel behaviour of the introduction of a toll ring in Trondheim, Norway in 1991. The results indicated that the major effect of the toll ring had been to bring about a moderate shift in the temporal structure of car travel. They found that there has been a marked reduction in the rate of trip making during the high toll period, while in low toll period shopping journeys increased significantly. However, due to the small absolute magnitude of the induced temporal changes in car trips across the toll ring (less than 10%) and the fact that the volume of trips crossing the toll ring during the tolled period itself accounted for less than 20% of total car movements, the overall impacts of the toll ring seemed to be small. This finding

corresponds with the conclusion of Ramjerdi (1994), in which she stated that the impacts of the toll rings in Norway on traffic were small as all of them had revenue raising as their objective.

Sullivan and Harake (1998) studied the effects of the introduction of the Express Lanes on California State Route 91 (SR 91). SR 91 is quite unique when compared to the other road pricing systems: tolled Express Lanes are alongside free lanes. The authors concluded that the impacts on corridor traffic had been positive and the overall level of ridesharing had not been adversely affected. They showed that commuters who used the toll lanes most frequently did have a higher income than those who used the lanes infrequently or not at all. They also found that driving comfort and the perception of greater safety appeared to be the principal perceived benefits motivating the users to choose paying toll under traffic conditions when the expected value of time savings was less than the toll paid.

Lam (2000) studied the SR 91 scheme and investigated the effect of variability of travel time on route and time-of-day choice. The author found that travellers would travel closer to their preferred scheduled time if they planned to take the tolled lanes because of the time savings and reduced time uncertainty. These commuters were thus less likely to switch back to free lanes en route.

Hickman et al. (2000) studied the usage of QuickRide programme on the Katy HOV lane in Huston and found that: (1) the total demand for HOV value pricing may be limited in major travel corridors, despite large potential time savings; (2) substantial shifts in mode and time of travel are possible with HOV value pricing and (3) household size and income are good indicators of different behaviour responses under the QuickRide programme.

Yelds and Burris (2000) studied the variable toll pricing programme in Lee county, Florida. The authors found that commuters and drivers on work-related travel were

less likely to reschedule their departure times as a result of toll. The result also indicated that those with flexibility in their travel plans do change their travel to take advantage of the variably priced tolls.

Burris and Pendyala (2002) reported on results from the LeeWay scheme (two bridges with variable tolls in the Lee county area of Florida – refer to Section 2.2.1 for more details about this scheme). They found that travellers who were retired or had flexitime at their place of employment, or had a flexible travel schedule were more likely to alter their time of travel with greater frequency to obtain the toll discount. Conversely, having a high household income or being on a commute trip decreased the likelihood.

Results of a study by Bonsall and Palmer (1997) from a driving simulator indicated that drivers took more risks when they were being charged for their use of road-space on the basis of time than they did when they were not subject to such charging. The effect was apparent even at very low charge levels and was observed irrespective of whether the charge was based on total travel time or time spent below a specified speed-delay limit. However, there were some differences in the types of risky behaviour induced by these two charging regimes. The authors suggested that these results have obvious and potentially serious implications for the implementation of time-based road-user charges.

Nielsen (2003) studied the route choice under a simulated distance-based charging system with GPS-based device in Copenhagen. The road pricing system comprised three virtual cordon rings with different charging rates. Simulated cost information was provided to 400 test car drivers who had known that an amount of money would be paid to them according to their observed route choice behaviour. The author found that the participants' attitudes to road pricing were less emotional than expected and most participants did not consider surveillance (that the cars can be tracked by the GPS system) as a problem.

Based on the same GPS data as used by Nielsen (2003), Schönfelder et al. (2005) studied how road pricing affected the choice of destinations and the size and structure of activity spaces. The authors found that the average number of trips, the kilometres driven and the departure time were clearly affected by the simulated road pricing. The investigation has also shown that different charging schemes affected the participants' OD pattern very differently. Compared with kilometre-based charging, cordon based charging reduced the traffic across cordons very efficiently but tended to leave internal traffic unchanged.

Polak et al. (1994) presented an initial assessment of the long-term effects of the Singapore ALS on travel behaviour. It was postulated that the dynamics of the long-term relationship between traffic flows and explanatory variables such as travel cost, income and car ownership could be represented. They found that in 1992 the level of car use in the RZ was still significantly below its pre-ALS level, despite a substantially reduced ALS charge and an almost two-fold growth in car ownership. The dynamics of the long-term relationship between traffic flows and explanatory variables such as travel cost, income and car ownership were represented by the model:

$$\text{Ln}(Q_{AMt}) = \theta_0 + \sum_l \theta_l \text{Ln}(X_{lt}) + \theta_Q \text{Ln}(Q_{AMt-1}) + \varepsilon_t \quad [2.3]$$

where:

Q_{AMt} is the volume of cars entering the RZ during the AM ALS period, in year t ;

X_{lt} is the explanatory variable X_l in year t ;

θ_l is the model coefficients for variable X_l ;

θ_0 is a constant;

ε_t is a disturbance term (which may be possibly serially correlated).

Zhang (2001) studied the impacts of ERP on the drivers' modes, routes and departure time choice, basing on SP data collected in Singapore in 1999. He

constructed a general linear model to represent the relationship between the traffic volume and the travel behaviour affected by the ERP charging rate. The model calibration obtained a vector value of {1.19, 1.26, 7.48} for the coefficients of three explanatory variables, which were defined as the percentages of the observations in changing their modes, routes, and departure times. According to these coefficient values, the author concluded that the effects of ERP on the travellers' departure time choice were much larger than that on the route and mode choices.

Li (1999) developed a simple but practical method for policy makers and transport planners to estimate the road pricing rates by using the commonly available traffic count data. The author derived a formula for estimating the theoretical congestion tolls for two fixed arterial road circuits (circuit A and B) in terms of the travellers' average wage rate ω (\$), value of waiting time δ_w , value of moving time δ_m and traffic flow x (vehicle/h/lane):

$$\begin{aligned} Toll_{circuitA}(x) &= \frac{(0.0353 \delta_w + 0.0581 \delta_m) \omega}{150} x \\ Toll_{circuitB}(x) &= \frac{(0.0596 \delta_w + 0.0511 \delta_m) \omega}{150} x \end{aligned} \quad [2.4]$$

Li (2002) derived the theoretical congestion toll estimate from a class of speed-flow relationships and proposed an iterative procedure to pinpoint the optimal congestion toll based on the speed-flow relationship and the value of generalised cost in the absence of a demand function. Through detailed deduction from the generalised Drake model, the author obtained the optimal congestion toll function for the cordon of RZ in Singapore as:

$$Toll = \frac{c}{u} \frac{\ln 42.08 - \ln u}{\ln u - \ln 8.82} \quad 8.82 \text{ km/h} < u < 42.08 \text{ km/h} \quad [2.5]$$

And for the expressways as:

$$Toll = \frac{c}{u} \frac{\ln 77.8 - \ln u}{\ln u - \ln 46.7} \quad 46.7 \text{ km/h} < u < 77.8 \text{ km/h} \quad [2.6]$$

where, u is the traffic speed (km/h). The generalised cost c (\$) is estimated by the value of travel time saving, which is usually expressed as a percentage of the wage rate.

2.2.5. Summary and Conclusions

Through the review of literature on road pricing systems, it is found that the differences in objectives, fee structure, technology and charging methods would lead to differences in scheme design and performance. It means that the findings of one study based on a specific system may not be applicable to another system. Therefore, when the results are compared to another scheme, one should be very careful to consider the context. This conclusion is further validated by reviewing the research of travel demand elasticity with respect to road pricing from the various charging systems.

From the literature on road pricing in Singapore, it is clear that the system's impacts in different phases were considerably different since its initial introduction in 1975 to this day. Almost all the studies showed that the effects on traffic were positive. However, there have been very few systematic and in-depth studies on the effects of ERP on traffic pattern so far. For example, it is still unknown how the ERP rates redistribute the traffic over the time of day.

Behavioural responses under several existing charging systems have been investigated by some studies. Reviewing the literature, one can find that most of these studies were focused on finding the relationships between drivers' socio-economic characteristics and their behaviour under road pricing. These studies can help in understanding more about the long-term (over several years) impacts of road pricing policy on different subgroups of travellers. However, since in the short term (within several weeks, or a few months) the socio-economic

characteristics of a particular population (i.e., the travellers) and the physical characteristics of the transportation networks are relatively stable, their impacts on travel responses would be much lower than those caused directly by the changes of charging rates. To forecast the traffic volumes shortly after a road pricing change, a short-term model would be more useful. Therefore, the short-term impacts of road pricing on travel responses are worthy of study.

Based on the actual traffic data collected in Singapore, Polak et al. (1994), Zhang (2001) and Li (1999; 2002) have contributed to this field of study. However, there remains a significant scope to extend the research that was earlier hampered by the limitations of data and methodology.

In summary, despite the widespread interest in the topic, there is still lack of a systematic study on the impacts of road pricing on actual travel behavioural responses and reliable models that can be used to estimate the short-term impacts of a road pricing system, especially a system with time-variable pricing such as implemented in Singapore.

2.3. SCHEDULING DECISION MODELS

2.3.1. Theory behind Discrete Choice Models

The classic technique for modelling individual choice behaviour is the discrete choice model derived from random utility theory. As cited by McFadden (2000), the concept of random utility theory was originated by Thurstone (1927). Later Marschak (1960) generalised this law to stochastic utility maximization in multinomial choice sets (RUM model).

Utility of choosing alternative i for individual n (U_{ni}) is modelled as a random variable and represented by two components:

- A measurable, systematic or representative part V_{ni} which is a function of the measured attributes $\mathbf{X}$ and coefficients $\boldsymbol{\theta}$; and
- A random part ε_{ni} which reflects the particular tastes of each individual, together with any measurement or observational errors made by the modeller.

Thus, the modeller postulates that:

$$U_{ni} = V_{ni} + \varepsilon_{ni} \quad [2.7]$$

Individual n selects the maximum-utility alternative, that is, the individual chooses alternative A_i if and only if:

$$U_{ni} \geq U_{nj}, \quad \forall A_i \in A(n) \quad [2.8]$$

Then the probability of choosing A_i is given by:

$$P_{ni} = \text{Prob} \{ \varepsilon_{nj} \leq \varepsilon_{ni} + (V_{ni} - V_{nj}), \quad \forall A_i \in A(n) \} \quad [2.9]$$

Assumption on the distribution of random errors leads to different families of discrete choice models. If the random error is assumed to be Normal-distributed, the model family is called Probit. If it is assumed that random error is Gumbel-distributed, then the models developed based on Equation [2.7] belong to the family of Logit models. In this family, multinomial logit model (MNL) is the most popular and practical model, according to which the probability of choosing alternative i by individual n is given by:

$$P_{ni} = \frac{e^{V_{ni}}}{\sum_j e^{V_{nj}}} \quad [2.10]$$

In comparison, Probit models are very flexible. Hausman and Wise (1978) first developed a conditional Probit model for qualitative choice, and Haaijer et al. (1998) provided an application by using a conjoint multinomial Probit model. However,

lacking a close form solution makes it less popular than its sibling – the Logit model (Walker, 2001). Approximations are required to solve it numerically. On the other hand, there are certain situations where even if it were possible to implement it, the full generality afforded by the Probit model would be an unnecessary luxury because specific forms for the utility functions of models would make the models to be very poor in terms of transferability (Ortúzar and Willumsen, 2001).

Luce (1959, cited by Ben-Akiva and Lerman 1985) first stated the property of Independence from Irrelevant Alternatives (IIA), which was the foundation of his probabilistic choice model. For any two alternatives i and m , the ratio of the logit probabilities is:

$$\frac{P_{ni}}{P_{nm}} = \frac{e^{V_{ni}} / \sum_j e^{V_{nj}}}{e^{V_{nm}} / \sum_j e^{V_{nj}}} = \frac{e^{V_{ni}}}{e^{V_{nm}}} = e^{V_{ni} - V_{nm}} \quad [2.11]$$

Luce showed that the ratio of the logit probabilities does not depend on any alternatives other than i and m . That is, the relative odds of choosing i over m are the same no matter what other alternatives are available or what the attributes of the other alternatives are. IIA is a disadvantage in the sense that the model will perform poorly when there are some alternatives that are very similar to others. However, IIA makes it logical to estimate a choice model using a sample of alternatives. Due to its advantages, MNL has been one of the most popular, practical and advanced modelling techniques employed in behavioural studies.

In estimation of the discrete choice model, the coefficient θ_l of an explanatory variable X_l , theoretically has an estimated variance S^2_l . Thus, if its mean $\theta_l = 0$, the statistic

$$t = \theta_l / S_l \quad [2.12]$$

has a standard Normal distribution $N(0, 1)$. For this reason it is possible to test

whether θ_l is significantly different from zero (it is not exactly a t -test as we are taking advantage of a large-sample approximation and t is tested with the normal distribution). Sufficiently large value of t (typically bigger than 1.96 for 95% confidence level) leads to the rejection of the null hypothesis $\theta_l = 0$ and hence to accepting that the attribute has a significant effect.

Ben-Akiva and Lerman (1985), Ortúzar and Willumsen (2001) as well as Train (1986; 2003) provided a good general discussion of the discrete choice theory, including models of general extreme value (GEV: multinomial logit, nested logit and cross-nested logit) and the Probit model.

2.3.2. Data Used for Discrete Choice Modelling

In the domain of travel behaviour research, most of the models are based on two kinds of data: revealed preference (RP) and stated preference (SP). RP data relate to people's actual choices in real-world situations, while SP data are data collected in experimental situations where respondents are presented with hypothetical choices.

There are advantages and limitations to each of these two types of data. On one hand, RP data have the advantage that they reflect actual choices. This is an important advantage, given the common problems of overreacting, misunderstanding and under-reporting phenomena in SP surveys. On the other hand, the advantage of SP data is that an experiment can be designed to contain as much variation in each attribute as the researcher thinks appropriate, or, it can be used to study a situation that does not currently exist (Train, 2003). Advantages and disadvantages of each type of data are discussed extensively by Ben-Akiva and Morikawa (1990), Polak and Meland (1994), Bates (1998), Louviere et al. (2000) and Ortúzar and Willumsen (2001).

It has been found that considerably different conclusions will be obtained from SP

and RP data in the field of road pricing study. Ghosh (2001) studied commuters' willingness to pay to reduce congestion and uncertainty under the San Diego I-15 Congestion Pricing Project (with HOT discount). He used both SP and RP data to study the mode choice between a tolled (driving solo) and a free alternative (ridesharing). Testing various disaggregate models, the author found that there was always a significant difference in values of time estimated from RP and SP data. An attempt to merge the two datasets was statistically rejected which seems to imply that commuters are behaving fundamentally differently. Thus, the author concluded that the difference between SP and RP data for congestion charging cannot be attributed to sample selection bias, but rather commuters responding differently to controlled experiments and actual choice situations. This means that the SP data may be unreliable, since in an interview survey commuters seem to systematically overestimate the time savings or other benefits from charging. The same conclusions were reached by Lam (2000) and Lam and Small (2001).

Despite the general consensus that RP data are much more reliable than the others for studying actual travel behaviour with respect to an existing transportation policy, few studies have used RP data for trip-timing decision investigations, especially in the field of road pricing due to the fact that RP data of road pricing are very scarce. Even in those few studies based on RP data, small samples (usually, less than 200) of respondents were used. The best individual RP data for travel response study under road pricing so far may be those used both by Lam (2000) and Lam and Small (2001). In their studies several observers drove up and down the study sites (SR 91, see the previous introduction of this system) to track the potential respondents in the summer of 1998. They only successfully recorded the choices of fewer than 700 respondents that could meet the requirements of their study. It is worth noting that the RP data collected in this way may lead to a sample bias problem. Statistics theory says that bias occurs when the components of the population of interest are complex whereas sample size is small. The travel

responses of these respondents possibly are not completely representative of the entire population of travellers.

It is also worth noting that most studies reported in the literature collected data pertaining to a single policy (especially in road pricing studies) from (one wave) cross-sectional surveys or two-wave panel surveys. In the panel surveys, the time interval between the two waves of data collection was usually more than 10 months. For example, Lam (2000) used the first wave of data collected in summer 1997, while his second wave of data was collected in summer 1998. The long interval between multi-wave surveys may introduce some unexpected noise into the data due to changes in the socioeconomic situation of respondents. The long-term socioeconomic changes consist of personal factors (such as respondents' age, income and household size), economic factors (such as the gasoline price and national car population) and possible changes in the transportation infrastructure. Therefore, data collected from this kind of panel surveys may not be suitable for modelling the short-term impacts of road pricing change on a complex population of travellers. In-depth studies of the advantages and disadvantages of panel data, as well as some methods to correct the biases (e.g., sample selection bias and attrition bias) in panel surveys can be found in Hensher (1987), Kitamura and Bovy (1987), and Kyriazidou (1997).

With the great progress of computer simulation technology, some vivid driving simulators are starting to be used for data collection, such as Leeds Advanced Driving Simulator (LADS) and Iowa Driving Simulator (IDS). These data, as well as those collected from simulated road charging systems, can be seen as experimental data. McFadden (2000) pointed out that the use of experiments rather than field surveys to collect data on demand has several major advantages: (1) the environment of hypothetical choice can be precisely specified with a design that allows straightforward identification of effects; (2) innovations in services can be

studied; (3) large quantities of relevant data can be collected at moderate cost. However, as with any experiment, one should be very careful in considering to what extent laboratory behaviour is a good predictor of field behaviour.

2.3.3. Disaggregate Models of Scheduling Decisions

The problem of modelling scheduling decisions (or trip timing) has been considered by many researchers, mainly in the context of peak spreading and traffic assignment. Reviews of the body of work were provided recently by Bates (1996), Mahmassani (2000), Batley and Clegg (2003) and Ben-Akiva and Bierlaire (2003). It has been recognised that drivers commonly respond to network congestion by changing their route and/or departure time. When congestion builds up and travel time increases, peak spreading is a commonly observed phenomenon.

This section summarises a few well-known studies on this subject, mainly in the context of discrete choice framework. The original theory for modelling peak spreading, which has been seen as an explicit reflection of travellers' scheduling decision, is reviewed first.

Vickrey (1969): Original Theory for Modelling Peak Spreading

As cited by Small (1982) and Hyman et al. (2000), the original theory for modelling peak spreading goes back to Vickrey (1969). His approach rests on the direct equilibrium of simple models of demand and network performance. He considered a situation in which a fixed number of homogeneous travellers move along a single link. Travellers choose their departure time from the origin according to a generalised cost composed of their travel duration (TRTIME) and schedule delay. Schedule delay was defined as the difference between their actual arrival time and preferred arrival time (PAT), which was assumed to exist for each traveller. Thus for a departure at time t , each traveller experiences a generalised cost $C(t)$, which in a deterministic form was expressed as:

$$C(t) = \tau \text{TRTIME}(t) + \beta_1 \text{Max} \{ 0, [PAT - t - \text{TRTIME}(t)] \} + \beta_2 \text{Max} \{ 0, [t + \text{TRTIME}(t) - PAT] \} \quad [2.13]$$

Vickrey's study provided a foundation for further modelling of peak spreading and scheduling decisions.

Small (1982): Discrete Choice Model of Scheduling Decision

The empirical estimation of utility functions involving travel time and schedule delay was pioneered by Small (1982) who investigated trip timing choices of car commuters. Although the scheduling decision is inherently continuous, it was modelled as a discrete choice among time intervals for two reasons: survey responses are usually rounded off to several minutes, and disaggregate models can easily portray the complex manner in which the key independent variable, travel time, varies across possible schedules.

According to Small's approach, a traveller's utility function of scheduling choice can be described by Figure 2.1. The traveller has a PAT for his travel. Any arrival time differing from the PAT would lead to an additional schedule delay utility, which was postulated linear. The rate of utility decrease caused by scheduling the arrival earlier (relating to *SDE*) than the PAT differs from that caused by scheduling it later (relating to *SDL*). The travel condition en route corresponds to the traveller's scheduling of his departure time, and then leads to a changing utility of travel time along the time of day. The traveller's scheduling choice is the result of his utility maximisation which involves a trade-off between the travel time and schedule delay from his PAT.

The model utility function $V(t)$ corresponding to arrival time t was expressed as:

$$V(t) = -\tau \text{TRTIME}(t) - \beta_1 \text{SDE} - \beta_2 \text{SDL} - \delta d_L \quad [2.14]$$

where the schedule delay terms SDE , SDL , and binary indicator variable d_L are defined as:

$$\begin{aligned} SDE &= \text{Max}(PAT - t, 0) \\ SDL &= \text{Max}(t - PAT, 0) \end{aligned} \quad [2.15]$$

$$d_L = \begin{cases} 1 & \text{if } t > PAT \\ 0 & \text{otherwise} \end{cases}$$

Figure 2.1: An example of utility formulation of scheduling decision (based on Small 1982)

For calibrating the model, Small used RP data with a sample of 527 car commuters in the San Francisco Bay Area: each reported his PAT and the actual arrival times. Using network-based estimation, travel times were estimated for 12 intervals of 5 minutes each. The model specification also included variables allowing for a tendency to round arrival times to 10 or 15 minute intervals. The coefficients were estimated by assuming a discrete choice among the possible arrival time intervals available to each respondent.

The choice model uses MNL for estimation purpose. Considering the IIA assumption of MNL model, Small noted that the conditions on the error terms of utility functions do not appear to be very reasonable: correlated errors may exist

among the alternatives (the 12 time intervals) which perhaps have a natural ordering. However, the tests he reported indicated that the parameter estimates appeared stable under more complicated assumptions. He also noted that substantial correlation was detected in subsequent analysis, but the parameters were not sensitive to the assumption of independence. Small concluded that the coefficients are robust to reasonable relaxation of the MNL error assumptions.

For the simplest model, Small obtained:

$$V(t) = -0.106 TRTIME(t) - 0.065 SDE - 0.254 SDL - 0.58 d_L \quad [2.16]$$

More detailed specifications in Small's model suggested that: the late parameter might be higher when lateness exceeded a commuter's flexibility level in arrival time; those who car-pooled had a lower sensitivity to early arrival.

Studies to Extend Small's (1982) Model

McCafferty and Hall (1982) developed a similar MNL model for a single decision of trip time. They found that travellers show a strong bias towards travelling in the peak, which is not simply a function of fixed work schedules but is also due to constraints related to their main activities during a day.

Hendrickson and Plank (1984) widened the MNL model to deal with simultaneous mode and departure time choice. They proposed the utility function as:

$$V_{ijt} = a_0 + a_1 FTT_{ijt} + a_2 CONG_{ijt} + a_3 (COST/Y)_{ijt} + a_4 ACC_{ijt} + a_5 WAIT_{ijt} + a_6 LATE_{ijt} + a_7 (LATE_{ijt})^2 + a_8 EARLY_{ijt} + a_9 (EARLY_{ijt})^2 \quad [2.17]$$

where:

- FTT* is free flow in-vehicle travel time;
- CONG* is congestion portion of total travel time;
- COST/Y* is monetary cost;

<i>ACC</i>	is walking time on home end;
<i>WAIT</i>	is waiting time;
<i>LATE</i>	is minutes of late arrival at work;
<i>EARLY</i>	is minutes of early arrival at work.

Their estimated result was:

$$V = -0.00046 \text{ } EARLY^2 - 0.143 \text{ } LATE + 0.0013 \text{ } LATE^2 \quad [2.18]$$

Small (1987) extended his earlier work with a cross-nested logit (CNL) model, where m adjacent time intervals were nested together, capturing their intrinsic correlation. He also employed an ordered generalised extreme value (OGEV) model. This model was explicitly designed to accommodate correlated errors among alternatives that may have a natural ordering.

Hyman (1998) extended the penalty term for schedule delay based on Small's basic model to include an indifference band around the PAT into the time choice disutility function. The indifference band does not mean that people are equally happy with arriving anywhere within the band, but rather that their maximum expected utility is consistent with a distribution of arrival times within a reasonable range; it is this range which could be said to constitute the band. This leads to the conclusion that the contribution of schedule delay utility may be zero or near when the arrival time is within this indifference band. Thus, the curve of schedule delay utility in Figure 2.1 can be revised to that shown in Figure 2.2.

Figure 2.2: Schedule delay utility curve in extended Small's formulation (based on Hyman 1998)

Mahmassani and Chang (1985) and Extensions

Mahmassani and Chang (1985) presented a theoretical framework describing the processes by which commuters' daily departure-time decisions respond to experienced congestion patterns and exogenously supplied information.

This framework was further extended in Mahmassani and Chang (1986). In the study, Mahmassani and Chang employed a longitudinal method to investigate travellers' dynamic adjustments of departure times with respect to the simulated profits change over successive days.

The data collected were not strictly based on SP methods. A simulation model was built to estimate arrival time at a central work location, given the departure time profile, with origins located at varying distances. Effectively, speed was a function of volume and capacity. A "real time" experiment was then set up with 100 volunteers, each of whom was taken as representative of 20 vehicles on the network. They were assigned to various origins, told the free flow speeds and asked to choose departure times, given a fixed work start time. The resulting profile was input to the simulation model, to generate an arrival time for each respondent. On subsequent days, they were told of the simulated time on the previous day, and

invited to reconsider their departure time. The respondents were contacted every weekday for as long as the experiment took to reach equilibrium. In practice, no one made further shifts in departure time after 25 days.

The analysis conceptualised commuter behaviour as a boundedly-rational search for an acceptable departure time. Rather than analysing the data on the basis of utility maximisation, it was postulated that respondents would stop shifting once they were within an indifference band about their PAT. This means that drivers look for gains only beyond a threshold, within which the results are indifferent for them.

To extend the previous work, Mahmassani (1990) investigated daily switching of departure time and route by individual commuters in response to congestion experienced in the system or to exogenously supplied information. He also studied the indifference band existing in the travellers' timing decisions from his laboratory-like experiment.

Jou and Mahmassani (1996) found that fewer than 10% of commuters maintained the same departure times (within a 5-minute threshold) every day over their 2-week period of survey. They concluded that the one-side threshold of indifference band of a traveller's PAT is between 5 and 10 minutes.

Mahmassani and Jou (1998) used survey data from Dallas, Texas, area to develop a particular model for early indifference band of departure time (IBDT) selection as:

$$IBDT_{it} = 23.26 + 7.61 AGE_i - 5.59 GENDER_i + 5.49 NFAIL_{it}^{1.16} + 4.17 \delta_{it} \left(\frac{\Delta TR_{it}}{\Delta DT_{it}} \right) + \varepsilon_{it} \quad [2.19]$$

and for late indifference band as:

$$IBDT_{it} = 17.82 + 4.51 AGE_i - 6.57 GENDER_i + 4.36 NFAIL_{it}^{0.78} + 2.98 \delta_{it} \left(\frac{\Delta TR_{it}}{\Delta DT_{it}} \right) + \varepsilon_{it} \quad [2.20]$$

where:

AGE is an individual characteristic;

$GENDER$ is an individual characteristic;

$NFAIL_{it}$ is the number of unacceptable early (late) arrivals till day t ;

ΔTR_{it} is the difference between travel time of commuter i on day t and $t-1$;

ΔDT_{it} is the departure time that commuter i has adjusted between t and $t-1$;

δ_{it} is a binary indicator variable, equal to 0 if $DT_{it} = DT_{it-1}$; otherwise 1;

ε_{it} is an error term for commuter i on day t .

Bates et al. (1990): Scheduling Decision under Road Pricing in Holland

Some researchers have considered scheduling decision in conjunction with road pricing. In a study for road pricing in Holland, Bates et al. (1990) estimated a scheduling decision model by conducting an SP experiment. The MNL model can be seen as one extension of Small's 1982 approach. It involves a ranking exercise with twelve treatments presenting trade-offs between time of arrival, journey duration and toll.

Respondents were all travelling at peak hours, and were segmented into "commuters" and "others". The SP design presented shifts forward and backward of 30, 60 and 90 minutes, dependent on the timing of the current journey relative to the peak. The respondents were asked which option they would prefer when the journey had taken longer: (a) depart earlier and arrive at the same time; or (b) depart at the same time and arrive later. On the basis of this response, the respondents were described as arrival-constrained or departure-constrained.

In this model, the values of the shift could be related to changes in travel time and

cost. After some experimenting it was concluded that in most cases the scheduling utilities were linear in the amount of the shift.

Analysis of Bates et al. (1990) showed that arrival-constrained people are less willing to move after peak hours than departure-constrained people. In the afternoon, people are generally more flexible to arrange their departure times and people with no departure constraints tend to leave much earlier than the peak. Overall, they showed that people who travel outside the middle of the peak hours are less willing to change their departure patterns and there are significant differences between commuters who are arrival-constrained and those who are departure-constrained. The authors concluded that there is definite indication that not all travellers are travelling at their PATs and some have already shifted to take advantage of travel time gains.

Polak et al. (1991): Scheduling Decision under Road Pricing in Norway

In a similar approach as that developed by Small (1982), Polak et al. (1991) carried out modelling based on SP data from Trondheim, Norway. The authors assumed that car travellers have one of the following responses:

- (1) Pay toll and travel at the preferred time period (with possible time savings);
- (2) Shift to a period earlier before the tolled period;
- (3) Shift to a time after the tolled period;
- (4) Change to public transport.

The choices were related to home-based tours rather than trips, and were dependent on: (1) period of operation of toll ring; (2) toll charge; (3) car travel time; (4) bus fare. The SP choices were analysed by an MNL model of simultaneous mode and travel time choice. Its basic functional specification of the alternatives had the following forms:

$$\begin{aligned}
 V_{pay} &= \alpha \cdot TOLL + \tau_1 \cdot CarTRTIME \\
 V_{early} &= \beta_1 \cdot CarSDE + \tau_1 \cdot CarTRTIME \\
 V_{late} &= \beta_2 \cdot CarSDL + \tau_1 \cdot CarTRTIME \\
 V_{bus} &= d_{bus} + \beta_3 \cdot BusSDE + \tau_2 \cdot BusTRTIME \\
 &\quad + \theta_1 \cdot BusWT + \theta_2 \cdot BusWKT + \theta_3 \cdot BusFr
 \end{aligned}
 \tag{2.21}$$

where:

<i>TOLL</i>	is toll charge;
<i>CarTRTIME</i>	is travel time by car;
<i>CarSDE</i>	is minimum early shift required to avoid the toll charge;
<i>CarSDL</i>	is minimum late shift required to avoid the toll charge;
<i>BusSDE</i>	is reported re-timing associated with switching to the bus;
<i>BusFr</i>	is the bus fare;
<i>BusWT</i>	is the bus waiting time;
<i>BusTRTIME</i>	is the bus travel time;
<i>BusWKT</i>	is the total walking time to and from bus stops.

For commuters with fixed work-time, the estimated result of Polak et al. (1991) model showed that lateness is more onerous than early arrival, with values of -1.019 for late shift and -0.66 for early shift, respectively.

Chin (1990): Departure Time Choice under Singapore's ALS

Chin (1990) used MNL and simultaneous nested logit (NL) models to analyse the commuters' choice of departure time under ALS, based on household data collected in Singapore in 1983.

In his NL model, the morning departure times for work were classified into three main periods, very early morning (6:00–6:59 AM), early morning (7:00–7:59 AM) and morning (8:00–8:44 AM). Each period was divided into four quarters except for the final morning period. Chin found that schedule delay, travel cost, and journey time had important influences on commuters' choice of trip departure time to work.

However, as commented by Bates (1996), the model estimated by Chin (1990) did not distinguish between early and late time. Bates also commented that in Chin's model, the ratio of the schedule delay to travel time coefficients is very high (>4.0), but the source of the travel time data was not discussed.

Lam (2000): Travel Responses under Tolloed HOV Lane in the US

Using the RP data collected from SR 91, Lam (2000) postulated the utility function in a MNL model for joint route and scheduling choice as:

$$V(r) = -\tau TRTIME(r) - \beta_1 SDE(r) - \beta_2 SDL(r) - \delta d_L(r) - \alpha Toll \quad [2.22]$$

where, r is the index for the choice of route, namely, free lanes or tolled lanes;

$SDE(r)$ and $SDL(r)$ are schedule early and late for route r respectively;

$d_L(r)$ is the delay dummy variable.

Lam took the departure time as a factor that affects the road users' route choice, and replaced the PAT term in the definitions of schedule delay by work-start time. However, this is not consistent with the finding of Jou and Mahmassani (1996) that commuters preferred to arrive at work an average of about 15 minutes prior to the official work start time.

The study of Lam (2000) was a rare systematic research on short-term impacts of road pricing on route/time choices. However, the particular study site he chose, SR 91, has a unique charging structure: free lanes are parallel to tolled lanes. It undoubtedly impacts the users' route choice (free lanes or tolled lanes) more directly than other behaviour, for instance, departure time choice and mode choice. This implies that travellers may respond to SR 91 differently than to the other road pricing systems.

Other Disaggregate Models of Scheduling Decision under Road Pricing

There are also other studies which used discrete choice models to find the relationship between drivers' socio-economic characteristics and their scheduling responses under road pricing. For example, Lam and Small (2001) used logit models to examine the relationship between drivers' socio-economic characteristics and their choice of using toll lanes. Bhat (1998) studied urban shopping trips in San Francisco Bay area, where a tolled bridge is located. He found that travellers are more likely to shift departure time than to change travel mode with respect to the toll. Burris and Pendyala (2002) developed binomial and MNL models based on the SP data from the LeeWay scheme.

2.3.4. Scheduling Models without PAT Information

In all the disaggregate methods which were based on Small's (1982) approach, PAT is a key variable in the model. However, as it is a latent variable, information on PAT is often unavailable without a SP survey.

Hyman et al. (2000): PAT estimation

Hyman et al. (2000) developed a model for PAT estimation:

$$PAT = AAT - SHIFT - SM + PT \quad [2.23]$$

where:

AAT is the actual arrival time at the destination;

SHIFT is the planned time shift;

SM is the personal safety margin to take account of uncertainty of travel time;

PT is the unplanned additional travel time, which varies according to the network performance (mainly related to time of day and to whether system is in "equilibrium");

However, the authors acknowledged that this model might not be reliable, since no existing dataset provided access to separate estimates of *SHIFT* and *SM*, except for their sum. Additional assumptions regarding these two key variables were made in order to produce an identifiable model. This means the PAT estimated by using this approach is questionable in the absence of important information.

Chin et al. (1995): Aggregate modelling

Some studies have tried to employ aggregate method to model scheduling decisions by excluding PAT as a variable. Chin et al. (1995) employed incremental logit model approach, assuming that the time profile will change from an observed position in line with the change in the travel time gradient.

Incremental logit model has been used extensively in the context of modal choice and distribution models and is similar in structure to the well-known multinomial logit model. For scheduling decision, the following form is specified:

$$P_j^s = \frac{P_j^0 \exp(\alpha \text{Cost}_j^s - \alpha \text{Cost}_j^0)}{\sum_k P_k^0 \exp(\alpha \text{Cost}_k^s - \alpha \text{Cost}_k^0)} \quad [2.24]$$

where:

P_j^0 is the base proportion of demand flow in time slice j ;

Cost_j^0 is the base cost for travel in time slice j ;

P_j^s is the new proportion of demand flow in time slice j ;

Cost_j^s is the new cost for travel in time slice j .

This model avoids the calibration issues of the multi-period model by taking the observed profile and the choice probabilities for each time interval as the base for “pivoting”, and using a logit sensitivity parameter (α) in place of an explicit transfer penalty. This method is appropriate for estimating traffic shares over time of day based on aggregate data.

However, two problems arise when it is applied to modelling individual scheduling decisions. One problem comes from the model structure. No arrivals of travellers observed in a particular time slice under the “pivoting” choice condition means zero base proportion for the traveller to choose this alternative. Then it leads to zero forecast of choice probability for this time slice under any new choice conditions according to the incremental logit model function. However, this may not be true since the zero base proportion is estimated based on limited observations for each particular traveller, and it can never be certain that the limited observations reflect exactly the traveller’s timing decision under specific time choice situations. Another problem is caused by the principle that incremental model uses the base shares as implicit measures of attractiveness for each time slice. That means there will be no difference for a traveller who prefers travelling in a time slice (say, slice 3) to choose other slices (say, slice 2 and slice 8) which have the same base shares and changed profiles, since there would be no penalty of scheduling delay within the incremental model.

These two problems make the incremental approach unpractical for modelling scheduling decisions based on individual data. However, it provides a simple method for modelling the change of travel demand with respect to a particular policy variable based on aggregate data.

2.3.5. Summary and Conclusions

The development and application of quantitative models of discrete choice behaviour has proved that they are a robust tool for estimating the factors in travellers’ choice making. This ability can assist researchers in analysing the impacts of a policy, e.g. road pricing, on the behavioural responses of road users.

Small’s (1982) original study and its extensions provide a standard microeconomic perspective for modelling traveller’s scheduling choice. It views the scheduling

decision as a result of trade-off between trip time/cost and schedule delay from the PAT. So far, this perspective has been the most popular and appropriate for quantitatively modelling the scheduling decision.

As a pre-requisite of the Small's approach, it is essential to obtain information on PAT. The efforts contributed by Hyman et al. (2000) and Chin et al. (1995) provided methods for scheduling modelling without PAT information under certain special situations. However, the methods are not suitable to be applied to behavioural modelling based on individual data. How to address the problem of the lack of PAT information is still a difficult question in this field of study.

The longitudinal method used by Mahmassani and Chang (1985; 1986) is good for investigating travellers' dynamic responses. However, the method for this kind of study needs a careful design. It should be ensured that the multi-wave panel data cover the full period of adaptation. A full period of adaptation means that within that period every individual has finished his exhaustive search for the best adaptation alternative. Although ERP transaction data include repeated observations (arrivals) for each traveller, the very large number of travellers in the system would mean that the definition of full period of adaptation is too complicated and impractical. Therefore, the method is not appropriate for the purpose of this study.

Among the few studies of scheduling decision under road pricing, the discrete choice model developed by Polak et al. (1991) may be the most promising and robust one. However, in their model, the authors assumed that car travellers had only three alternatives of time choice. The model was suitable for a scheme with a flat toll. However, it cannot reflect the delicate decision of scheduling under a time-variable road pricing system.

Overall, it is the scarcity of empirical data that has greatly hampered the study on the actual impact of road pricing on travellers' scheduling decisions. The

disadvantages of SP and laboratory-like experiments make such data to be a poor substitute of empirical data. There are two main reasons why few studies have used RP data so far. Firstly, there are very few road pricing systems implemented in the world. Secondly, there are technical difficulties in collecting the actual individual data from most of the schemes. An electronic pricing system as implemented in Singapore can solve this problem, but few of the schemes in the world have used this technique so far. To use this unique and ample source of actual data to investigate the short-term impact of road pricing on travellers' scheduling decisions, a new modelling methodology is needed.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1. INTRODUCTION

This chapter discusses the proposed research methodology to be undertaken in this study. The major tasks of the study are: pricing sensitivity analysis, motorist population segmentation, framework for modelling and forecasting traffic with respect to road pricing change and construction of scheduling decision models, as well as model calibration and validation. Methodological approaches to forecasting traffic with respect to a new ERP gantry and rate adjustment are presented separately.

3.2. TRAVEL DEMAND SENSITIVITY TO ROAD PRICING

As demonstrated in the literature review, travel demand sensitivity to road pricing is found to vary under different charging structures and different areas. These differences in sensitivity may lead to quite different travel responses. Therefore, an investigation of the pricing sensitivity is necessary.

An explicit method for analysing the pricing sensitivity is to estimate the travel demand elasticities with respect to road pricing. Traffic flow data collected from both Singapore ALS and ERP systems will be used to investigate the elasticity values for different vehicle types, time periods and road categories. The differences between long-term and short-term elasticities can be observed by using the time-series model initially developed by Polak et al. (1994). Overseas experiences will also be compared with the Singapore results.

3.3. SPECIFICATIONS OF SCHEDULING DECISION MODEL

The time-variable pricing method used in the ERP system leads to a more efficient use of the road capacity, by encouraging motorists to reschedule their trips in addition to affecting the total travel demand. Correspondingly, the overall framework for forecasting the impacts of ERP (both of pricing introduction and rate adjustment) on traffic includes two key components: (1) prediction of the total traffic volume; and (2) prediction of the traffic distribution over time intervals.

To predict the traffic distribution over time, modelling the motorists' scheduling decisions under road pricing is an effective method. Methodologies for predicting the total traffic volume will be presented later in the overall forecasting framework, separately for the case of introduction of a new ERP gantry and the case of rate adjustment. As a common part, the specification of a basic scheduling decision model is described in this section. In general, the model specification corresponds to the modelling perspective of motorists' decision making, as well as the characteristics and constraints of the data used.

3.3.1. Basic Microeconomic Perspective

This study will employ the basic microeconomic perspective that traces back to Small (1982) for modelling scheduling decisions. As explained in Chapter 2, this well-accepted paradigm is rooted in utility maximisation theory, applies discrete choice techniques and assumes that each motorist has a PAT for his travel.

Applied to road pricing, this perspective views the individual scheduling decision as a trade-off resulting when the individual takes into account schedule delay from his PAT, travel time, charging rate and external constraints in scheduling his travel. The definitions of PAT in the previous studies were somewhat different from each other depending on their study objectives (see Chapter 2). The main interest of this study is to forecast the impacts of road pricing on traffic flows at the ERP charging point

location. Therefore, PAT will be defined here as the time that an individual would most like to arrive at the charging site if there were no ERP charges and no congestion at any time of day.

As argued by Mahmassani and Chang (1985; 1986) and proposed by Hyman (1998) for a scheduling decision model, it is postulated that there exists an indifference band around a motorist's PAT, an arrival within which is assumed to contribute zero or nearly zero to the schedule delay utility. This concept will be applied to the specification of individual's time choice options in this study.

3.3.2. Variable Selection

A motorist's scheduling decision may be influenced by many factors. However, it may never be possible to include all these variables in modelling. One of the first tasks a modeller faces is to decide which variables are going to be selected into the model. Some variables related to the decision making will not be included at all, either because the modeller lacks the knowledge of them or simply because the theory behind the model does not focus on them.

For the purpose of transportation planning and policy making, the focus will be on policy variables. In this study, charging rate is of particular interest. According to the basic microeconomic view, travel time and schedule delay from PAT are crucial variables in an individual's scheduling decision. Hence, these variables will be included in the model. It is also postulated that there are some latent reasons, e.g., travel inertia and constraints in time choice flexibility, leading a motorist to prefer arrival at his PAT. To represent these unknown factors, a dummy variable is used.

A model involving individual characteristics of drivers (income, gender, age, etc.) is useful for understanding the impacts of a policy on a particular subgroup of motorists. However, this kind of information is neither commonly available nor included in the

ERP transaction dataset. Hence, individual characteristics (other than vehicle type) would not be considered in this modelling study. It is hoped that valid models can be calibrated even in the absence of these characteristics. This is consistent with the aim of this study which is to develop a practical methodology for forecasting traffic in the ERP system planning, which requires that all input values of the model should be commonly available or available from the system itself.

3.3.3. Variable Specifications

Among the selected variables, a modeller should also decide which are going to be predicted by the model and which are possibly required as inputs to it.

ERP rates charged for each vehicle pass are included in the system dataset and hence the transaction values are the inputs to the model.

Travel time is not known directly from the dataset. Given the traffic volumes, speed-flow relationship can be employed to predict the average traffic speeds for each time interval. Given the speed and trip length, the average travel time can be calculated. However, it is sometimes too difficult to determine the length of the trip segment affected by ERP. In this situation, travel time per unit distance can be included as the variable to represent the congestion level, which to a certain degree reflects the travel time factor that is considered by motorists in making the scheduling decisions. This variable will be called congestion penalty in this study and its values are going to be predicted by the model based on traffic flows.

The values of schedule delay from PAT are also going to be predicted by the model since PAT is unknown from the system dataset. The method for the schedule delay prediction relates to the methodology for model calibration which is designed to address the unknown PAT issue. This will be discussed later in detail.

3.3.4. Choice-set of Scheduling Options

Specification of the choice-set for a discrete choice model includes two major issues: the number of alternatives in the choice-set and the definition of each alternative. In modelling scheduling decisions, the specification of time alternative corresponds to the notion of how an individual would like to round off his scheduling decision to a time slice with several minutes. The length specification of each time alternative also relates to the definition of indifference band of PAT.

Following the literature review presented in Chapter 2, fifteen minutes per time alternative is adopted, based on the following evidence:

- (1) It is consistent with the SP survey by Small (1982) that travellers have a tendency to round arrival times to 5, 10 or 15 minute intervals;
- (2) Jou and Mahmassani (1996) found from their survey that the one-side threshold of indifference band of a traveller's PAT is between 5 and 10 minutes. That means the interval from 10 to 20 minutes may be a traveller's indifference band of PAT. As the average value of this range, 15 minutes is a reasonable value.

In choice-set specification, given a typical RP data set, an analyst also has to decide which alternatives are available to each individual. Brute force method is employed to solve this problem: it is assumed that everybody has all the alternatives available and hence lets the model decide that the choice probabilities of unrealistic options are low. Therefore, for each motorist, the number of alternatives in the choice-set is equal to the peak period of interest divided by the length of interval corresponding to one time alternative.

3.3.5. Utility Function Form

Almost all of the existing scheduling decision models constructed the utility function using linear-in-the-parameters expressions, mainly due to two reasons: (1)

linear form function can portray the trade-off relationship between travel cost and schedule delay more simply than non-linear; (2) most of the existing professional software (e.g., Limdep 7.0 and NLogit 3.0) are suitable only for calibrating linear form models. To make the model clearer and more comparable to the existing models a linear form is preferred, while a non-linear form of utility function also will be tested in this study.

The deterministic part of utility associated with time choice option i for a motorist with PAT in interval j is proposed as:

$$V_{ij} = \alpha ERP_i + \tau TRTIME_i + \beta_1 SDE_{ij} + \beta_2 SDL_{ij} + \gamma H_{ij} \quad [3.1]$$

where:

ERP_i = ERP rate during period i ;

SDE_{ij} = schedule delay earlier from period j to i when i is earlier than j ;

SDL_{ij} = schedule delay later from period j to i when j is earlier than i ;

$H_{ij} = \begin{cases} 1 & \text{if } i = j \\ 0 & \text{otherwise} \end{cases}$ binary variable indicating travelling at PAT;

$TRTIME_i$ is predicted travel time per road segment (or per kilometre) corresponding to period i ;

$\alpha, \tau, \beta_1, \beta_2$ and γ are model parameters.

Figure 3.1 depicts an example of motorist's utility function for scheduling choice. It is assumed that the motorist has a PAT for his travel. Any arrival time differing from the indifference band of this PAT would lead to an additional schedule delay penalty in utility. The travel condition en route as well as the charging rate at the gantry fluctuates with time of day, and leads to a changing utility of congestion penalty (or travel time) and monetary cost. The motorist's time choice is the result of his utility maximisation which involves a trade-off consideration of congestion penalty (or travel time), charging rate, benefit of staying at PAT and schedule delay from his PAT.

Figure 3.1: An example of utility formulation of scheduling according to Eq. [3.1]

3.4. PREDICTION OF TRAFFIC AFTER ERP INTRODUCTION

3.4.1. Model Specification

Before the ERP is implemented on a site, observations of individual behaviour are difficult to capture and assemble. Only traffic volume data are commonly available in this situation. Therefore, in planning a new gantry, an aggregate model which predicts the new gantry's impacts on traffic based on the current traffic volume is more practical than models that require data on individual motorists as input values.

The proposed aggregate model concerns choices faced by motorists using a road where a single new ERP gantry is introduced and charges apply during the peak period only. The study period is divided into M 15-minute intervals and thus there are M scheduling alternatives. It is assumed that avoiding the toll is possible by choosing an alternative route or mode. This option represents all those that are priced-off the road and is called the re-routing option. Hence, the model is a joint

model for predicting the total traffic volume (i.e., the number of motorists that choose to be charged) and the traffic distribution over time intervals (i.e., the proportion of motorists choosing each time option).

As presented in Section 3.3, the utility associated with time options will be a linear function of ERP fee, travel time, and length of scheduling delay from the motorist's PAT. For the re-routing option, the utility is assumed to be constant. As reviewed in Chapter 2, MNL is the most popular, practical and long established technique in modelling scheduling decisions. It will be employed in this study.

3.4.2. Framework for Traffic Forecasting

As discussed in Section 3.3.3, the motorists' scheduling decisions will determine the traffic volumes which in turn affect the motorists' travel times. Thus, applying the model to forecast traffic after ERP introduction requires an iterative procedure, combined with travel time prediction. Figure 3.2 shows the flowchart of traffic prediction. The corresponding modelling approach is outlined below:

- (1) Use the traffic volume data observed before ERP to initialise the travel time.
- (2) Use the scheduling model to forecast the traffic volumes for each time interval after ERP introduction. Model input values include traffic volume data before ERP, ERP charging rates and the initialised/predicted travel time.
- (3) Test convergence by comparing the forecast traffic volumes obtained from Step (2) with those obtained from the last iteration: if the differences are less than a pre-defined convergence threshold, stop the procedure and accept the current forecast traffic volumes as the final results, otherwise continue the calibration procedure by going to Step (4).
- (4) Use the forecast traffic volumes to predict the travel time, and then continue the procedure by going to Step (2).

Figure 3.2: Framework for forecasting traffic volumes after ERP introduction

3.4.3. Model Calibration

Two sets of traffic volume data will be used: one set was collected before ERP introduction and the other one after. From the traffic volume data, what is actually observed are not the numbers of motorists making individual time or re-routing choices but traffic volumes comprising individuals with different combinations of choices. In the case of a scheduling decision model, the total traffic observed in an interval comprises all those who chose to arrive in this interval, regardless of their original PAT. The model can be calibrated with the help of the traditional non-linear-least-squares (NLLS) method. The principle of the NLLS calibration method is to find such values of the unknown parameters which minimise the sum of squared differences between the estimated and observed volumes. To test the goodness-of-fit of the model, percentage root mean square error (RMSE) will be used.

The model calibration procedure is similar to that for applying the model to forecast traffic after ERP, also comprising 4 steps performed iteratively. The only differences

are: (a) in Step (2) (see Figure 3.2) traffic volume data observed after ERP introduction are used to estimate the model parameters; and (b) the outcome of the procedure is the model parameters (i.e., the model). At each subsequent iteration, a constrained NLLS estimation is performed in Step (2). The calibration procedure will be presented in detail in Chapter 5.

3.4.4. Model Validation

The performance of any model should be judged against data other than that used to calibrate it and, ideally, taken at another point in time (Ortúzar and Willumsen, 2001). Another set of traffic volume data collected with different ERP charging rates will be used to validate the model. Percentage RMSE will be used to evaluate its performance.

3.5. PREDICTION OF TRAFFIC AFTER ERP RATE ADJUSTMENT

3.5.1. Motorist Segmentation

The ERP transaction data will be used to model and forecast the impacts of rate adjustment on traffic. The motorist population using the ERP system is complex. Systematic taste variations affecting the utility of different individuals are likely to exist among members of this population. Market segmentation, also called traveller or motorist segmentation in transportation studies, is usually used to search for systematic variations of taste parameters among the population categories in order to include them explicitly in the specification of the model utility.

Using elasticity analysis to segment motorists based on obvious factors such as vehicle type and road category is a simple and effective method. Different travel demand elasticities with respect to road pricing may indicate different behavioural responses among the motorist groups. For example, if elasticity values are found to vary among vehicle types, a relevant segmentation of motorists should be conducted.

However, this elasticity analysis method will be difficult to use for further

segmenting of a large group of motorists (e.g., a category including more than 10,000 passenger cars). From a large ERP transaction database which stores the transaction records of the whole motorist population, calculating and comparing the elasticity values among any possible subgroups of the population would be very laborious. Furthermore, based on elasticity values sometimes it is difficult to tell which segmentation criteria are more important than others.

For this reason, data mining will be employed in this study due to its recognised capacity in discovering patterns from huge body of data. Some advanced data mining techniques will be applied to identify the most important but hidden patterns among the motorists that might lead to different responses under road pricing. Based on that, motorists will be divided into several categories. Then separate models will be developed corresponding to this segmentation.

3.5.2. Selection of Modelling Approach for Scheduling Decisions

The selection of the model form for a particular category of motorists involves the adoption of a perspective on how these motorists make their decisions. For some categories, e.g., passenger cars, motorcycles and good vehicles, discrete choice modelling will be employed, due to the advantages of this technique in transportation modelling (see Section 2.3.1). MNL with a linear utility function will be the model form.

However, discrete choice modelling may not always be appropriate for certain categories of motorists. For example, a taxi driver does not have a PAT in his travels and arrival times of a taxi at an ERP gantry do not reflect the driver's scheduling decisions with respect to the charging rates. Different passengers decide the taxi's arrivals and make them look random. Therefore, a discrete choice model developed for taxis based on individual data would make no sense in terms of behavioural analysis. However, the change of taxi volumes with respect to pricing adjustment would reflect the impact of road pricing on the total demand for taxi travel. For

modelling this impact based on taxi transaction data, an aggregate model is more appropriate than a disaggregate model. Incremental logit approach, which has been reviewed in Section 2.3.4, provides a practical way for modelling this special category of motorists in their demand distribution over time of day. For minor and special categories of motorists who are insensitive to road pricing (e.g., ERP exempted vehicles), simplified assumptions will be made and tested.

3.5.3. Framework for Traffic Forecasting

Similar to the prediction of travel time, prediction of congestion penalty is based on the forecast traffic volumes. As presented in Section 3.3.3, this prediction requires an iterative procedure in both of the model calibration and application.

Figure 3.3 presents the approach for using ERP transaction data to forecast the traffic after a rate adjustment. The process is iterative and includes the following steps:

- (1) Based on historical ERP transaction data, motorists are segmented. After that, use the models of travel demand elasticity with respect to road pricing to forecast the total number of passes for each motorist category under the new ERP charging rates.
- (2) Use the traffic volumes obtained from the historical dataset to initialise the congestion penalty.
- (3) Apply the separate scheduling decision models for each motorist category to predict their distribution proportions over the time intervals under the new charging rates.
- (4) For each category calculate the number of passes within each interval by multiplying the category's distribution proportion by its total number of passes. The numbers of passes within each time interval aggregated for all categories are the forecast traffic volumes under the new charging rates.
- (5) Test convergence by comparing the forecast traffic volumes with those

obtained from the last iteration: if the difference is less than a pre-defined threshold, stop the procedure and accept the current traffic volumes as the forecasting results; otherwise continue by going to Step (6).

- (6) Use the forecast traffic volumes to predict the congestion penalty, and then continue the procedure by going to Step (3).

Figure 3.3: Framework for forecasting traffic volumes after ERP rate adjustment

3.5.4. Estimation of PAT and Model Calibration

PAT is the kernel of the basic microeconomic perspective for discrete choice modelling of scheduling decisions. As a special latent variable that cannot be observed, PAT is usually obtained from SP surveys. However, the ERP transaction data do not include information on motorists' PATs.

Given the scheduling decision model utility function and a motorist's transaction records at a particular ERP gantry, the likelihood function for evaluating whether motorist's PAT is within a particular time interval can be quantified. Among the choice-set of his scheduling decision, the time interval corresponding to the highest likelihood function value is the interval of his most likely PAT (MLPAT). Since the calibration of the scheduling decision model depends on each motorist's PAT which in turn is dependent on the model utility function, model calibration combined with MLPAT estimation requires an iterative procedure.

Two sets of transaction data will be used for the model calibration: one recorded before an ERP rate adjustment and the other one after. The calibration approach is iterative and consists of the following steps shown in Figure 3.4:

- (1) Use the individual transaction data recorded before ERP rate adjustment to initialise MLPAT for each motorist belonging to a category involving discrete choice models.
- (2) Use the traffic volume data (obtained from the transaction data) before rate adjustment to initialise the congestion penalty.
- (3) Use the travel demand elasticity with respect to road pricing to forecast the total number of passes for each motorist category after rate adjustment.
- (4) Use the transaction data recorded after ERP rate adjustment to calibrate the separate models. The discrete choice models can be calibrated by employing traditional discrete choice modelling method, whereas the aggregate models

can be calibrated by using NLLS method. Input values include individual transaction information, the initialised/predicted congestion penalty and the initialised/estimated MLPATs. Volume distribution over time intervals after rate adjustment for each motorist category can be calculated from the calibrated models.

- (5) For each category calculate the number of passes within each interval by multiplying the category's distribution proportions by its total number of passes. The numbers of passes within each time interval aggregated for all categories are the forecast traffic volumes after rate adjustment.
- (6) Test convergence by comparing the forecast traffic volumes for each time interval with those obtained from the last iteration: if the differences are less than a pre-defined convergence threshold stop the procedure and accept the current models as the calibration results; otherwise continue the calibration procedure by going to Step (7).
- (7) Use the individual transaction data recorded before rate adjustment and the calibrated discrete choice models to estimate MLPAT for each motorist involved.
- (8) Use the forecast traffic volumes to predict the congestion penalty, and then continue the procedure by going to Step (4).

Figure 3.4: Flowchart for model calibration based on ERP transaction data

3.5.5. Model Validation

At a micro level, the goodness-of-fit of a discrete choice model can be evaluated by the traditional t -test and the ρ^2 index. Accuracy of the model in forecasting individual time choices is also a performance indicator. At a macro level, percentage RMSE is appropriate for evaluating the model performance in traffic volume forecasting.

The modelling framework including the separate models for each motorist category can also be evaluated by its performance in forecasting traffic volumes at a different point in time than that which has been used to calibrate the models. Its application procedure in traffic forecasting has been presented in Section 3.5.3.

CHAPTER FOUR

ANALYSIS OF TRAFFIC DEMAND ELASTICITY

4.1. BACKGROUND

The impacts of road pricing on motorists' behaviour at the macro level are reflected as traffic volume changes over time and space. A study of traffic demand elasticity with respect to pricing is useful for understanding motorists' sensitivity to pricing. Through investigation of elasticity values for different time of day, types of vehicles and categories of roads (with different charging systems), some factors that may lead to different responses under road pricing can be identified.

The time-series model developed by Polak et al. (1994) provides a suitable platform to study the difference between the long- and short-term demand elasticities with respect to road pricing. Their analysis provides a good reference for this study in modelling the impacts of road pricing on short-term travel responses, especially when considering two issues: whether it is necessary to model the responses separately and which variables should be included in the models.

By comparing the elasticity values of Singapore with some overseas experience, the potential reasons leading to different performance of different road pricing systems can be studied. Such an investigation is also helpful for evaluating transferability of models.

The elasticity study described in this chapter is based on the past 30 years' actual traffic flow data, observed before and after each pricing adjustment in Singapore.

4.2. DEFINITIONS OF ELASTICITY

Demand elasticity is defined as the ratio of percentage change in the quantity demanded (Q) to the percentage change in the variable postulated to be inducing that change, e.g. the price (C). In general, elasticity is not constant but depends on the value of C .

As discussed in Chapter 2, Oum (1989) as well as Luk and Hepburn (1993) provided a useful review of elasticity concepts and formulae. According to them, there are various definitions for demand elasticity with respect to road pricing. The following are most commonly used:

- (1) Point elasticity (E_P): see Chapter 2 and Equation [2.1] for its definition;
- (2) Arc elasticity (E_A): see Chapter 2 and Equation [2.2] for its definition;
- (3) Elasticity deduced from a log-log model (E_L):

$$E_L = \frac{\ln(Q^0 / Q)}{\ln(C^0 / C)} \quad [4.1]$$

If the observations of Q^0 and Q are made within a few months (i.e. shortly before and after the price change), Equations [2.2] and [4.1] would produce short-term elasticity. It is postulated that long-term elasticity values are higher as some impacts on the entire population of travellers may take several years to materialise. To estimate those long-term effects, one needs a time series model of demand.

4.3. EFFECTS OF ROAD PRICING UNDER THE ALS

The ALS operated between 1975 and 1998 in the RZ of Singapore. During its 23 years of operation, the ALS had a series of refinements and extensions. A considerable body of literature includes discussions about these changes and their impacts (see Chapter 2).

Table 4.1 shows the changes in the volumes of passenger car traffic entering the RZ corresponding to the changes in charging levels over the years. The corresponding elasticities were calculated using the arc definition (Equation [2.2]).

Table 4.1: Changes in RZ inbound car traffic in response to ALS revisions*

Events	Charge period	C^0 (S\$)	C (S\$)	C as percent (%) of earning#	Q^0 (Vol.)	Q (Vol.)	E_A (Arc)
1975 ALS cordon introduced	07:30–10:15	0.00	3.00	13.5	42790	11459	–0.578
1976 fee increased	07:30–10:15	3.00	4.00	16.9	12106	10754	–0.414
1989 AM fee reduced	07:30–10:15	5.00	3.00	6.20	19026	20963	–0.194
1989 PM fee introduced	16:30–18:00	0.00	3.00	6.20	18960	8374	–0.387
1994 Mid-day fee introduced	10:15–16:30	0.00	2.00	4.79	72313	55514	–0.263

* Arc elasticity values for 1975 and 1989 estimated by Luk (1999)

Average daily earnings

It seems that the initial introduction of the ALS in 1975 had the most dramatic effect on inbound car volumes (70% reduction). This can be explained by the elimination of through traffic and by the relatively high level of charging, which created the initial shock, resulting in structural changes in travel behaviour. Subsequent adjustments of the morning ALS fee levels showed a decreasing elasticity trend. As noted by Polak et al. (1994), the real value of the ALS fee decreased considerably over the years due to rising incomes and inflation: in 1975 the S\$3.00 fee amounted to 13.5% of the average daily wage, while in 1994 it was only 4.8%. The decreasing values of elasticity shown in Table 4.1 could imply that the elasticity is higher at the higher real level of charging.

4.4. LONG-TERM ELASTICITY UNDER THE ALS

The availability of annual counts of traffic entering the RZ made it possible to model the relationship between flow, the level of ALS charges and other exogenous explanatory variables. Such a time series model can help in gaining a better understanding of the long-term effects on traffic flow of the monetary cost of travel (including ALS fees and parking fees) as well as income and the level of car ownership.

Polak et al. (1994) proposed a time series partial-adjust model for assessing the ALS effects (see Chapter 2 and Equation [2.3]). Although more complex specifications were possible, the model had two important advantages. Firstly, the log-log formulation meant that each coefficient θ_i had a direct interpretation as the short-term elasticity (E_{ST}) of AM flow with respect to variable X_i . Polak et al. (1994) considered Car population ($CARS$), National income (GDP), ALS cost ($CALS$) and Parking cost (CP) for years 1974–1993 as the explanatory variables in their model. Secondly, the geometric lag structure that is implicit in the use of the lagged dependent variable ($Q_{AM,t-1}$) provided a characterisation of adjustment dynamics, leading to the following estimate of long-term elasticity (E_{LTl}) with respect to variable X_i :

$$E_{LTl} = \theta_i / (1 - \theta_Q) \quad [4.2]$$

The model proposed by Polak et al. (1994) was re-examined and estimated using an expanded dataset and described by Olszewski and Xie (2002). Equation [2.3] was estimated using a 2-stage generalised least squares approach developed by Hatanaka (1976), which takes account of serially correlated disturbances and produces parameter estimates that are asymptotically equivalent to unconditional maximum likelihood estimates. The estimation dataset consisted of 20 observations covering the period 1974 to 1993. However, due to the lagged structure of the model and the

2-step estimation procedure, the first two observations (corresponding to 1974 and 1975) only contribute indirectly (via their lagged values) to the estimation. Thus, the estimated relationships refer to the response of the peak period travel market after any structural change which may have occurred as a result of the introduction of the ALS in 1975.

Several combinations of explanatory variables were tried. Variables which did not contribute to explaining the variation of Q_{AM} were first identified and eliminated. These variables did not show as statistically significant either on their own or in combination with others. These turned out to be: parking capacity, MRT operation dummy, PM ALS charging dummy and the driving cost. Table 4.2 summarises the estimation results for the best performing models.

Table 4.2: Estimation results for time series model of RZ traffic

		Model coefficients (<i>t</i> -statistics)	
Model/Equation		D1	D2
Constant		0.896 (1.1)	5.142 (5.4)
Log of variable	Lagged flow $Q_{AM,t-1}$	0.324 (2.0)	0.294 (2.2)
	ALS cost, $CALS$	-0.361 (-4.3)	-0.214 (-2.9)
	Parking cost, CP	-0.410 (-3.1)	-0.224 (-2.2)
	Car population, $CARS$	0.549 (3.8)	–
	Income, GDP	–	0.432 (5.0)
Number of observations		18	18
R-squared		0.961	0.969
F-statistic		106.1	133.9

All the parameters of the models have the expected sign. Given the small sample size, the levels of significance of the coefficients and the overall model fit are satisfactory. The models including the GDP variable performed better than those including the CARS variable. Although logically both these variables have an effect on traffic, they are highly correlated and therefore cannot be both included in the model.

The value of the coefficient on lagged flow indicates that there are significant delays in the response of the peak period travel market to price changes, with around 70% of the full effect of a price change being apparent in the first year.

The values of elasticity estimated from model D1 with all significant variables are shown in Table 4.3. The short-term road pricing elasticity is not high, but close to arc elasticity observed during later years of ALS (Table 4.1). Table 4.3 shows that elasticity with respect to parking fees is of a similar order of magnitude. It is also within the range of the studies reviewed by Oum et al. (1992) and Goodwin (1992). The level of sensitivity of traffic volume entering RZ to price changes is likely to be a reflection of, amongst other things, the ready availability of alternative modes of travel serving the RZ and the availability of alternative routes for through traffic.

Table 4.3: Elasticities estimated from time series model

Elasticity with respect to	Short-term	Long-term
ALS fee	-0.214	-0.303
Parking cost	-0.224	-0.317

The long-term elasticity to road pricing charges is about 42% higher than the short-term value. It suggests that the long-run impacts of road pricing on travellers are much more complex than the short-run. Besides car population, national income and parking cost, there may remain some other factors in the long-term that lead to further responses to road pricing adjustment than in the short-term. Some possible factors include: change of destination, public transport changes, travellers' habit adjustment, carpool formation and so on.

4.5. ELASTICITY UNDER THE ERP

Although the ALS was a low-cost system which served its purpose of controlling traffic congestion for over two decades, the paper licence scheme has been

considered to be inconvenient and inflexible. Hence the Singapore authorities decided in 1993 to upgrade the system (see Section 2.2.2 for details). After an extensive evaluation of alternative technologies (Menon and Chin 1998), in September 1998 the manual ALS scheme was converted to a fully automated state-of-the-art ERP system (Luk 1999; Menon 2000). Although the ERP rates were set lower than ALS rates (for example, a maximum of S\$2.50 for cars as compared to S\$3.00 whole-day ASL fee) a significant drop in the inbound traffic volume was observed, amounting to about 15% (Menon, 2000). This could be attributed to two reasons:

- (1) Under the ALS many drivers used to make multiple entries to RZ during the day for the price of one Daily Licence.
- (2) Those who bought monthly ALS licences did not perceive any extra cost for making additional trips.

As the inbound traffic volume dropped to below the expected level, the rates were revised downwards in November 1998, two months after the ERP introduction. This revision created the first opportunity to estimate the elasticity under the new system.

4.5.1. Elasticity by Time of Day

Tables 4.4 and 4.5 show changes in RZ traffic, which occurred between October and November 1998. The rates for cars were reduced by \$0.50 for all the time intervals. As the rates were different for different vehicles and varied in half-hourly (or even shorter) intervals, the values of C^0 and C in the tables are calculated as averages weighted by volume to represent the true average rates paid by drivers entering in each time interval. The traffic volumes were averages of three weekdays in October 1998 (denoted as traffic volume Q^0) and five weekdays in November 1998 (denoted as traffic volume Q).

Table 4.4: Changes in passenger car volume entering RZ by time interval

Time interval	C^0 (\$\$)	C (\$\$)	Q^0	Q	E_A (Arc)	E_L (Log)
07:30 – 09:30	2.56	2.06	23923	24479	–0.106	–0.106
09:30 – 15:00	1.50	1.00	45761	47285	–0.082	–0.081
15:30 – 17:30	1.50	1.00	18131	19045	–0.123	–0.121
17:30 – 19:00	2.15	1.65	10424	11357	–0.324	–0.322
07:30 – 19:00	1.83	1.33	98240	102166	–0.123	–0.122

Table 4.5: Changes in other vehicle volume entering RZ by time interval

Time interval	C^0 (\$\$)	C (\$\$)	Q^0	Q	E_A (Arc)	E_L (Log)
07:30 – 09:30	0.96	0.77	19080	19160	–0.019	–0.019
09:30 – 15:00	0.54	0.34	58645	60814	–0.080	–0.078
15:30 – 17:30	0.54	0.34	23918	25615	–0.151	–0.148
17:30 – 19:00	0.79	0.61	11773	12380	–0.189	–0.188
07:30 – 19:00	0.64	0.44	113416	117969	–0.106	–0.105

The elasticity values in Tables 4.4 and 4.5 were calculated using both the arc definition (Equation [2.2]) and assuming the “log-log” model (Equation [4.1]). The two equations gave almost identical results. Arc elasticities for different time periods are also shown in Figure 4.1.

Figure 4.1: Elasticity of traffic entering RZ to ERP by time interval

As indicated by Figure 4.1, both car and other vehicle elasticities increased in the late afternoon. Evening peak traffic flows showed the highest demand sensitivity, with values of -0.324 and -0.189 for cars and other vehicles, respectively. Low elasticity values corresponded to the morning peak. This is expected as there is less flexibility for retiming the morning commuting trips. Many drivers can postpone their evening trips to avoid the high charge in the peak hours if they wish to do so. During the off-peak period, changing the travel time would not result in economically significant saving, hence the medium value of elasticity. However, the elasticity in the off-peak hours does reflect the impact of the ERP charges on non-essential traffic demand.

4.5.2. Elasticity for Different Road Categories

In Phase 2 of ERP implementation in 1999, AM peak charging was introduced on three radial arterial road segments and three more expressway segments, in the direction leading to the city. The LTA developed a policy of reviewing the ERP rates every 3 months, in response to traffic conditions, expressed in terms of average traffic speed (see details in Section 2.2.2).

The Phase 2 implementation and subsequent rate revision created an opportunity to compare the elasticities of ERP on expressways, arterial roads and the Restricted Zone. Table 4.6 shows the traffic volume changes for cars and other vehicles observed on different roads due to the ERP introduction and rate revisions. The volumes shown were the totals for two expressways (Pan-Island Expressway – PIE and Ayer Rajah Expressway – AYE), three arterial roads (Thomson Road, Bendemeer Road and Kallang Road) as well as for the roads entering the RZ. Table 4.6 shows that the travel demand on expressways was more elastic than that on the roads leading towards and entering the RZ. This is mainly due to the fact that travellers on expressways had some alternative routes to avoid the ERP charging, and hence a higher flexibility.

Table 4.6: Elasticity for different road categories during AM peak hours

Road class/event		Vehicle class	C^0 (S\$)	C (S\$)	Q^0	Q	E_A (Arc)	E_L (Log)
RZ	ERP rates revision in Oct., 1998	Cars	2.56	2.06	23923	24479	-0.106	-0.106
		Others	0.96	0.77	19080	19160	-0.019	-0.019
		All	1.85	1.50	43003	43639	-0.069	-0.069
Arterials	ERP started in Sept. 1999	Cars	0.00	0.50	12399	9186	-0.149	-
		Others	0.00	0.33	10007	7850	-0.121	-
		All	0.00	0.42	22406	17036	-0.136	-
Expressways	ERP started in Sept. 1999	Cars	0.00	1.43	15019	9688	-0.216	-
		Others	0.00	0.90	12661	8195	-0.214	-
		All	0.00	1.18	27680	17883	-0.215	-
	ERP rates revision in Oct. 1999	Cars	1.43	1.01	9688	10365	-0.195	-0.194
		Others	0.90	0.59	8195	8525	-0.097	-0.095
		All	1.18	0.82	17883	18890	-0.151	-0.149

4.5.3. Elasticity for Various Vehicle Types

To examine the effect of the ERP on different types of users, traffic demand elasticities were calculated separately for different vehicle types. The classification corresponds to the different ERP charging classes, except that heavy goods vehicles, very heavy goods vehicles and buses were combined. Table 4.7 shows the elasticity estimates for vehicles entering RZ in the AM peak hours (7:30–9:30) while Table 4.8 presents similar data for two expressways (PIE and AYE, 7:30–9:00 AM) based on rates revision in October 1999. Figure 4.2 shows the comparison of elasticities for the different vehicle types.

Table 4.7: Elasticity for various vehicle types entering RZ during AM peak hours

Category	C^0 (\$\$)	C (\$\$)	Q^0 Oct 98	Q Nov 98	E_A (Arc)	E_L (Log)
Cars	2.56	2.06	23923	24479	-0.106	-0.106
Motorcycles	1.29	1.04	3159	3186	-0.040	-0.040
Taxis	0.88	0.70	9240	9271	-0.015	-0.015
LGVs	0.66	0.53	3264	3280	-0.023	-0.023
HVs	1.17	0.94	3417	3422	-0.007	-0.007
All vehicles	1.85	1.50	43003	43639	-0.069	-0.069

Table 4.8: Elasticity for various vehicle types on expressways during AM peak hours

Category	C^0 (\$\$)	C (\$\$)	Q^0 Oct 98	Q Nov 98	E_A (Arc)	E_L (Log)
Cars	1.43	1.01	9688	10365	-0.195	-0.194
Motorcycles	0.69	0.44	1698	1801	-0.134	-0.131
Taxis	1.01	0.69	2523	2632	-0.112	-0.110
LGVs	0.70	0.45	2425	2472	-0.044	-0.044
HVs	1.25	0.83	1549	1620	-0.109	-0.107
All vehicles	1.18	0.82	17883	18890	-0.151	-0.149

Figure 4.2: Elasticity by vehicle type at RZ and on expressways

It seems that passenger car demand was the most elastic, with values of -0.106 and -0.195 , for RZ and expressways, respectively. Light goods vehicles had the lowest elasticity of only -0.023 to -0.044 . This illustrates the effectiveness of road pricing as an instrument to control traffic congestion. The percentage of passenger cars is usually the highest among all vehicle categories, comprising over half of the total traffic volume. Its highest sensitivity to price changes means that ERP can effectively control the total traffic volume on the road.

4.6. COMPARISON WITH OVERSEAS EXPERIENCE

The results presented in the previous sections show that elasticity values can vary over a wide range. The observed sensitivity of traffic to pricing seems to depend on many factors, the most important being availability of alternatives for re-routing and re-timing of the trip. Table 4.9 shows some of the toll elasticity values reported in the literature as well as the summary of the Singapore ERP effects. Most of the values reported for urban tolls range between -0.03 and -0.5 and the Singapore ERP results are within this range.

When the Singapore results are compared with overseas experience, one has to be very careful to consider the context. The differences in elasticity could be due to the location (urban, rural), toll application method (point, cordon or distance-based) and the fee structure (fixed or time-variable rate). For example, most of the tolls on rural motorways in Europe are distance-based and therefore would comprise a larger part of the trip cost. This could explain apparently higher elasticity values reported by Matas and Raymond (2002).

Among the urban tolls few have time-variable charges, which means that re-timing of trips would not bring any saving and thus is not a viable alternative. Some time-variable tolls have been experimentally introduced in USA in San Francisco and Florida. However, based on elasticity values reported (Gifford and Talkington, 1996; Cain et al., 2001) it seems that the traffic volumes are not more sensitive to

the level of variable tolls. Singapore expressway elasticities are within the range of values found in USA.

Table 4.9: Comparison of toll elasticities from different countries

Location	Elasticity range	Remarks	Source
Six bridges and two tunnels in New York City area, US	−0.09 to −0.50	Cars	Hirschman et al. (1995)
	−0.09 to −0.39	All vehicles	URS (2001)
Two bridges in Lee County, Florida, US	−0.03 to −0.36	All vehicles, off-peak	Cain et al. (2001)
Golden Gate Bridge, San Francisco, US	−0.05 to −0.19	All vehicles	Gifford and Talkington (1996)
Spanish motorways (distance-based)	−0.21 to −0.83	All vehicles	Matas and Raymond (2002)
Central London, UK	−0.11 to −0.75	Cars	Markose et al. (2006)
Oslo, Norway (toll ring)	−0.03 to −0.04	Cars	Ramjerdi (1994)
	−0.22	Cars, substitution effects considered	Jones and Hervik (1992)
Alesund, Norway (point toll)	−0.45		
Trondheim, Norway (toll ring)	−0.30	Cars, AM peak	Polak and Meland (1994)
	−0.10	Cars, all day	
Singapore Restricted Zone (ERP, cordon)	−0.11	Cars, AM peak	This study
	−0.13	All vehicles, all day	
Singapore expressways (ERP, point toll)	−0.20 to −0.22	Cars, AM peak	
	−0.15 to −0.22	All vehicles, AM peak	

Among the overseas pricing schemes, the Norwegian toll rings in Oslo and Trondheim most closely resemble the Singapore RZ scheme. The toll charges there

were set at a much lower level and this could be the reason why very low elasticity was initially observed (Ramjerdi 1994). Subsequent evaluation by Jones and Hervik (1992) as well as Polak and Meland (1994) found the levels of elasticity consistent with those observed in Singapore. One notable difference is that in Trondheim, unlike Singapore, the AM peak elasticity appears to be higher than elasticity averaged over the whole day. This could perhaps be explained by differences in duration of the peak and off-peak pricing periods. Despite the differences, a general trend emerges from both Singapore and Norwegian studies: cordon pricing seems to have a lower elasticity than tolls applied at a point (expressway or arterial segments).

4.7. CONCLUDING REMARKS

This chapter presented a broad picture of traffic demand elasticities with respect to the road pricing charges in Singapore. The evidence leads to the following conclusions:

- (1) The first introduction of road pricing in the form of ALS in 1975 had the most dramatic effect on traffic volumes and showed the highest elasticity which was never observed again. It can be argued that this was due to elimination of through traffic and created a major structural change in travel patterns.
- (2) The time series model of car traffic entering the RZ shows that long-term elasticity is about 42% higher than the short-term. It suggests that the long-run impacts of road pricing on travellers are much more complex than the short-run. Thus development of a behavioural model for the long-term impacts of road pricing should be much more careful in the variable selection and specifications than a model for the short-term impacts.
- (3) The elasticity of traffic entering the city centre in the evening peak is much higher than observed at other times. This shows that drivers have more

flexibility to adjust their travel time in the evening than in the morning peak. The medium elasticity of the off-peak hours indicates that the ERP does affect the non-essential travel demand to a certain extent.

- (4) The higher elasticity value on expressways as compared to the RZ may be due to the fact that drivers have more alternatives for rerouting their trips or waiting until the end of the morning charging period.
- (5) Passenger car traffic is the most sensitive to the ERP rate changes among all the vehicle categories. Goods vehicles have a much lower elasticity. This difference among vehicle types provides justification for motorist segmentation in developing scheduling decision models.

The variability of observed elasticities across time periods, locations and vehicle types suggests the need to model the various travel responses separately. The methodological difficulties of assessing the effects of road pricing are considerable, and consequently there remains a significant scope to refine and extend the current analysis by using individual ERP transaction data.

CHAPTER FIVE

MODELLING SCHEDULING DECISIONS BASED ON TRAFFIC VOLUME DATA

5.1. INTRODUCTION

In planning a new road pricing system, a model for forecasting the traffic volume change from an existing situation to the new scheme would be very helpful. A sophisticated disaggregate model using observations of changes in the behaviour of individual motorists subjected to road pricing would in general be more reliable and transferable than an aggregate model. However, such data are difficult and costly to capture and assemble, especially for a location without an existing ERP system.

The lack of essential individual data from the site of interest undoubtedly hampers the application of a disaggregate model in planning of a new ERP gantry. Therefore, an attempt was made in this research to develop a model using only traffic counts (volume data) which are more commonly available.

The model focused on the effects of a new single charging point on traffic volumes. It concerns choices faced by motorists in using a road where a new charging scheme is introduced and charges apply only during the peak hours. Motorists' scheduling decisions are central to the volume changes and thus are of special interest.

5.2. PROPOSED DISCRETE CHOICE MODEL

The basic microeconomic perspective of scheduling decision making views an individual's scheduling decision as a utility trade-off resulting in which schedule delay from PAT, travel time, charging fee and external constraints are taken into

account. Therefore, the length of scheduling early/late from PAT (*SDE/SDL*), travel time (*TRTIME*) and ERP fees (*ERP*), as well as a binary indicator variable (*H*) representing unknown benefits/constraints for staying at one's PAT, are included as explanatory variables in the models for time choice options (see Section 3.3 for more details).

5.2.1. *SDE, SDL and Choice-set Determination*

The variables *SDE* and *SDL* are theoretically defined as:

$$\begin{aligned} SDE &= \text{Max} [(PAT - t), 0] \\ SDL &= \text{Max} [(t - PAT), 0] \end{aligned} \quad [5.1]$$

where, *t* is the chosen scheduling time of arrival.

As noted in Chapter 3, the choice-set determination is based on the brute force method which assumes that everybody has all alternatives available and hence lets the model decide that the choice probabilities of unrealistic options are low or zero. It means that, the whole morning period, which in this study extends from 7:00 to 10:00 AM, is assumed to be available to all motorists for travel. As discussed in Section 3.3.4, the specification of each alternative is based on experience of past studies and thus a 15-minute interval is adopted. Therefore, there are a total of twelve options available to each motorist.

When a new ERP gantry is introduced, besides the time interval choice, motorists can also choose to avoid paying the charges by changing their route or travel mode. Based on the above discussion, the motorists have four kinds of choices when facing a new ERP scheme: (1) push the arrival time forward; (2) no change in arrival time; (3) postpone the travel; (4) change route/mode. The first three choices can occur at any of the twelve 15-minute time intervals (7:00–10:00 AM, denoted as 1, 2, ..., *M*). The option of changing route/mode is denoted as *M*+1 and represents all those that are priced off the road. As re-routing is the most frequent response

under the circumstances being considered here, this option will hereafter be referred to as the “re-routing” option. The structure of the choice-set is shown in Figure 5.1.

Figure 5.1: Choice-set for a trip after ERP introduction

Thus, making use of the discrete time intervals the functions of SDE and SDL for a motorist with PAT in interval j ($j=1, \dots, M$) to choose interval i ($i=1, \dots, M$) can be written as:

$$\begin{aligned} SDE_{ij} &= \text{Max} [15(j-i), 0] \\ SDL_{ij} &= \text{Max} [15(i-j), 0] \end{aligned} \quad [5.2]$$

5.2.2. Utility Function

As discussed in Section 3.3.5, the utility function is proposed to be a linear-in-the-parameters expression, in order to be explicitly understandable and comparable to the existing models. The following specification for the deterministic part of utility associated with timing choice is proposed:

$$V_{ijk} = \alpha_k ERP_{ik} + \tau_k TRTIME_i + \beta_{1k} SDE_{ij} + \beta_{2k} SDL_{ij} + \gamma_k H_{ij} \quad [5.3a]$$

where:

ERP_{ik} = ERP rate for motorists of category k during period i ;

$TRTIME_i$ = travel time corresponding to period i ;

$$H_{ij} = \begin{cases} 1 & \text{if } i = j \\ 0 & \text{otherwise} \end{cases} \quad \text{binary variable indicating travelling at PAT;}$$

α_k , τ_k , β_{1k} , β_{2k} and γ_k are model parameters for motorists of category k .

For the re-routing option, the utility is assumed to be constant for each category k :

$$V_{M+1,jk} = \delta_k \quad [5.3b]$$

5.2.3. Choice Probability and Traffic Volume

An MNL model is employed, as the most widely used technique in modelling scheduling decision (see Chapter 2). The probability of choosing to travel in interval i (or being re-routed for $i = M+1$) can be expressed as:

$$P_{ijk} = \frac{\exp(V_{ijk})}{\sum_{m=1}^{M+1} \exp(V_{mjk})} \quad (i = 1, \dots, M+1; j = 1, \dots, M; \text{ and } k = 1, \dots, K) \quad [5.4]$$

where, V_{ijk} is the deterministic part of utility of motorist belonging to category k with PAT in interval j travelling in interval i , under ERP.

Defining:

F_{jk} number of motorists of category k with PAT in interval j ($j = 1, \dots, M$ and $k = 1, \dots, K$),

P_{ijk} probability that a driver of category k with PAT in interval j will travel in interval i under ERP ($i = 1, \dots, M; j = 1, \dots, M; k = 1, \dots, K$),

$P_{M+1,jk}$ probability that a motorist of category k with PAT in j will change route/mode under ERP ($j = 1, \dots, M$ and $k = 1, \dots, K$),

Q_{ik} expected traffic volume of category k in interval i under ERP,

$Q_{M+1,k}$ expected volume of category k that will change route/mode under ERP.

Using a matrix notation, the expected volume vector for category k can be found as:

$$\mathbf{Q}_k = \mathbf{P}_k \mathbf{F}_k \quad [5.5]$$

where, $\mathbf{Q}_k$ is the vector of Q_{ik} ;

$\mathbf{P}_k$ is the matrix of P_{ijk} ; and

$\mathbf{F}_k$ is the vector of F_{jk} .

The total traffic volume vector $\mathbf{Q}$ can be obtained by adding up traffic volumes for all K categories of motorists.

$$\mathbf{Q} = \sum_{k=1}^K \mathbf{Q}_k \quad [5.6]$$

5.3. MODEL CALIBRATION USING TRAFFIC VOLUME DATA

The general model presented above is suitable for discrete choice modelling with individual data. However, it can also be calibrated by using only traffic volume (count) data. The data, methodology of model calibration based on traffic volume data, as well as model calibration results are described below.

5.3.1. Collection of Traffic Count Data

The traffic count data used in this research were collected by the Vehicle Presence Detectors (VPDs), which is a system component installed at each ERP gantry (the main components of the ERP system and their roles will be further discussed in Chapter 6). As a vehicle crosses under a gantry, its position and width are detected by the VPD and recorded by the system. The VPD is able to count the number of vehicles when the ERP charge is not in operation. This makes it possible to obtain counts from the system for the time outside the operating hours, e.g. 7:00–7:30 AM. For a new ERP charging point, usually the VPDs start operation a few months

earlier than the system begins to charge vehicles. This is why some VPD count data could be recorded before ERP charging was introduced.

The count accuracy of the VPD is 99.99% (LTA 2005). The traffic counts represent the total mixed traffic volumes for each time interval. Information on traffic composition such as proportions of different vehicle types is not captured by the VPDs. It is noted that traffic composition data at any location would have to be manually collected.

The VPD data captured on one expressway (AYE, ERP Gantry OS 36) and two arterial roads (Thomson Road OS 39 and Bendemeer Road OS 40) were used in this research for testing the proposed modelling methodology. Details of these data will be discussed in Section 5.3.3 and 5.3.4.

5.3.2. Method for Model Calibration

Method for Model Estimation using Traffic Volume Data

The problem of estimating the scheduling decision model from traffic counts is similar in nature to estimation of an OD matrix using only traffic volumes observed on some roads. In both cases, what is actually observed are the totals comprising individuals with different combinations of choices, but not the exact numbers of drivers making individual time (or route) choices. In the case of scheduling, the total traffic observed in interval i comprises all those who chose interval i regardless of their original PAT. The numbers (or shares) of motorists corresponding to elements of the $\mathbf{P}$ matrix (Equation [5.5]) are not known. The implication of this is that none of the standard logit model estimation techniques (maximum likelihood, linear regression) can be used. However, the model can be estimated with the help of the non-linear-least-squares (NLLS) method developed by Tamin and Willumsen (1989) to estimate a trip distribution model based on traffic counts.

To address the issue of heterogeneity of motorists' behaviour, traffic counts should be classified by vehicle type (cars, taxis, motorcycles, goods vehicles, etc.) as each group may have different ERP rates and different model parameters. However, since such classified counts were not available from the VPD, for illustration purposes the model was estimated for a mixed traffic stream, comprising all vehicles subjected to ERP. In this case $K = 1$ and consequently subscript k was dropped from all equations. The values of ERP_i used in this simplified case represent the average ERP rates, which were calculated as the total of ERP fees collected divided by the total traffic flow within a time interval.

According to Equation [5.3] and [5.4], for a given set of ERP rates and the corresponding travel times, the choice probabilities depend on:

$$\mathbf{P} = f(\mathbf{X}, \boldsymbol{\theta}) \quad [5.7]$$

where, $\mathbf{X}$ is the vector of variables (i.e.: ERP , $TRTIME$, SDE , SDL and H) and $\boldsymbol{\theta}$ is the vector of unknown model parameters (i.e.: α , τ , β_1 , β_2 , γ and δ).

The principle of the NLLS calibration method (Tamin and Willumsen, 1989) is to find such values of the unknown parameters which minimise the sum of squared differences between the estimated and observed volumes.

$$\text{Minimise: } LS = \sum_{d=1}^D \sum_{i=1}^{M+1} (Q_{id}^* - Q_i)^2 \quad [5.8]$$

where:

Q_{id}^* = observed 15-minute traffic volume in interval i ($i = 1, \dots, M$) and re-routed volume ($i = M+1$) on day d under ERP ($d = 1, \dots, D$);

Q_i = traffic volume in interval i which is a function of $\mathbf{P}$ and $\mathbf{F}$ estimated from Equation [5.5].

In order to find a set of unknown θ_l (for $l = 1, \dots, L$, representing $\alpha, \tau, \beta_1, \beta_2, \gamma$ and δ , etc.) which minimises Equation [5.8], the following equations are required:

$$\begin{aligned}
 \frac{\partial LS}{\partial \theta_l} &= -2 \sum_{d=1}^D \sum_{i=1}^{M+1} \left[(Q_{id}^* - Q_i) \frac{\partial Q_i}{\partial \theta_l} \right] \\
 &= -2 \sum_{d=1}^D \sum_{i=1}^{M+1} \left\{ \left[Q_{id}^* - \sum_{j=1}^M (F_j P_{ij}) \right] \sum_{j=1}^M \left(F_j \frac{\partial P_{ij}}{\partial \theta_l} \right) \right\} \\
 &= -2 \sum_{d=1}^D \sum_{i=1}^{M+1} \left\{ \left[Q_{id}^* - \sum_{j=1}^M (F_j P_{ij}) \right] \sum_{j=1}^M \left\{ F_j P_{ij} \left[X_{lij} - \frac{\sum_{m=1}^{M+1} [X_{lmj} \exp(V_{mj})]}{\sum_{m=1}^{M+1} \exp(V_{mj})} \right] \right\} \right\} \\
 &= 0
 \end{aligned} \tag{5.9}$$

where, X_{lij} is the variable related to parameter θ_l for travellers with PAT in j who will travel in interval i under ERP.

Equation [5.9] produces a system of L (the number of unknown parameters for estimation) simultaneous equations. Newton's method can be used to solve Equation [5.9].

Model Evaluation

To test the goodness-of-fit of the model, this study employs RMSE which is often used to express accuracy encompassing both random and systematic errors in modelling/forecasting. The percentage RMSE is defined as:

$$\text{RMSE} = \sqrt{\frac{\sum_d \sum_i [(Q_{id}^* - Q_i)/Q_{id}^*]^2}{D(M+1)}} \times 100\% \tag{5.10}$$

Assumption of PAT

It was assumed that the time distribution of traffic volumes observed before ERP introduction gave a good indication of the PAT distribution, that is: $F \approx Q^0$. This assumption is correct provided that no serious congestion exists on the road which

would lead to peak spreading. It can be claimed that serious congestion did not exist on the roads considered, as the maximum flow-to-capacity ratio during the peak hour ranged from 0.84 to 0.87, based on capacity estimates obtained by Fan et al. (1995). Further evidence to this claim is based on analysis of day-to-day variability of traffic volumes, which will be discussed in Section 5.3.3.

Travel Time Variable Prediction

Most of the previous studies obtained the information of travel time in one of two ways: either via a SP survey or through estimation with a speed-flow model (Hyman et al. 2000). Since the actual travel time for each traveller was not observed while traffic volumes were captured in this study, speed-flow relationship has to be employed to estimate the average traffic speed for travelling in each interval.

For expressways in Singapore, the following speed-flow relationship was developed and recommended by Fan et al. (1995):

$$q = 77.91u (4.334 - \ln u)^{0.529} \quad [5.11]$$

where, u is the speed (in km/h), and q is the flow rate (in pcu/h/lane) which can be calculated as:

$$q = Q_t f_c / (\Delta t N_L) \quad [5.12]$$

where Q_t is the total traffic volume in interval Δt (here Δt is defined as 0.25 hour, i.e., 15 minutes, see Section 5.2.1), f_c is the traffic composition adjustment factor to convert vehicles to pcu, and N_L is the number of lanes.

To estimate the traffic speed for the given traffic flow, a transformation of the speed-flow function is necessary. Here a function for expressway traffic speed estimation was calibrated by a curve-fitting method, based on data obtained from

Equation [5.11]. Such a function is convenient for the repeated estimation of speed while the traffic flow values are updated.

This curve-fitting procedure starts from the formula of Bureau of Public Roads (BPR, 1964), which is probably the most commonly-used function for the estimation of travel time per unit distance:

$$TTPK = t_0 \left[1 + a \left(\frac{q}{c} \right)^b \right] \quad [5.13]$$

where, c is the road capacity (in pcu/h/lane), a and b are parameters to be calibrated.

According to Function [5.11], the travel time constant value t_0 in Equation [5.13] is 0.7869 ($=60/e^{4.334}$ minute/km, when the free flow speed is 76.25 km/h), and the expressway capacity c is 2499 pcu/h/lane (when the flow speed is 44.92 km/h).

By employing a curve-fitting method, a and b were calibrated using SAS Version 8.0 (SAS, 2003) for the range of traffic flows increasing from free-flow traffic to capacity flow. Since the road studied (AYE) had no serious congestion, curve-fitting for speed under congested situation (upper curve section of traffic flow decreasing from road capacity, see Figure 5.2) is not necessary. Table 5.1 shows the calibration result. With the calibrated parameters a and b , the curve of the BPR travel time-flow relationship fits the Fan et al. (1995) speed-flow relationship function well for the relevant range (see Figure 5.2). Detailed results such as the goodness-of-fit of this curve-fitting are shown in Appendix B.

Table 5.1: Calibration result of BPR function

Range of u (km/h)	Range of q (pcu/h/lane)	a	b
44.92 – 76.25	0 – 2499	0.4989	4.4312

Figure 5.2: Comparison of the fitted BPR travel time-flow function with the speed-flow relationship of Fan et al. (1995)

Given the total traffic volume Q_i on the expressway in a time interval i , the travel time per unit distance (in minute/km) for this interval can be calculated:

$$TTPK_i = 0.7869 \left[1 + 0.4989 \left(\frac{Q_i f_c}{624.8 N_L} \right)^{4.4312} \right] \quad [5.14]$$

Values of f_c were calculated based on ERP transaction data captured on the roads considered and the values were found to be within the range from 0.96 to 1.05. Since traffic composition data before ERP are unavailable, the f_c is assumed to be 1.

The values of $TRTIME_i$ is the average travel time on the road segment directly affected by the toll in time interval i . It is assumed that drivers who wish to avoid paying the ERP charge can re-route their trips by leaving the expressway before the ERP gantry or joining it after the gantry. Therefore, any reduction of travel time due to road pricing would apply only to the road segment between the last exit before

the toll point and the first entry after the toll point. The estimated travel time on that section is used in the model of AYE.

The travel time (in minutes) for time interval i on expressway segment can be obtained from:

$$TRTIME_i = \text{Segment_Length_involved} \cdot TTPK_i \quad [5.15]$$

For arterial roads, it was practically impossible to determine the length of the road segment affected directly by the road pricing due to the complex road network. Furthermore, the estimation of travel time effects would be much more difficult as the relationship between traffic flow and travel time is not straightforward when traffic-actuated signal control is used as is the case in Singapore. Therefore, the travel time variable was excluded from the utility specification of the arterial roads.

Calibration Procedure for the AYE Model

In the model for AYE, since $TRTIME_i$ depends on traffic volume Q_i (Equations [5.14] and [5.15]) which is dependent on P_{ij} (Equations [5.5] and [5.6]) that in turn is a function of $TRTIME_i$ (Equations [5.3] and [5.4]), both model calibration and application require an iterative procedure.

For an iterative procedure, a pre-defined criterion is required for examining when one should stop the procedure. In the proposed method, a convergence indicator ω plays this role. It is defined as the maximum percentage difference between two consecutive iterations (e.g., iterations $r-1$ and r) of traffic volumes forecast for each time interval:

$$\omega^r = \max_{i \in (1, \dots, M+1)} \left\{ \frac{\left| Q_i(\mathbf{ERP}, \mathbf{TRTIME}^r, \boldsymbol{\theta}^r) - Q_i(\mathbf{ERP}, \mathbf{TRTIME}^{r-1}, \boldsymbol{\theta}^{r-1}) \right|}{Q_i(\mathbf{ERP}, \mathbf{TRTIME}^{r-1}, \boldsymbol{\theta}^{r-1})} \right\} \quad [5.16]$$

The iterative procedure for model calibration is shown in Figure 5.3 and described below (r denotes the current iteration number):

Initialisation Stage:

- (1) Postulate the PAT distribution (see Section 5.2.3).
- (2) Initialise **TRTIME** (denoted as **TRTIME**⁰) based on **Q**⁰ using Equations [5.14] and [5.15].

Calibration Stage:

- (3) Perform a constrained NLLS model estimation with Equations [5.2] to [5.9]. The input values of **TRTIME** ^{$r-1$} are those calculated at the end of the previous iteration (using **TRTIME**⁰ at the first iteration). The output values of this estimation include model parameter vector **θ^r** , choice probability matrix **P^r** and traffic volume vector **Q^r** .

Convergence Test Stage:

- (4) Calculate the current convergence indicator ω^r using Equation [5.16] and test convergence: if $\omega^r <$ the pre-defined threshold, stop the procedure and accept the current parameters **θ^r** as the model calibration results; otherwise continue to Step (5).
- (5) Use the forecast traffic volumes to predict **TRTIME** ^{r} using Equations [5.14] and [5.15]; and then continue the procedure by going to Step (3).

Figure 5.3: Framework for model calibration based on traffic volume data

The convergence threshold in this study was set at 0.50%. Any other reasonable positive value can be set as the threshold. A lower threshold in general corresponds to more iterations in the calibration procedure. When the threshold is set too high, say at 20%, it may lead to wrong conclusion about the convergence of an actually non-convergent model.

When the model is applied to traffic forecasting, an iterative procedure is also required since the prediction of Q_i is dependent on $TRTIME_i$ (Equations [5.2] – [5.6]) which in turn is a function of Q_i (Equations [5.14] and [5.15]). The forecasting procedure in model application from Step (1) to Step (5) is similar to that for model calibration. The only differences between procedures of calibration and application are: (a) Step (3) in model application does not include model estimation; and (b) the outcome of the procedure is the forecast traffic volumes after ERP introduction.

5.3.3. Results for the AYE Model

In September 1999, the morning peak ERP with a variable-pricing was introduced on AYE. Traffic volume data were counted by the VPDs, for 5 working days before and 5 working days after the introduction. As the impact on traffic volumes was larger than expected (25% reduction during the peak period), the rates were revised in October 1999, one month after the ERP introduction. The count data for 5 working days after this revision provide an opportunity to validate the model.

The day-to-day variability of traffic volumes in each 15-minute interval was examined to check whether equilibrium conditions existed during the survey periods. Coefficient of variation (COV) is employed for this examination. It is defined as standard deviation divided by mean of the distribution:

$$\text{COV} = \frac{\text{SD}(\mathbf{X})}{\bar{\mathbf{X}}} \times 100\% \quad [5.17]$$

where, $\text{SD}(\mathbf{X})$ is standard deviation of the distribution, and $\bar{\mathbf{X}}$ is its mean value.

On AYE, the mean COV value of 15-minute volumes which was 3.87% during the week before ERP, decreased to 3.32% after the ERP introduction and then decreased further to 2.84% in the week after the rate revision. This shows that flow equilibrium conditions developed very quickly after a change in pricing.

The controlled-access expressway segment affected by the pricing was 5.2 kilometers long. As shown in Figure 5.4, this is the distance between the last exit before the ERP gantry point (Bouna Vista Road interchange) and the first entry after the ERP gantry point (Lower Delta Road interchange).

Figure 5.4: Location of ERP OS 36 on AYE

As described in Section 5.3.2, the model for AYE was calibrated in an iterative procedure. Figure 5.5 shows the differences in volumes forecast between any two consecutive iterations. The value of the convergence indicator (Equation [5.16]) went from 2.62% in the second iteration to 0.28% in the sixth iteration. Since the value of convergence indicator had a clear decreasing trend and crossed the pre-defined convergence threshold 0.50%, the model calibration procedure was deemed convergent and stopped after the sixth iteration. In this case the threshold of 0.50% means a 15-minute volume accuracy of ± 10 vehicles (as 2000 was the highest number of passes observed for a 15-minute interval on AYE).

During this calibration procedure, the percentage RMSE values obtained after each iteration decreased gradually from 10.32% to 8.56% (see Figure 5.6). This decreasing trend of percentage RMSE value implies that the calibration improved the traffic forecasting results during the procedure.

Figure 5.5: Convergence monitoring during the calibration of the AYE model

Figure 5.6: RMSE (%) after each iteration in the model calibration procedure

The results of model estimation described above are shown in Table 5.2 (model M1,

was the basic model of AYE). All the coefficients have expected signs and their magnitude is reasonable.

Table 5.3 shows the effect of pricing on travel times. The travel times decreased by 12% on average during the charging period (7:30–9:30 AM) after the ERP introduction, but increased by 2% outside the charging period. However, the travel times did not vary significantly among the time intervals, with the COV value of 4.61% after the introduction of ERP. This implies that the influence of travel time variable on motorists' scheduling decisions may not be sufficient to alleviate congestion in the peak period without the additional cost imposed by road pricing.

Figure 5.7 shows the comparison of traffic volumes before and after the introduction of ERP — observed and predicted by model M1. The model did reflect correctly the peak spreading effect of the “shoulder pricing” scheme.

Table 5.2: Results for AYE

Variable	Parameter	Model M1	Model M2	Model M3	Model M4
<i>ERP</i>	α	−0.49	–	−0.48	−0.46
	α_1	–	−0.28	–	–
	α_2	–	−0.95	–	–
<i>TRTIME</i>	τ	−0.28	−0.30	−0.30	−0.33
<i>SDE</i>	β_1	−0.11	−0.14	−0.09	−0.15
	ζ_1	–	–	–	+0.94
<i>SDL</i>	β_2	−0.19	−0.31	−0.11	−0.14
	ζ_2	–	–	–	+1.07
<i>H (at PAT)</i>	γ	+0.93	+0.99	+0.86	+0.70
<i>Re-route</i>	δ	−2.79	−2.93	–	−2.66
	δ_1	–	–	−3.20	–
	δ_2	–	–	−1.36	–
Number of parameters		6	7	7	8
Percentage RMSE (%)	Estimation	8.56	4.63	3.91	7.22
	Validation	11.1	8.82	8.25	9.87

Table 5.3: Effect of ERP on travel times

Interval start time	Travel time (minute)		Change (%)
	Before ERP	After ERP *	
7:00	4.22	4.27	+1.17
7:15	4.53	4.86	+7.30
7:30	4.60	4.18	-9.10
7:45	5.22	4.33	-17.0
8:00	5.16	4.41	-14.6
8:15	5.14	4.60	-10.6
8:30	5.09	4.44	-12.7
8:45	4.87	4.27	-12.2
9:00	4.81	4.38	-8.93
9:15	4.72	4.16	-11.7
9:30	4.64	4.65	+0.11
9:45	4.37	4.38	+0.14
COV (%)	6.74	4.61	—

Note: * TRTIME

Figure 5.7: Traffic pattern at AYE OS 36

Table 5.2 also shows the validation result of model M1. The percentage RMSE was 11.1% for model M1 prediction with the revised set of rates (validation set),

obtained after seven iterations with a 0.50% convergence threshold.

Since the model was calibrated based on a mixed traffic stream, the parameter values are interpreted as the average impacts of ERP introduction on the entire population of motorists. Some general trends emerge:

- (1) Positive utility is associated with travelling at one's habitual time (PAT). This implies that, all else being equal, the motorists were more likely not to alter their arrival times even when they faced a certain level of ERP charge.
- (2) Postponing arrival is about twice (−0.19 versus −0.11) as onerous as bringing it forward. The main reason behind this may be that most commuters should not arrive later than their work start time in the morning hours.

In the elasticity analysis, traffic sensitivity to road pricing was found to vary over the time of day. Therefore, two other specific models were investigated to test the hypothesis that motorists who used to travel in the high peak hour (8:00–9:00 AM) are less willing to make adjustments. Model M2 proposes a different ERP charge coefficient for this group:

$$V_{ij} = \begin{cases} \alpha_1 ERP_i + \tau TRTIME_i + \beta_1 SDE_{ij} + \beta_2 SDL_{ij} + \gamma H_{ij} & \text{for } j \in 8:00-9:00 \\ \alpha_2 ERP_i + \tau TRTIME_i + \beta_1 SDE_{ij} + \beta_2 SDL_{ij} + \gamma H_{ij} & \text{otherwise} \end{cases} \quad [5.18]$$

As in model M1, a constant utility was assumed in model M2 for the re-routing option (Equation [5.3b]).

Model M3 has the same utility function (Equation [5.3a]) as model M1, but introduces a different re-routing penalty for motorists who used to travel in the high peak hour (8:00–9:00 AM):

$$V_{M+1,j} = \begin{cases} \delta_1 & \text{if } j \in 8:00-9:00 \\ \delta_2 & \text{otherwise} \end{cases} \quad [5.19]$$

The procedure for calibrating model M2 reached 0.50% convergence threshold after six iterations, with the final percentage RMSE value of 4.63%. The percentage RMSE for model M3 was 3.91%, obtained in seven iterations with the same convergence threshold. The procedures for validating models M2 and M3 both reached 0.50% convergence threshold after seven iterations. The percentage RMSE values are also shown in Table 5.2.

In model M2, the magnitude of the α coefficient is indeed lower ($|\alpha_1| < |\alpha_2|$) for motorists whose PAT is in the high peak hour (8:00 to 9:00 AM), indicating that these travellers are less sensitive to ERP charges. In model M3, the value of parameter δ_1 turns out to be more than twice as large as δ_2 , indicating that those originally travelling during the high peak are more reluctant to change route. This finding is consistent with model M2 – both models imply these motorists possibly have more constraints on choosing their trip options than the other motorists.

A non-linear form of utility function was also tested. In model M4, two power parameters ζ_1 and ζ_2 are proposed for variables of SDE and SDL , respectively, with a hypothesis that the disutility caused by schedule delay from PAT is not linearly proportional to time:

$$V_{ij} = \alpha ERP_i + \tau TRTIME_i + \beta_1 SDE_{ij}^{\zeta_1} + \beta_2 SDL_{ij}^{\zeta_2} + \gamma H_{ij} \quad [5.20]$$

As in model M1, a constant utility was assumed in model M4 for the re-routing option (Equation [5.3b]).

For model M4, the procedure reached 0.50% convergence threshold after seven iterations for model calibration and eight iterations for mode validation. Table 5.2 also shows these results. The values of parameters ζ_1 and ζ_2 are 0.94 and 1.07, respectively, both close to 1. This implies that the schedule delay disutility is analogous to a linear relationship with the variables of SDE and/or SDL .

Compared with M2 and M3, model M4 has more parameters but higher RMSE both for calibration and validation datasets. Model M3 has the same number of parameters as model M2 but lower RMSE. Therefore, it seems preferable to use model M3 for predicting the traffic response.

Direct and cross-point elasticities can be calculated from an MNL model (Ortúzar and Willumsen, 2001). The direct point elasticity, which in this study is defined as the change in motorists' probability of choosing time interval i with respect to a marginal change in the ERP charging rate of interval i , is simply given by:

$$E_{P_i} = \alpha ERP_i (1 - P_i) \quad [5.21]$$

while the cross-point elasticity is also simply calculated by:

$$E_{P_{i,m}} = -\alpha ERP_m P_m \quad [5.22]$$

where P_i and P_m are the motorists' probabilities of choosing time intervals i and m respectively. The cross-point elasticity here is the change in motorists' probability of choosing time interval i with respect to a marginal change in the ERP charging rate of interval m .

Table 5.4 shows the direct and cross-point elasticities of model M3. The values on the diagonal are direct elasticities, while the others are cross elasticities. These direct and cross elasticities to a certain degree tell us how the motorists would respond to the changes of charging rates. For example, the negative values of direct point elasticities mean: if the charging rate in a particular time interval increases while charging rates in the other intervals remain the same, the probability for motorists to select arriving at this time interval will decrease. The positive cross-point elasticities indicate that an increase of charging rate in a particular time interval will encourage motorists to choose the other time intervals.

However, these elasticities may not fully reflect the motorists' response to road pricing. The cross elasticities of any option time interval i with respect to ERP_m of option m are equal, as they are independent from timing alternative i . This implies that the influences of pricing change in time interval m on motorists for choosing any other time intervals are the same. As different time intervals for a particular traveller incur different values of SDE/SDL, the penalty of rescheduling cannot be reflected properly in these elasticity values. Furthermore, it is difficult and inadequate to apply these elasticities to predict the traffic volumes under time-variable road pricing. Forecasting of traffic volume for a particular time interval should consider the charging rates in its own and the other time intervals, as well as factors other than charging rates.

Table 5.4: Direct and cross-point elasticities of model M3

		Time interval m (interval start time)											
		7:00	7:15	7:30	7:45	8:00	8:15	8:30	8:45	9:00	9:15	9:30	9:45
Time interval i (interval start time)	7:00	0.00	0.00	0.03	0.03	0.05	0.06	0.07	0.06	0.02	0.01	0.00	0.00
	7:15	0.00	0.00	0.03	0.03	0.05	0.06	0.07	0.06	0.02	0.01	0.00	0.00
	7:30	0.00	0.00	-0.39	0.03	0.05	0.06	0.07	0.06	0.02	0.01	0.00	0.00
	7:45	0.00	0.00	0.03	-0.38	0.05	0.06	0.07	0.06	0.02	0.01	0.00	0.00
	8:00	0.00	0.00	0.03	0.03	-0.56	0.06	0.07	0.06	0.02	0.01	0.00	0.00
	8:15	0.00	0.00	0.03	0.03	0.05	-0.56	0.07	0.06	0.02	0.01	0.00	0.00
	8:30	0.00	0.00	0.03	0.03	0.05	0.06	-0.74	0.06	0.02	0.01	0.00	0.00
	8:45	0.00	0.00	0.03	0.03	0.05	0.06	0.07	-0.75	0.02	0.01	0.00	0.00
	9:00	0.00	0.00	0.03	0.03	0.05	0.06	0.07	0.06	-0.18	0.01	0.00	0.00
	9:15	0.00	0.00	0.03	0.03	0.05	0.06	0.07	0.06	0.02	-0.19	0.00	0.00
	9:30	0.00	0.00	0.03	0.03	0.05	0.06	0.07	0.06	0.02	0.01	0.00	0.00
	9:45	0.00	0.00	0.03	0.03	0.05	0.06	0.07	0.06	0.02	0.01	0.00	0.00

5.3.4. Results for the Arterial Road Models

A flat ERP peak period toll was introduced at both arterial road sites (Bendemeer Road OS 40 and Thomson Road OS 39) in September 1999. Five-day VPD traffic count data were collected before and after the ERP introduction. As in the case of AYE, the day-to-day COV of volumes in each 15-minute interval was examined. The mean COV value at the Bendemeer Road site was below 2.89% for five days both before and after ERP introduction, whereas at the Thomson Road site, it increased slightly from 3.50% to 4.39%. These values again indicate that flow equilibrium conditions existed during the periods considered.

In the case of arterial roads, the estimation of travel time effects would be more difficult as it was practically impossible to determine the length of road segment affected by ERP. Furthermore, the relationship between traffic flow and travel time is not straightforward (see Section 5.3.2). Therefore, the *TRTIME* variable was excluded from the utility specification and the following expression was used:

$$V_{ijk} = \alpha_k ERP_{ik} + \beta_{1k} SDE_{ij} + \beta_{2k} SDL_{ij} + \gamma_k H_{ij} \quad [5.23]$$

For the re-routing option a constant utility was again assumed (Equation [5.3b]).

The results of model calibration are shown in Table 5.5 and Figure 5.8. As expected, the absolute value of the re-routing penalty δ was higher at the Thomson Road location where fewer alternative routing opportunities existed compared with Bendemeer Road. On the other hand, a higher ERP coefficient α was obtained for the Bendemeer Road site. This implies that more alternatives for re-routing may correspond to higher sensitivity to road charging rates.

Table 5.5: Results for two arterial roads

Variable	Parameter	Bendemeer Road	Thomsom Road
<i>ERP</i>	α	−0.85	−0.45
<i>SDE</i>	β_1	−0.10	−0.09
<i>SDL</i>	β_2	−0.09	−0.10
<i>H (at PAT)</i>	γ	+0.52	+0.35
<i>Re-route</i>	δ	−0.90	−2.02
Percentage RMSE (%)		4.03	8.31

Figure 5.8: Traffic pattern at the Bendemeer Road ERP gantry.

5.4. DISCUSSION AND CONCLUSIONS

5.4.1. Summary of the Model Development

This chapter described the development of an MNL-based model that was calibrated using traffic counts. The model focused on the effects of a new single toll point on traffic volumes during the peak hours. The proposed modelling methodology was tested using traffic volumes that were observed before and after the introduction of ERP on one expressway and two arterial roads. The testing

results show that this methodology is effective and practical.

Although parameter values of the utility function vary somewhat from site to site, they all have correct signs and reasonable magnitudes. The actual peak spreading effect of road pricing scheme on traffic over time of day is correctly reflected by the model. Some of the findings suggested by the model are summarised below:

- (1) A positive utility is associated with travelling at one's preferred time interval;
- (2) Postponing travel is generally more onerous than bringing it forward;
- (3) Those travelling during the morning high peak show lower sensitivity to the charging rates than the other motorists;
- (4) More alternatives for re-routing in order to avoid charges correspond to higher sensitivity to charging rates.

5.4.2. Conclusions from the Model Calibration

The performance of the proposed methodology for modelling based on traffic volume data with acceptable forecasting accuracy in both model calibration and validation proves that the model is practically useful for transportation planning in predicting the effects of a new single toll point on traffic volumes. The modelling methodology is also expected to be helpful in evaluating the effects of a road pricing scheme at its initial stage. For evaluation purpose the model parameters need to be re-calibrated by using the traffic counts collected at the site considered. The re-calibrated parameter values will provide insight into motorists' scheduling considerations, which will be of assistance in further policy decision-making.

5.4.3. Limitations and Possible Solutions

Although the modelling results show that it is possible to calibrate a scheduling decision model using traffic volume data, one should be careful in applying the model as it has several limitations. These limitations are the following:

- (1) Models were estimated using the total mixed traffic volumes as the information on traffic composition was not captured at the time. This is a considerable simplification as it has been noted in the elasticity analysis that sensitivity to ERP is quite different for different vehicle types. One can expect that the drivers of cars and goods vehicles (for example) face quite different time constraints. Model parameters would be more meaningful if classified traffic counts were available and thus separate utility function could be estimated for every type of vehicle. Due to the limitation of mixed traffic volume data, one should treat the model calibration results as illustrative only in further transportation analyses, for instance, when comparing the value of travel time ($\approx \tau/\alpha$, in S\$/minute) with overseas results which usually were estimated for private cars only. As the main purpose of using the VPD data here was to test the proposed modelling methodology, no attempt was made to capture additional classified count data although they may be more useful than the VPD data for transportation policy analyses.
- (2) The estimation of travel time in the model leads to several questions. Firstly, defining the travel time – which part of the trip should be taken into consideration? As the model is concerned with the impact of pricing on time distribution of traffic volume on a particular road segment, it seems justifiable to include only the travel time on the road directly affected. If the total journey time were to be considered, the problem would have to be redefined as a network equilibrium problem with multiple paths joining multiple origins and destinations. This kind of study requires extra survey data other than data available from the ERP system and thus is not within the stated scope of this research. Secondly, the current approach is more appropriate to roads with access control, and is difficult to use for arterial roads. Besides the problem of complex access control, the relationship between traffic flow and travel time is difficult to model when traffic actuated signal control is used as is the case in

Singapore. These two problems prevented the inclusion of travel time variable for arterial roads. Thirdly, travel time of the re-routing option should ideally be included in a joint model of scheduling and routing decision. However, this kind of joint model also needs extra network data and hence it is not considered in this study.

- (3) The PAT distribution of motorists was assumed to be the distribution of arrivals before the introduction of ERP. This assumption is justified by the fact that serious congestion did not exist on the roads studied. However, it should be noted that this would not always be the case, especially as road pricing is meant to alleviate congestion and therefore should be introduced on congested roads. A normal way to address this problem for developing a more general model is using SP data to estimate the distribution of PAT. However, this again is not consistent with the objectives of this study.
- (4) Statistical evaluation of the model calibrated using only traffic volumes is difficult. This is because the individual choices are not observed but only their aggregate effect on traffic volumes. Apart from the RMSE goodness-of-fit measure, there are no readily available statistical tests for finding the most appropriate model specification or for testing the significance of explanatory variables. This problem could be overcome by using individual ERP transaction data to develop a model, which will be presented in the following chapters.

CHAPTER SIX

ANALYSIS OF ERP TRANSACTION DATA

6.1. INTRODUCTION

As argued in Chapters 1 and 3, the quarterly revisions of ERP rates create a need for an explicit model to use the ERP transaction data to predict the impacts of rate adjustment on motorists and traffic.

This chapter presents the collection of ERP transaction data and describes statistical analyses of the transaction data sets that will be used in this study. The approach of motorist market segmentation is also described in this chapter.

6.2. DATA COLLECTION THROUGH THE ERP SYSTEM

6.2.1. Operation of the ERP System

The ERP system consists of three main components: the in-vehicle units (IU), the gantries and the central computer system. The IU is an electronic device installed in every vehicle that accepts a pre-paid smart card. Figure 6.1 shows the configuration of the outstation equipment at an ERP charging point. The charging method for a passing vehicle is described below:

- (1) Vehicle is detected when it comes within 10 metres of the first antenna;
- (2) Antenna interrogates the IU, determines its validity, classifies the vehicle and sends instructions about the appropriate ERP charge to the IU;
- (3) Vehicle travels between the two gantries, which are spaced about 15 metres apart;
- (4) The IU deducts the appropriate charge and confirms that it has done so to the

second antenna;

- (5) New balance in the pre-paid smart card is displayed on the IU for 10 seconds;
- (6) The VPD detects the passage of the vehicle and the transaction is considered valid.

Figure 6.1: Configuration of the outstation equipment at an ERP charging point

6.2.2. Transaction Data Recording

Every valid transaction is recorded and stored in the central computer system. If for some reason the ERP charge is not deducted, the enforcement camera (see Figure 6.1) will take a digital image of the rear licence plate of the vehicle, record the reason (e.g., no pre-paid smart card) and send this information with the digital image to the control centre for further action. Exempted vehicles also have an IU so that they will not be photographed as violators. The transaction information of each entry during the restricted hours is recorded in the system dataset. The reliability of the ERP system at correctly charging passes and recording transactions was found to be as accurate as 99.99% (LTA, 2005).

Figure 6.2 shows an example of raw data of the ERP transaction records. Information incorporated in each record is summarised in Table 6.1. Each vehicle

can be identified by the ERP system with its unique IU code (“Field 5” in Figure 6.2). The code number differs from the vehicle’s license plate number in order to allay any confidentiality and privacy concerns. By tracing vehicle’s IU code, its arrival times at a particular gantry can be captured together with the ERP fees charged. The system dataset does not include the socio-demographic characteristics of drivers, and no transaction data are captured outside of the system operating hours.

Field 1	Field 2	Field 3	Field 4	Field 5	Field 6
3	6	2	0	0	3
0	3	0	6	2	5
0	7	3	0	1	0
2	C	0	5	9	7
3	2	4	0	0	.
5	0	0	5	0	0
1	7	2	0	0	3
0	3	0	6	2	5
0	7	3	0	1	0
2	A	5	1	1	2
4	7	4	0	0	.
0	5	0	0	2	3
1	6	7	0	1	.
0	0	0	0	0	0
1	9	2	0	0	3
0	3	0	6	2	5
0	7	3	0	7	1
0	M	0	2	4	1
5	7	2	0	0	.
0	2	5	0	0	5
3	6	2	0	0	3
0	3	0	6	2	5
0	7	3	0	1	0
4	G	0	0	5	3
5	4	6	0	0	.
2	2	2	0	0	3
0	3	0	6	2	5
0	7	3	0	1	0
2	A	6	3	0	6
6	0	4	0	0	.
0	5	0	0	0	0

Figure 6.2: Example of raw records in the ERP transaction dataset

Table 6.1: Information included in each ERP transaction record

Field number	Information	Description
1	Gantry code	Charging location
2	Transaction date	Year, month and day
3	Time of entry	Hour and minute
4	Charge category	Vehicle type code
5	Vehicle’s IU code	Unique and encrypted code
6	ERP fee (\$\$.cc)	0 for exempted vehicles or violations

6.2.3. Data Sets for this Study

As discussed in Chapter 3, two sets of data collected before and after ERP rate adjustment are used in developing a scheduling model.

Three sets of individual transaction data for this study were provided by LTA which manages the operation of the ERP system. Each data set covers 5 working days

(from Monday to Friday). These sets of data were collected in 2003: from May 19 to May 23 (hereafter referred to as “May dataset”), June 23 to June 27 (hereafter referred to as “June dataset”) and June 30 to July 4 (hereafter referred to as “July dataset”). Two ERP rate revisions took place during this period: one on May 28, and the other on June 30. Overall, the three sets contained 3,991,143 ERP transaction records. The May and June datasets will be used in model calibration. The calibrated model will be validated by applying it to forecast the effects of ERP rate adjustment on June 30.

6.2.4. Selection of the Study Site

The datasets cover records collected from all gantries (in 2003 there were 45 charging points). For gantries on the RZ cordon, both the operating hours and the ERP rates did not change during these three months (from May to July). Among the gantries on expressways and arterial roads, only two gantries, located at the Central Expressway (CTE) after Braddell Road (ERP Gantry OS 31) and the slip road from PIE into CTE (ERP Gantry OS 42), changed the ERP rates and kept the same operating hours. At the other charging points, the ERP rates as well as the operating hours were adjusted during this period. Details of the operating hours at each gantry for each of the three months are shown in Appendix C.

The data to be used in this modelling exercise require time periods of an equal length for the different sets of observations. Hence, two datasets collected within the same operating hours from a site with changed ERP rates would be needed for behaviour studies. Since individual transaction data are not recorded outside the system operating hours, the suitable sites for this modelling are Gantry OS 31 and Gantry OS 42.

In these subsets there are 236,943 records (about 8000 entries per hour) and 19,751 records (about 650 entries per hour) from sites OS 31 and OS 42, respectively. Gantry OS 31 is located along CTE which is one of the most heavily travelled

expressways in Singapore, carrying the main traffic between the northern region and the Central Business District (CBD). Therefore, CTE OS 31 was selected as the study site.

6.3. DESCRIPTIVE STATISTICS

To process the raw ERP transaction data (see Figure 6.2) into a more meaningful form for investigation, statistical software SAS 8.0 is used. Results of statistical analyses on the transaction data at CTE Gantry OS 31 are described below.

6.3.1. Traffic Volumes

Total Traffic Volumes

Table 6.2 shows the total traffic volumes and the average charging fee per pass for each month at CTE OS 31 during the operating hours (7:30–9:30 AM). The average charging fee in June is lower than in the other two months in which the ERP rates were the same. As found in the analysis of travel demand elasticity, road pricing is a significant factor affecting the travel demand. This implies that if other factors are constant during these three months, a higher total traffic volume would be expected for June than for the other two months since the average fee charged was lower in June. However, the opposite was observed: with a lower average fee charged, the total passage volume at CTE OS 31 in June was 8.01% less than that of May. In May and July, the ERP rates were the same, with the total traffic volumes differing by only 1.28%. Therefore, factors other than road pricing must have significantly affected the travel demand in June.

Table 6.2: Traffic volume and ERP rate at CTE OS 31 during the operating hours

	May	June	July
Total 5-day traffic volume	81505	74974	80464
Average ERP rate (S\$)	1.80	1.59	1.80

It is hypothesised that the main reason leading to the unexpected effect is the local school holidays. As shown in Figure 6.3, the observation period in June was within the school holiday period of the primary and secondary schools, while during the observation period in May and July the schools were in their normal sessions.

Figure 6.3: Data collection periods and local school holidays in 2003

The hypothesis that the traffic drop in June was mainly due to the local school holidays can be verified by referring to the traffic volume changes during the same periods at the other sites where ERP rates did not change. As shown in Table 6.3, the total traffic volume at Nicoll Highway ERP Gantry OS 2 during the same hours (7:30–9:30 AM) decreased 9.20% from 29507 in the May period to 26793 in the June period. In the July period the total traffic volume went up to 28966, differing only 1.83% from that of May. Since the ERP rates at Nicoll Highway were kept constant during these three months, it can be concluded that the traffic drop in June observed at both sites was caused by factors other than road pricing. It is also logical to conclude that this traffic drop was most probably caused by the school holidays. Similar phenomena were observed at almost all charging points.

Table 6.3: Total traffic volume at Nicoll Highway during 7:30–9:30 AM

	May	June	July
Total traffic volume in 5 days	29507	26793	28966
Percent change w.r.t. May (%)	–	–9.20	–1.83

Distribution of Traffic Volumes over Time Intervals

In addition to restraining the total travel demand, the major objective of a time-variable pricing scheme such as the ERP system in Singapore is to encourage the spread of traffic from peak period to other time intervals. Therefore, in addition to the change of total traffic volume, the traffic distribution is also expected to reflect the impacts of ERP rate adjustment on motorists. As shown in Figure 6.4, traffic distribution over time in May differed significantly from that of June, and was similar to July at the CTE site. It is shown that the traffic distribution responded to the adjustment of road pricing. The ERP rates in June were lower in the intervals 7:30–8:15 AM and 8:30–9:00 AM. Further analysis found that the traffic proportions for these intervals, (except for the interval of 7:30–7:45 AM), had an increase from May to June.

Figure 6.4: Traffic distribution at CTE OS 31

Again, referring to the traffic distribution over time at Nicoll Highway there is an indication that in June there was a significant drop of traffic (see Figure 6.5)

corresponding to the interval 7:30–7:45 AM. However, unlike that observed at CTE, within the intervals 8:00–8:15 AM and 8:30–9:00 AM there were no obvious differences in traffic across the three months.

Figure 6.5: Traffic distribution at Nicoll Highway from 7:30 AM to 9:30 AM

Considering that there was a rate adjustment at CTE and none at Nicoll Highway, it seems that the reduction of rates at some intervals induced the motorists to reschedule their arrival times. Meanwhile, the school holidays led to a great decrease in the traffic volume before 7:45 AM, although the fee for interval 7:30–7:45 AM was also decreased.

Test of Traffic Equilibrium

As presented in Chapter 5, the day-to-day COV of 15-minute volumes (Equation [5.17]) can be used to evaluate whether flow equilibrium conditions existed during each 5-day period of the three data collection weeks. At CTE, the mean COV values related to the three datasets were 2.54%, 2.83% and 2.26%, respectively. The COV

values for each 15-minute volume are shown in Table 6.4, from which it can be seen that all the values were not higher than 3.36%. The low COV values imply that traffic flows were under equilibrium conditions during each of the three weeks.

Table 6.4: Day-to-day COV (%) of 15-minute volumes at CTE

Interval start time	7:30	7:45	8:00	8:15	8:30	8:45	9:00	9:15	Mean
May	1.38	2.08	1.88	3.36	2.96	2.73	3.04	2.88	2.54
June	3.07	2.51	2.97	3.28	2.74	2.77	2.18	3.12	2.83
July	1.97	2.01	1.84	2.56	2.82	2.25	2.70	1.95	2.26

6.3.2. Traffic Composition by Vehicle Type

Based on elasticity studies, vehicles under the ERP system can be classified into six types: (1) cars; (2) motorcycles; (3) light goods vehicles (LGVs); (4) buses, heavy and very heavy vehicles (HVs); (5) taxis; and (6) exempted vehicles.

Figure 6.6 shows the average traffic composition at CTE by vehicle type during the three weeks of data collection. It shows that cars contributed almost 60% of the total traffic volume. The second largest category was taxis, followed by LGVs, motorcycles and HVs. The smallest fraction was exempted vehicles.

Figure 6.6: Traffic composition by vehicle type at CTE

Again, COV was used to examine the changes of traffic composition among the three weeks. As shown in Table 6.5, the proportions by vehicle type were quite stable, as their COVs were within the range from 2.23% to 5.53%.

Table 6.5: Traffic composition by vehicle type (%) for each observation week

Vehicle type	May	June	July	COV (%)
Cars	58.90	61.33	58.89	2.36
Motorcycles	7.91	7.46	7.65	2.91
LGVs	9.64	9.15	9.53	2.76
HVs	2.74	2.70	2.98	5.53
Taxis	19.85	18.37	20.00	4.63
Exempted vehicles	0.95	0.98	0.94	2.23
Total (%)	100.00	100.00	100.00	

In the short term, a significant change in traffic composition is not expected, except when there is a major change in the transportation policy (e.g., introduction of road pricing). According to the data in this study, the adjustment of ERP rates, combined with the effects of school holiday period, did not lead to a significant change in the composition. Stable traffic compositions were also found at the other charging points during the three months.

6.3.3. Composition of Cars, Motorcycles, LGVs and HVs

As discussed in Chapter 3, it is proposed to model the scheduling decisions of cars, motorcycles, LGVs and HVs by employing discrete choice modelling techniques, which require that observations of behavioural changes follow the changes of model variables. This section analyses the transaction data related to these four types of vehicles at CTE OS 31 further.

Multiple-passes

From the transaction dataset, some motorists of the above vehicle types were found

having been charged more than once in the same morning. This might be caused by non-recurrent reasons, such as going back home on urgent matters. The times of these passes do not reflect the motorists' scheduling decisions with respect to the ERP or traffic conditions. Therefore, these passes, called "multiple-passes" in this study, will be excluded from the discrete choice models.

Table 6.6 shows the number of multiple-passes and their contributions to the traffic volumes for each vehicle type. Most (61.7%) of the multiple-passes were generated by cars. For each vehicle type, the contributions of multiple-passes were within the range from 0.34% to 0.96%, all less than 1%. It means that the proportion of multiple-passes in the total traffic volume is minor. Overall, multiple-passes contributed 0.33% to the traffic.

Table 6.6: Multiple-passes at CTE for 3 observation weeks

Vehicle type	Multi-passes	Proportion (%)	Percentage (%) of all passes
Cars	481	61.7	0.34
Motorcycles	136	17.5	0.75
LGVs	99	12.7	0.45
HVs	63	8.1	0.96
Total for 3 weeks	779	100.0	0.33 (of the total traffic)

Table 6.7 shows the distribution of multiple-passes over time. Over the three months, the total numbers of multiple-passes was stable. At each time interval, the numbers of multiple-passes seem stable across the three months.

Table 6.7: Distribution of multiple-passes

Interval start time	Number observed in 5 working days								
	7:30	7:45	8:00	8:15	8:30	8:45	9:00	9:15	Total
May	45	38	28	22	27	33	29	45	267
June	40	34	25	21	21	34	28	46	249
July	44	38	24	21	24	36	32	44	263

The multiple-passes generated by taxis (4773 passes) and ERP exempted vehicles (189 passes) were not incorporated in the above calculation since these two motorist categories will not be modelled at a micro level and their multiple-passes should be seen as part of their total travel demand.

Regular Motorists

In the calibration of discrete choice models for cars, motorcycles, LGVs and HVs, two sets of transaction data will be used, as discussed in Chapter 3. The first set of data is used to estimate the MLPAT for individual motorists and the second is used to calibrate the separate models. This approach requires that the individual data used in the model calibration should relate to those motorists that had transaction records in both of the two datasets, i.e., were captured passing under the gantry in both May and June. These motorists are defined as “regular motorists” in this study.

The passes of regular motorists and their proportions for each vehicle type are shown in Table 6.8. The percentages of regular motorists for cars are the highest among the four types of vehicles, with about 65%. Overall, the regular motorists contributed 61.5% to the total number of passes generated by these four types of vehicles in May, and 63.1% in June.

Table 6.8: Passes of regular motorists at CTE for May and June

Vehicle type	May			June		
	Passes of regular	Total passes	Regular (%)	Passes of regular	Total passes	Regular (%)
Cars	31267	47836	65.4	29911	45861	65.2
Motorcycles	3521	6423	54.8	3365	5574	60.4
LGVs	3650	7809	46.7	3675	6790	54.1
HVs	1100	2213	49.7	1053	1987	53.0
Total	39538	64281	61.5	38004	60212	63.1

Commuters, Non-commuters and Weekly Travel Frequency of Cars

During the ERP operating hours (AM peak hours) at CTE OS 31, a considerable proportion of car drivers are commuters, most of whom are driving from the north region of Singapore to work in the CBD. It is logical to assume that commuters have a higher weekly travel frequency (WTF) than the other motorists, although it may not always be so for particular individuals. In this study, cars with a WTF of 3 and above are defined as “commuters”, and the other cars as “non-commuters”. The true WTF for each car is unknown from the transaction data, since entries before or after the ERP operating hours are not captured. In this study, WTF is defined as the number of days that a car was charged by the system in one week.

Figure 6.7 shows the distribution of car passes by WTF at CTE. Cars with WTF 5 contributed the largest proportion of car volume, 34.5%, of the total number of car passes on average for the three data collection weeks. Cars with WTF 2 and 3 had the lowest proportions, both being about 13%. Overall, commuters contributed 66.2% of passes, i.e., of the car traffic volume.

Figure 6.7: Distribution of car passes by weekly travel frequency at CTE

The percentage of the total car passes contributed by commuters had a small fluctuation over the three weeks. It reduced from 67.2% in May to 63.9% in June, and then increased back to 67.5% in July.

Table 6.9 shows the average WTF of cars for each period. It can be seen that the average WTF of commuters was stable, with a COV of 1.17%. The same conclusion can be drawn for non-commuters, with a COV of 0.45%.

Table 6.9: Average WTF for cars at CTE

	May	June	July	COV (%)
Commuter cars	4.20	4.11	4.19	1.17
Non-commuter cars	1.24	1.25	1.24	0.45
All cars	2.35	2.25	2.36	2.72

6.4. SEGMENTATION OF CAR MOTORISTS

Cars contribute a major percentage, about 60%, of the total traffic (see Figure 6.6). Among such a large population, there may exist systematic habit variations affecting the utility function parameters (Chesher and Santos-Silva, 2002). Therefore, it may be necessary to further segment car motorists. However, from the ERP transaction dataset, it is difficult to detect evidence for dividing cars into different categories that respond differently when road pricing changes. This section describes the application of data mining techniques to discover possible segmentation rules.

6.4.1. Introduction to Data Mining

Data mining, sometimes called “knowledge discovery”, is the process of analyzing data from different perspectives and summarising it into useful information. Technically, it is an analytical process of finding consistent patterns and/or systematic relationships among fields in large relational databases.

Generally, the available analysis techniques in data mining are as follows (Berry and Linoff, 2000):

- (1) Artificial neural networks: Non-linear predictive models that learn through training and resemble biological neural networks in structure.
- (2) Genetic algorithms: Optimization techniques that use processes such as genetic combination, mutation, and natural selection in a design based on the concepts of natural evolution.
- (3) Decision trees: Tree-shaped structures that represent sets of decisions. These decisions generate rules for the classification of a dataset. They provide a set of rules that predict which records will have a given outcome. Specific decision tree methods include Classification and Regression Trees (CART) and Chi Square Automatic Interaction Detection (CHAID). CART segments a dataset by creating 2-way splits while CHAID segments using chi square tests to create multi-way splits.
- (4) Nearest neighbour method: A technique that classifies each record in a dataset based on a combination of classes of the records most similar to it in a historical dataset.
- (5) Rule induction: The extraction of useful if-then rules from data based on statistical significance.
- (6) Data visualization: The visual interpretation of complex relationships in multidimensional data. Graphics tools are used to illustrate data relationships.

Data mining has been applied to a wide variety of areas in science, engineering and business. Introduction to the theories, techniques and applications of data mining are provided by a considerable body of literature (e.g. Berry and Linoff, 2000; Dunham, 2003; Larose, 2005).

In this study, data mining will provide suggestions for motorist market

segmentation and this segmentation will be further tested in discrete choice modelling. Complex rules for segmenting the motorists are not necessary and impractical in discrete choice models. For instance, a rule with two variables (fields) in defining the classification of motorists will normally lead to at least four (2^2) categories of motorists, whereas a rule with three variables will lead to at least nine (3^2) categories. Therefore, in this study data mining is employed to discover a few (1 or 2) but most important variables that can help to classify the car motorists into categories that respond differently to the changes of ERP rates.

To achieve this objective, the following two-step method is proposed: (1) use the decision tree technique to classify the motorists and draw the classification rules; and then (2) use the data visualization technique to illustrate the most significant relationships (classification rules). In the mining of decision trees, CHAID was used. Data mining software GhostMiner 2.0 (FQS, 2003) was employed to complete these tasks.

6.4.2. Definition of Variables

Before constructing a decision tree, a decision variable should be defined. The mining is an optimization process which extracts as little as possible in number of descriptive classification rules in terms of this decision variable, with an as high as possible classification accuracy. The values of this decision variable are the categories of outcome that the decision tree aims to draw rules about, by using the independent variables in the dataset to predict which category of outcome each record will be classified into.

Decision Variable

In this study, the values of decision variable are the motorists' responses under road pricing, which were classified as either "rational" or "irrational" in the sense of whether a motorist's arrival time shifting led to savings in the ERP fees paid after the rate adjustment.

The average ERP fee paid by motorist n in the week before the rate change can be calculated as:

$$C_n^0 = \frac{\sum_{i=1}^M (D_{in}^0 \cdot ERP_i^0)}{\sum_{i=1}^M D_{in}^0} \quad [6.1]$$

where:

ERP_i^0 is the ERP rate for time interval i before rate adjustment;

D_{in}^0 is the number of times motorist n was charged in interval i in the week before rate adjustment;

$\sum_{i=1}^M D_{in}^0$ is the total number of passes in a week by motorist n , equal to the weekly travel frequency (WTF_n^0).

After the rate adjustment, the average fee paid by motorist n for each pass is:

$$C_n = \frac{\sum_{i=1}^M (D_{in} \cdot ERP_i)}{\sum_{i=1}^M D_{in}} \quad [6.2]$$

where:

ERP_i = the new ERP rate for time interval i after rate adjustment;

D_{in} = the number of times motorist n was charged in interval i in the week after rate adjustment.

Suppose that the motorist did not change his arrival times and WTF, then his average cost per pass would have been:

$$C_n^* = \frac{\sum_{i=1}^M (D_{in}^0 \cdot ERP_i)}{\sum_{i=1}^M D_{in}^0} \quad [6.3]$$

By comparing the motorist's "predicted cost without behaviour change" C_n^* with the observed cost C_n in the week after rate adjustment, the values of decision variable are defined as:

$$\text{"Rational behaviour"} = \begin{cases} \text{True} & \text{if } C_n^* > C_n; \\ \text{False} & \text{otherwise.} \end{cases} \quad [6.4]$$

Two examples of behaviour classification are provided in Table 6.10. The motorist of "Car 1" is classified as "rational" (i.e., "Rational behaviour" = "True") because his observed C_n was less than predicted C_n^* . The motorist of "Car 2" is classified as "irrational" (i.e., "Rational behaviour" = "False") because his C_n was larger than C_n^* .

Table 6.10: Examples of decision variable classification

Int. start time	7:30	7:45	8:00	8:15	8:30	8:45	9:00	9:15	C_n	C_n^*	Class
ERP_i^0	1.27	1.50	2.00	2.00	2.83	2.67	1.00	0.83	—	—	—
ERP_i	0.83	1.00	1.83	2.00	2.50	2.27	1.00	0.83			
Car 1	D_{in}^0	0	0	1	2	0	0	0	1.83	2.00	Rational
	D_{in}	0	0	3	0	0	0	0			
Car 2	D_{in}^0	1	2	1	0	0	0	0	1.71	1.17	Irrational
	D_{in}	0	1	1	2	0	0	0			

Such a classification of behaviour may not accurately reflect a particular motorist's responses to the road pricing adjustment. For instance, some motorists' changes of arrival times have been defined as "irrational", just because of the randomness in the arrivals leading to a higher average cost in the week after the rate adjustment; some motorists may have shifted arrival times from a high charge period to a lower charge period after rate change due to personal reasons rather than road pricing and their shifting behaviour have been defined as "rational". However, for motorists as a whole, the categories of "rational" and "irrational" can correctly reflect the trends in their sensitivity to the road pricing adjustment. It should be noted that data mining applied in this study does not attempt to predict particular motorists' behaviour, but

provides useful guidelines for motorist market segmentation in discrete choice modelling.

Independent Variables

The mining process of a decision tree is to draw classification rules based on the following independent variables:

- (1) WTF in the week before rate adjustment.
- (2) Arrival time shifting range in the week before rate adjustment. It is the motorist's latest arrival time minus his earliest arrival time in the week. This variable to a certain degree represents the timing flexibility of the motorist.
- (3) Median arrival time (MAT) in the week before rate adjustment.
- (4) Mean arrival time in the week before rate adjustment.

6.4.3. Input Data of the Decision Tree

The May and June datasets were used in this data mining. Overall, there were 9956 regular cars (as defined in Section 6.3.3) at CTE OS 31. Among them, 4196 cars were categorised as “rational” according to Equation [6.4]. The transaction data of these 9956 cars were used in the data mining.

At first, it seems that there are no significant differences between the distributions of “rational cars” and “irrational cars” along any two dimensions of the four variables. For example, as shown in Figure 6.8, along the dimensions of MAT (X axis) and arrival time flexibility (Y axis), the distribution of “rational cars” (left figure) seems not different than that of “irrational cars” (right figure). This implies that it is not simple and easy to detect rules to classify these two kinds of cars based on their transaction records before data mining.

Figure 6.8: Distributions of “rational” and “irrational” cars according to the MAT and arrival time flexibility before data mining

6.4.4. The Decision Tree

The decision tree obtained 21 rules for classifying the 9956 cars into either “rational” or “irrational” categories, as shown in Figure 6.9. The independent variables were used to define the rules. For example, the 3rd rule is:

“if May_WTF > 3.5 and median_arrival_time > 500 and median_arrival_time < 522 then class Not.”

which means that if a car’s WTF before rate adjustment is 4 or 5 and its MAT in the week is within the period from 8:20 to 8:42 AM, its response to the road pricing adjustment is classified as “irrational”.

In these rules, three of the four independent variables were involved, except the variable of mean arrival time. A possible reason for no rules involving mean arrival time to classify the “rational” or “irrational” cars is that this variable is highly correlated to the MAT variable. Among the rules, none involved less than two independent variables. This implies that there is not one simple independent variable which can define a car motorist as “rational” or “irrational”.

Figure 6.9: Classification rules (“rational” and “irrational”, are denoted as “Yes” and “Not” in the rules)

The prediction accuracy of these rules for classifying cars is 60.5%, as shown by Figure 6.10. This accuracy value indicates what percentage of cars is classified by the rules correctly – consistent with the definition of “rational” or “irrational” by Equation [6.4].

Figure 6.10: Prediction accuracy of the classification rules

6.4.5. Data Visualization

With 21 descriptive rules, classifications are difficult to be understood. It is possible to apply all these rules to divide the motorists into two segments (i.e., “rational” and “irrational”) and then develop separate choice models accordingly. However, when applied to traffic forecasting, the predicted volumes would look like a result that came from a “black box”. Why a particular car motorist is identified by the rules as “rational” and its transaction data should be used as input to the “rational” model? It would be a question that even the modeller cannot answer. Therefore, it is impractical to segment the car motorists based on all the rules. An explicit and practical method is to identify a few most significant rules, and use these identified rules to develop separate discrete choice models. To identify such rules, the most effective way is to visualize the classifications defined by the 21 rules and point out clear trends.

Figure 6.11 shows the distributions of “rational” and “irrational” cars along the dimensions of MAT and arrival time flexibility after data mining. Compared with Figure 6.8, Figure 6.11 has a much clearer division of the cars belonging to the two classes. It shows that cars with MAT within the period 8:00–9:00AM are less sensitive to road pricing than the other cars. Along the dimension of arrival time flexibility, Figure 6.11 does not show any clear trend.

Figure 6.11: Distributions of “rational” and “irrational” cars according to MAT and arrival time flexibility

The distributions of “rational” and “irrational” cars along the dimensions of MAT and WTF after data mining are shown by Figure 6.12. The following trend can be seen: there is a more clear “cut” of MAT for classifying cars with high WTF (3, 4 and 5 WTF, as described in Section 6.3.3; these motorists are called commuter cars) than cars with low WTF (non-commuter cars).

Figure 6.12: Distributions of “rational” and “irrational” cars according to MAT and WTF

Based on the foregoing discussion, three conclusions are obtained from the data mining results: (1) as expected, data mining magnified the differences between cars, when using descriptive rules based on independent variables; (2) commuter cars behaved differently than non-commuter cars when road pricing changed; (3) commuter cars with MAT within the period 8:00–9:00 AM in general may have a different sensitivity to road pricing than the other commuter cars.

These results suggest the need to segment car motorists into three classes, as shown in Table 6.11. The table shows that commuter car motorists with MAT before 8:00 AM or after 9:00 AM in general were more likely to change their arrival times after ERP rate adjustment in order to save money than the other car motorists. Compared with non-commuter cars, commuter cars with MAT within the period 8:00–9:00 AM had a lower probability of “rational” response to the rate adjustment.

Table 6.11: Classification of car motorists implied by data mining

Class	Passes	Percentage of “rational” (%)
Non-commuter cars	3866	41.4
High peak commuter cars*	3735	37.8
Low peak commuter cars*	2355	50.3

* High peak commuter cars are those with MAT within the period 8:00–9:00 AM; the other commuter cars are called low peak commuter cars.

6.5. SUMMARY OF MOTORIST MARKET SEGMENTATION

Analysis of travel demand elasticity with respect to road pricing found that different vehicle types show different sensitivities to the ERP charge rate (see Chapter 4). This implies the necessity to develop separate models for different types of vehicles.

Study of transaction data for cars, motorcycles, LGVs and HVs found that multiple-passes should be excluded from the separate discrete choice models. These passes can be seen as a special part of the traffic volume and thus should be treated independently.

The application of data mining techniques to the transaction data of cars implied that commuter cars and non-commuter cars should be modelled separately. Further segmenting the commuter cars by different MAT is possible. The car segmentation implied by the data mining will be further tested in discrete choice modelling.

Based on the above discussion, it is recommended to divide the motorists into eight categories based on the ERP transaction data. Their contributions to the total pass volume at CTE in May are shown in Table 6.12. According to the table, commuter cars contributed about 39% to the total number of passes, highest among all categories. The second largest category is taxis, followed by non-commuter cars, LGVs, motorcycles and HVs. Two minor categories are ERP Exempted Vehicles and multiple-passes, both of which contributed less than 1% to the total traffic flow.

Table 6.12: Distribution of passes by motorist category at CTE in May

Motorist category	Passes	Proportion (%)
Commuter cars	32141	39.43
Non-commuter cars	15695	19.26
Motorcycles	6423	7.88
LGVs	7809	9.58
HVs	2213	2.72
Taxis	16181	19.85
Multiple-passes	267	0.33
Exempted vehicles	776	0.95
Total	81505	100.00

Separate models will now be developed corresponding to each of the above motorist categories. In the following chapters, the proposed motorist segmentation described will also be examined statistically.

CHAPTER SEVEN

MODELLING BASED ON ERP TRANSACTION DATA

7.1. INTRODUCTION

For preparing the quarterly revisions of the charging rates at existing ERP gantries, a model using the latest ERP transaction data to forecast the traffic volume after rate adjustment would be very useful. A modelling methodology was proposed for such a purpose, with the focus on short-term impacts of ERP rate adjustment on the peak period traffic for a single charging point.

However, substantial difficulties in modelling based on transaction data exist. As discussed in Chapter 6, the motorist population using the ERP system is varied and the information contained in the transaction dataset looks sparse when compared with the modelling data used in the past travel behaviour studies. Therefore, there are some special issues in this modelling that require new methods. The main issues to be addressed include: selection and application of advanced modelling techniques applicable to different motorist categories, modelling with limited information, and iterative traffic forecasting and model calibration.

The methodological approach for addressing these issues, as well as the overall framework for model development, was experimentally tested on the ERP transaction data collected from the study site CTE Gantry OS 31.

7.2. OVERALL FRAMEWORK FOR TRAFFIC FORECASTING

Prediction of the 15-minute traffic volumes after ERP rate adjustment within the morning peak hours is the final objective. The morning peak in this study is defined as the ERP operating hours at each charging point. For example, in case of

the study site CTE OS 31 the operating hours are from 7:30 AM to 9:30 AM, so the model will focus on the changes of traffic volumes with respect to the charging rates within the eight 15-minute intervals during this 2-hour charging period.

7.2.1. Modelling Method for Each Motorist Category

In Chapter 6 it was proposed to segment the motorists into eight categories (see Table 6.12). Separate models should be developed for the different categories of motorists due to their different behavioural responses to road pricing. These modelling methods are described below and also shown in Figure 7.1 (Page 136).

Commuter Cars, Non-commuter Cars, Motorcycles, LGVs, HVs and Taxis

As argued in Chapter 3, the approach to forecast traffic volumes after rate adjustment includes two steps: (1) prediction of the total volume; and (2) prediction of its distribution over the time intervals. This 2-step approach is applied separately to the forecasting involving motorist categories of commuter cars, non-commuter cars, motorcycles, LGVs, HVs and taxis. Details of this approach will be presented in Section 7.3.

To predict the volume distribution over the time intervals for categories of commuter cars, non-commuter cars, motorcycles, LGVs and HVs, separate scheduling models were developed. The discrete choice model MNL was employed, due to its advantages in modelling and predicting the impacts of multiple factors on behavioural decisions of individual motorists (see Section 2.3).

A scheduling model was also developed for predicting the distribution of taxi travel demand over the time intervals. An incremental logit model was proposed due to its advantages in taking the observed profiles and the choice probabilities for each time interval as the base for “pivoting” and avoiding the calibration issues of the multi-period MNL model (see Section 2.3.4).

Defining:

- Q_k Total number of passes after rate adjustment for motorist category k ($k = 1, \dots, K$),
- P_{ik} Proportion of passes within interval i for motorist category k after rate adjustment ($i = 1, \dots, M$),
- Q_{ik} Expected pass volume of category k in interval i after rate adjustment.

Thus, for commuter cars, non-commuter cars, motorcycles, LGVs, HVs and taxis, the expected traffic volumes are given by:

$$Q_{ik} = Q_k P_{ik} \quad [7.1]$$

Multiple-passes and Exempted Vehicles

Since there are no direct impacts of ERP on exempted vehicles, it is logical to assume that their volume for each time interval remains constant when ERP rates are adjusted. The impacts of rate adjustment on multiple-passes are unknown. However, this category contributes the smallest proportions of the total traffic (0.33%, see Section 6.3.3). Therefore, its 15-minute volumes are also assumed constant.

7.2.2. Traffic Forecasting Approach

Figure 7.1 shows the framework of traffic forecasting, in which the total traffic volume Q_i for each time interval after rate adjustment is obtained by adding the predicted pass volumes for all motorist categories.

Figure 7.1: Motorist categories and the overall framework of traffic forecasting

As presented in Chapter 3, the scheduling decision models for predicting volume distributions involve the congestion penalty variable ($TTPK$, as defined in Chapter 3). The values of this variable are predicted from the speed-flow relationship and thus depend on the outcome of the overall traffic forecast. Therefore, the overall framework for traffic forecasting must include an iterative procedure. The iterative part of this framework is indicated in Figure 7.1.

The input for this forecasting framework is the historical ERP transaction dataset captured at the site of interest. Motorists observed in this dataset are segmented into different categories, corresponding to their definitions presented in Chapter 6. The total number of passes and the volume distribution over the time intervals for each category, as well as the ERP rates charged, can be found from the dataset.

Congestion penalty is initially estimated based on the traffic volume counts. The models developed are employed separately to predict how these motorists would respond to the adjustment of charging rates, changing in both of the total numbers of passes and the volume distribution over time intervals. These changes result in prediction of traffic volumes under the new charging rates and thus lead to a changed congestion penalty. This calls for a new round of predictions of the motorists' responses. Therefore, the forecasting process is iterative. A convergence indicator is required, with which the iterations are monitored and stopped when convergence is reached. The steps in such an iterative forecasting process have been described in detail in Section 3.5.3.

7.3. MODELS OF PEAK TRAFFIC VOLUME

Under the traffic forecasting framework, prediction of the total traffic volume (number of passes) during the peak period for each category of commuter cars, non-commuter cars, motorcycles, LGVs, HVs and taxis is the first step. If road pricing is seen as the only factor that leads to changes in total traffic volume, separate elasticity models can be employed to estimate these changes. However, under some circumstances traffic is affected by road pricing as well as other factors, e.g., school holiday, and the prediction of the number of passes is more complex. In this study the prediction of total number of passes is done in two steps: (1) estimation of the effects of factors other than road pricing on the total number of passes for each motorist category by using comparative method, which is referring to historical data collected under similar circumstances or comparing with a "control area" where similar factors exist but there are no impacts of ERP rate adjustment; and (2) estimation of the effects of rate adjustment on the total number of passes by employing the elasticity model.

7.3.1. Effects of Factors other than Road Pricing

As argued in Chapter 6, traffic flows during the data collection periods in May and June might have been affected by the period of local school holidays. At Nicoll Highway Gantry OS 2 for the same data collection periods, traffic had a significant drop in June, although the charging rates at this site were the same as in May.

Table 7.1 shows the changes in the number of passes for each motorist category at Nicoll Highway between May and June. It shows that the number of passes of non-commuter cars increased by 2.34% from May to June. For all the other motorist categories, the numbers of passes decreased by more than 10%. Motorcycles and taxis had the highest percentage of decrease from May to June. They were followed by LGVs, HVs and commuter cars.

It is postulated that the impact of factors other than road pricing on the total traffic volume at CTE was the same as at the Nicoll Highway. Then the number of passes for each motorist category can be estimated as shown in Table 7.1 assuming that the charging rates had not changed at CTE OS 31 from May to June.

Table 7.1: Number of passes estimated for CTE in June with the assumption that ERP rate had not changed from May

Motorist category	Nicoll Highway OS 2			CTE OS 31	
	May	June	Change (%)	May	Q_k^a #
Commuter cars	13093	11714	-10.5	32141	28756
Non-commuter cars	6319	6467	+2.34	15695	16063
Motorcycles	2567	2158	-15.9	6423	5400
LGVs	1563	1354	-13.4	7809	6765
HVs	971	850	-12.5	2213	1937
Taxis	4854	4081	-15.9	16181	13603

Estimated number of passes before rate adjustment.

7.3.2. The Impacts of Road Pricing

As presented by Equation [2.2], given two values of price and travel demand, the elasticity of travel demand with respect to road pricing can be calculated. Conversely, given the elasticity value and the “before” price and demand, the demand “after” with respect to the price “after” can be estimated as:

$$Q_k = Q_k^a \frac{C_k^0 + C_k + (C_k - C_k^0)E_{Ak}}{C_k^0 + C_k - (C_k - C_k^0)E_{Ak}} \quad [7.2]$$

where:

Q_k^a is the adjusted number of passes for motorist category k before rate adjustment with the assumption that the charging rates had not changed. Its value is shown in Table 7.1.

E_{Ak} is the arc elasticity for motorist category k . Its value can be found from Table 4.8, which was estimated for each vehicle type.

C_k^0 is the average fee charged before rate adjustment for motorist category k .

C_k is the average fee charged after rate adjustment for motorist category k .

Based on the elasticity model [7.2], the total number of passes (Q_k) for motorist category k after rate adjustment was calculated as shown in Table 7.2. The prediction errors are within the range from 0.24% to 1.31% for the six motorist categories. The low error values indicate a good performance of the 2-step approach of travel demand prediction. However, the exact accuracy for each of the two steps in predicting the effects of road pricing and the other factors respectively on the total travel demand is unknown. Since good performances of the approach were consistently observed in the predictions for the six motorist categories, this 2-step approach is believed to be able to correctly reflect the complex reasons affecting the total travel demand under road pricing. It will be validated later in Chapter 8.

Table 7.2: Predicted and observed number of passes for CTE in June

Motorist category		Commuter cars	Non-com-muter cars	Motor-cycles	LGVs	HVs	Taxis
Q_k^a		28756	16063	5400	6765	1937	13603
C_k^0 (S\$)		1.763	1.763	0.881	1.763	2.833	1.763
C_k (S\$)		1.533	1.533	0.767	1.533	2.465	1.533
E_{Ak}		-0.195	-0.195	-0.134	-0.044	-0.109	-0.112
Q_k	Observed	29308	16553	5574	6790	1987	13776
	Predicted	29546	16504	5501	6806	1967	13817
	Error (%)	+0.81	-0.30	-1.31	+0.24	-1.01	+0.30

7.4. MODELS OF SCHEDULING DECISIONS

7.4.1. Scheduling Decision Model for Taxis

The incremental logit model, also called the pivot-point model, has been developed to estimate future travel demand on the basis of knowledge of the current levels of demand and changes in the variables of interest for each alternative.

Kumar (1980) gave an incremental form of the MNL model of mode choice as:

$$P_i = \frac{P_i^0 \exp(V_i - V_i^0)}{\sum_{m=1}^M P_m^0 \exp(V_m - V_m^0)} \quad [7.3]$$

where:

P_i is the new proportion of trips using mode i ;

P_i^0 is the base proportion of trips by mode i ;

$V_i - V_i^0$ is the change in the utility of using mode i .

In scheduling decision, the relocation of taxi travel demand is due to the changes in utility of arrival within each time interval. Under road pricing, the change in

utility is expressed by the change of ERP charging rate and the change of congestion penalty in each interval. The incremental logit model is applied to modify the taxi demand proportion in each time interval according to the changes in the generalised utility of each interval i ($i = 1, \dots, M$):

$$P_{it} = \frac{P_{it}^0 \exp[\alpha_t(ERP_{it} - ERP_{it}^0) + \tau_t(TTPK_i - TTPK_i^0)]}{\sum_{m=1}^M P_{mt}^0 \exp[\alpha_t(ERP_{mt} - ERP_{mt}^0) + \tau_t(TTPK_m - TTPK_m^0)]} \quad [7.4]$$

where:

P_{it}^0 is the proportion of taxi demand in time interval i before rate adjustment;

P_{it} is the expected proportion of taxi demand in time interval i after rate adjustment;

ERP_{it}^0 is the taxi charging rate in time interval i before rate adjustment;

ERP_{it} is the taxi charging rate in time interval i after rate adjustment;

$TTPK_i^0$ is the congestion penalty in time interval i before rate adjustment;

$TTPK_i$ is the congestion penalty in time interval i after rate adjustment.

The NLLS calibration method presented in Chapter 5 can be used to find the values of α_t and τ_t which minimise the sum of squared differences between the estimated and observed taxi demand proportions:

$$\text{Minimise: } LS = \sum_{i=1}^M (P_{it}^* - P_{it})^2 \quad [7.5]$$

where P_{it}^* is the observed proportion of taxi demand in time interval i after rate adjustment.

In order to find α_t and τ_t which minimise Equation [7.5], the following equations are required:

$$\begin{cases} \frac{\partial LS}{\partial \alpha_t} = -2 \sum_{i=1}^M \left[(P_{it}^* - P_{it}) \left(\frac{\partial P_{it}}{\partial \alpha_t} \right) \right] = 0 \\ \frac{\partial LS}{\partial \tau_t} = -2 \sum_{i=1}^M \left[(P_{it}^* - P_{it}) \left(\frac{\partial P_{it}}{\partial \tau_t} \right) \right] = 0 \end{cases} \quad [7.6]$$

The derivation process of Equation [7.6] is similar to that of Equation [5.9]. Again, Newton's method can be applied to solve Equation [7.6]. Percentage RMSE (Equation [5.10]) is used to evaluate goodness-of-fit of the model.

7.4.2. Scheduling Decision Models of Commuter Cars, Non-commuter Cars, Motorcycles, LGVs and HVs

As presented in Section 3.3.1, the basic microeconomic perspective of discrete choice modelling views individual's scheduling decision as a trade-off resulting when the individual takes into account schedule delay from his PAT, travel time, charging rate and external constraints. Based on this perspective, the specifications of separate scheduling models for commuter cars, non-commuter cars, motorcycles, LGVs and HVs (separately denoted as motorist category $k=1, \dots, K$) are presented below.

Scheduling Decision Utility Function and Time Choice Probability

As discussed in Section 3.3.5, the functional form of utility for discrete choice modelling of scheduling decisions is proposed to be linear-in-the-parameters.

Suppose that a motorist n belongs to motorist category k , has PAT in time interval j and WTF equal to D_n . The total number of motorists included in category k is N_k . As defined previously, motorist n has M 15-minute intervals in his choice-set (see Section 3.3.4).

According to the model specification presented in Chapter 3, the deterministic part

of utility for motorist n to choose interval i is:

$$V_{in} = \alpha_k ERP_{ik} + \tau_k TTPK_i + \beta_{1k} SDE_{in} + \beta_{2k} SDL_{in} + \gamma_k H_{in} \quad (i = 1, \dots, M \text{ and } k = 1, \dots, K) \quad [7.7]$$

where:

ERP_{ik} is the ERP rate for category k during time interval i ;

$TTPK_i$ is the congestion penalty corresponding to time interval i , equal to the travel time per unit distance;

$$H_{in} = \begin{cases} 1 & \text{if } i = j \\ 0 & \text{otherwise} \end{cases} \quad \text{binary variable indicating travelling at PAT;}$$

α_k , τ_k , β_{1k} , β_{2k} , and γ_k are model parameters for motorists of category k .

The definition of schedule delay earlier (SDE_{in}) and later (SDL_{in}) is the same as that in Chapter 5 (Equation [5.2]). Their values depend on interval j (i.e., the interval containing PAT of motorist n).

As a result of data mining presented in Section 6.4.5, it was found that commuter cars with MAT within the period 8:00–9:00 AM have a different sensitivity to road pricing than the other commuter cars. Therefore, separate ERP charge coefficients (α_1 and α_2) for these and the other commuter cars are proposed:

$$V_{ij} = \begin{cases} \alpha_1 ERP_{ik} + \tau TTPK_i + \beta_1 SDE_{in} + \beta_2 SDL_{in} + \gamma H_{in} & \text{for MAT} \in 8:00 - 9:00 \\ \alpha_2 ERP_{ik} + \tau TTPK_i + \beta_1 SDE_{in} + \beta_2 SDL_{in} + \gamma H_{in} & \text{otherwise} \end{cases} \quad (i = 1, \dots, M) \quad [7.8]$$

The vector of model parameters (in model [7.7] they are: α_k , τ_k , β_{1k} , β_{2k} and γ_k ; whereas in model [7.8] they are: α_1 , α_2 , τ , β_1 , β_2 , and γ) is denoted as θ_k . Vectors $\mathbf{ERP}_k$ and $\mathbf{TTPK}$ are the system variables and together with SDE , SDL and H they form a matrix of explanatory variables $\mathbf{X}_n^s$ for motorist n under ERP charging rates s .

Similarly to the model developed in Chapter 5, the probability for motorist n to choose time interval i can be expressed in an MNL form as:

$$P_{in} = \frac{\exp(V_{in})}{\sum_{m=1}^M \exp(V_{mn})} \quad (i = 1, \dots, M \text{ and } n = 1, \dots, N_k) \quad [7.9]$$

The probability of choosing time interval i for motorist category k can be estimated by:

$$P_{ik} = \frac{\sum_{n=1}^{N_k} (P_{in} D_n)}{\sum_{m=1}^M \sum_{n=1}^{N_k} (P_{mn} D_n)} \quad (i = 1, \dots, M \text{ and } k = 1, \dots, K) \quad [7.10]$$

PAT Issue

In this study, PAT is defined as the time that an individual would most like to arrive at the gantry point if there were no ERP charges at all and there was no congestion at any time of day (see Section 3.3.1). From ERP transaction data, PAT for each particular motorist is unknown.

Assuming that the timing decisions made each day by a motorist are independent, maximum likelihood method can be applied to estimate his PAT. This method is based on the idea that although a sample could originate from several populations, a particular sample has a higher probability of having been drawn from a certain population than from others. Therefore, the maximum likelihood estimate is the parameter which will generate the observed sample most often (Ortúzar and Willumsen, 2001). Here, we seek the most likely PAT (MLPAT) that leads to the least error in modelling the traveller's scheduling decisions.

Denote S^0 as the total number of charging conditions involved in the ERP transaction data used for MLPAT estimation (respectively, they are “data before

rate adjustment” used in model calibration and “historical data” used in model application, see Chapter 3). Define D_{in}^s as the number of days that motorist n chooses time interval i under ERP charging rates s . With his observed arrival times under the ERP conditions, the likelihood function for evaluating whether his PAT is within time interval j can be expressed as:

$$\pi_n(j|\theta_k) = \prod_{s=1}^{S^0} \prod_{i=1}^M P_n(i|\theta_k, \mathbf{X}_n^s, PAT = j)^{D_{in}^s} \quad [7.11]$$

With parameter vector θ_k , $\mathbf{X}_n^s$ and given PAT value as j , the time choice utilities V_{in} ($i = 1, \dots, M$) for motorist n can be calculated with Equation [7.7] (or Equation [7.8] for commuter cars). Thus, the probability for him to choose time interval i under the ERP charging rates s $P_n(i|\theta_k, \mathbf{X}_n^s, PAT = j)$ in Equation [7.11] (i.e., P_{in} in Equation [7.9]) can be quantified.

Now, the optimisation problem comes to be: seeking the time interval J_n for motorist n among all the possible intervals, which meets the requirement below:

$$\pi_n(J_n|\theta_k) \geq \pi_n(j|\theta_k), \quad \forall j, J_n \in (1, \dots, M) \quad [7.12]$$

Equation [7.12] implies an assumption that PAT of motorist n is within the charging hours (covering the time intervals from 1 to M). This assumption can be explained as follows: if a motorist’s PAT is earlier or later than the charging period, he would not reschedule his arrival times to this period, which results in additional ERP cost and heavier traffic flows. In the real world there may be some motorists who would not behave according to this assumption. However, the proportion of these motorists should be very small and is ignored in this study. Thus, time interval J_n is accepted as the MLPAT of motorist n .

Denote S as the total number of charging conditions involved in the transaction

data for calibrating the scheduling decision models (i.e.: “ERP transaction data after rate adjustment”, see Chapter 3). With the MLPAT estimated for each motorist in category k , the likelihood function for estimating the scheduling decision model for this category can be described as:

$$L(\boldsymbol{\theta}_k) = \prod_{s=1}^S \prod_{n=1}^{N_k} \prod_{i=1}^M P_n(i | \boldsymbol{\theta}_k, \mathbf{X}_n^s, PAT = J_n) ^{D_m^s} \quad [7.13]$$

Likelihood function [7.13] is a classical likelihood function for discrete choice modelling. Therefore, the parameter vector $\boldsymbol{\theta}_k$ for model [7.7] (or Equation [7.8] for commuter cars) can be estimated by employing conventional discrete choice modelling techniques. Goodness-of-fit of the models can be evaluated by traditional methods used in discrete choice models, such as t -test and the ρ^2 index.

7.4.3. Approach for Calibrating the Scheduling Models

An iterative procedure is required for calibrating the scheduling decision models for two reasons: (1) the calibration of models uses congestion penalty as an input variable, which in turn depends on traffic volumes which are forecast using the schedule decision models; (2) the calibration of models requires PATs of individuals, the most likely values of which are estimated by a likelihood function that is based on models’ utility functions.

The congestion penalty for a time interval in the utility function of the scheduling decision model (Function [7.7] and [7.8]) is defined as the travel time per kilometre corresponding to this interval. As described in Section 5.3.2, the congestion penalty value for each 15-minute interval can be estimated by using Equation [5.14].

The convergence indicator used in this modelling is defined similarly to the one that has been used in forecasting of traffic volumes with respect to a new ERP

gantry (see Chapter 5) – it was defined as the maximum percentage difference of the forecast traffic volumes between two consecutive iterations (denoted as iterations $r-1$ and r):

$$\omega^r = \max_{i \in (1, \dots, M)} \left\{ \frac{|Q_i(\text{MLPAT}^r, \text{TTPK}^r, \theta^r) - Q_i(\text{MLPAT}^{r-1}, \text{TTPK}^{r-1}, \theta^{r-1})|}{Q_i(\text{MLPAT}^{r-1}, \text{TTPK}^{r-1}, \theta^{r-1})} \right\} \quad [7.14]$$

where, $Q_i(\text{MLPAT}^r, \text{TTPK}^r, \theta^r)$ is the forecast traffic volume for time interval i obtained in iteration r .

The overall framework for calibrating the scheduling decision models is similar to the framework for traffic forecasting. Two sets of ERP transaction data are required, collected “before” and “after” a rate adjustment from the same site. Motorists observed in this dataset are segmented into different categories according to the segmentation definitions. Regular motorists (as defined in Section 6.3.3) for the categories of commuter cars, non-commuter cars, motorcycles, LGVs and HVs are identified in these two datasets. The total number of passes and the volume distribution over the time intervals for each category, as well as the ERP charging rates, can be found from the datasets. The iterative approach for calibrating the models includes the following steps:

- (1) For each regular motorist, use his MAT observed in the “before” dataset to initialise his MLPAT.
- (2) Use the traffic volumes observed in the “before” dataset to initially calculate the values of congestion penalty variable (using Equation [5.14]).
- (3) Predict separately the total number of passes after the rate adjustment for categories of commuter cars, non-commuter cars, motorcycles, LGVs, HVs and taxis (refer to Section 7.3 for the methods). The pass volumes of multiple-passes and exempted vehicles are assumed to remain constant from the “before” to the “after” situation (as discussed in Section 7.2.1).

- (4) Based on the regular motorists' transaction records incorporated in the "after" dataset, traditional discrete choice modelling technique is employed to calibrate the separate scheduling decision models [7.7] and [7.8] for categories of commuter cars, non-commuter cars, motorcycles, LGVs and HVs (see Section 7.4.2). Based on taxi volumes observed from the "after" dataset, the incremental logit model [7.4] is calibrated (see Section 7.4.1).
- (5) Forecast the 15-minute traffic volumes after the rate adjustment, using methods presented in Section 7.2.
- (6) Test convergence of traffic forecasting by comparing the convergence indicator value (Equation [7.14]) with the pre-defined convergence threshold. If convergence is achieved, stop the calibration process and accept the current models as the calibration results; otherwise continue by going to Step (7).
- (7) With the calibrated model parameters, re-estimate the MLPAT for each regular motorist based on his transaction records in the "before" dataset, using the estimation methodology presented in Section 7.4.2.
- (8) Use the forecast traffic volumes to predict the congestion penalty by using Equation [5.14], and then continue the procedure by going to Step (4).

The methodological approach consistent with the above calibration steps has been presented in Section 3.5.4 and shown in Figure 3.4 (where the prediction approach for motorist categories of multiple-passes and exempted vehicles was not specifically pointed out).

7.5. PREDICTIONS OF MULTIPLE-PASSES AND EXEMPTED VEHICLES

The assumption of constant volumes of multiple-passes and exempted vehicles was tested by assuming their 15-minute pass volumes in June equal to the volumes observed in May.

This prediction yielded percentage RMSE (see Equation [5.10]) values of 10.5% and 8.4%, for multiple-passes and exempted vehicles respectively. The differences between the observed and forecast pass volumes in June as well as the percentage error for each time interval are shown in Table 7.3.

Table 7.3: Observed and forecast 15-minute volumes of multiple-passes and exempted vehicles at CTE

Interval start time		7:30	7:45	8:00	8:15	8:30	8:45	9:00	9:15
Multiple-passes	Observed	40	34	25	21	21	34	28	46
	Predicted	45	38	28	22	27	33	29	45
Exempted vehicles	Observed	94	86	75	106	89	102	93	92
	Predicted	115	83	85	105	93	110	95	90
Percentage error (%)		+19.4	+0.83	+13.0	0.00	+9.09	+5.15	+2.48	-2.17

Note: The 15-minute volumes here are the aggregated results for 5 working days.

7.6. CALIBRATION RESULTS OF THE SCHEDULING DECISION MODELS

The proposed scheduling decision models were calibrated by using two sets of ERP transaction data collected at CTE OS 31 (see Chapter 6 for analyses of these data). The May dataset was defined as the “before” dataset which was used to estimate the MLPATs and initialise the congestion penalty; and the June datasets was defined as the “after” dataset and used to calibrate the models.

7.6.1. Convergence of Model Calibration Process

The convergence threshold was set at 0.50%, and with that the calibration procedure reached convergence in its seventh iteration. As shown in Figure 7.2, the convergence indicator (Equation [7.14]) after the 2nd iteration was 3.05%. Its value has reduced gradually from 2.45% in the 3rd iteration to 1.13% in the 6th iteration. After the 7th iteration, this indicator value was 0.13%, less than the pre-defined convergence threshold, and thus the calibration process was stopped.

Figure 7.2: Convergence indicator values in the calibration process

The volume within each time interval contributed by multiple-pass and exempted vehicle categories (Table 7.3) as well as the total number of passes for each of the other motorist categories (Table 7.2) were held constant during the calibration iterations. The only differences in traffic forecasting from iteration to iteration were the volume distributions over time intervals of taxis, commuter cars, non-commuter cars, motorcycles, LGVs and HVs, which were predicted by the separate scheduling decision models (see Figure 7.1).

The reduction of differences between volumes predicted for individual motorist categories in two consecutive iterations can also reflect the trend of convergence to a certain degree. For each of the motorist categories, the prediction differences of volume distribution were smaller and smaller between iterations, as shown in

Figure 7.3. From the 6th to 7th iteration, the mean values of prediction difference for each of the motorist categories were all less than 0.50%, (the largest was 0.35% for the motorcycle model). In other words, when the model calibration met the pre-defined convergence criteria based on iteration-to-iteration forecast traffic volumes, the separate models reached a stable status simultaneously. This implies that the model parameters obtained were also steady in the 7th calibration iteration. This statement will be further validated in Chapter 8.

Figure 7.3: Reduction of differences in volume distribution predictions between iterations.

During the calibration process, the forecasting accuracy of 15-minute traffic volumes has improved: the values of percentage RMSE in the traffic forecasting decreased from 7.56% in the first iteration to 4.57% in the final iteration. As can be seen in Figure 7.4, this traffic forecasting performance increased smoothly and finally became steady when the process reached convergence. The changes in forecast traffic volumes led to small iteration-to-iteration changes of congestion penalty values.

Figure 7.4: Percentage RMSE in forecast 15-minute traffic volumes during the calibration process.

7.6.2. Estimation Results of MLPAT

As PAT is a key variable in the scheduling decision models, its input value MLPAT is crucial to the prediction of volume distribution. In the process of model calibration, the initialisation of each regular motorist's MLPAT is his MAT observed in the “before” dataset. Based on these initialised MLPAT, the discrete choice models were calibrated. Then, with the calibrated utility function of scheduling decision model for a particular motorist category, the MLPAT for each motorist in this category can be estimated based on his ERP transaction records contained by the “before” dataset, by using the method proposed in Section 7.4.2.

Figure 7.5 shows the distribution of motorists according to their final MLPAT and their MAT over the time intervals for the category of commuter cars, and Figure 7.6 for categories of non-commuter cars, motorcycles, LGVs and HVs. As expected, the estimated MLPATs had a significant change from its initialisation, consistent for each of the five motorist categories.

Figure 7.5: Distribution of motorists by their MAT and MLPAT for commuter cars.

7.6.3. Calibration Results of Scheduling Decision Models

Software Limdep 7.0 (Greene, 1995) was used to calibrate the discrete choice models of scheduling decisions. Table 7.4 shows the coefficient values obtained in each of the calibration iterations for the model of commuter cars. One can see that the model coefficient values had changed significantly during the process. In the first iteration, the coefficient value of congestion penalty variable (*TTPK*) had a positive sign. In the second and third iterations, this coefficient obtained negative values, but was not significant at the 5% significance level. The coefficients for all variables obtained in the sixth iteration were close to the final results. The best ρ^2 index was obtained in the last iteration and was equal to 0.4962. Details of model's goodness-of-fit are shown in Appendix D.

Figure 7.6: Distribution of motorists by their MAT and MLPAT for non-commuter cars, motorcycles, LGVs and HVs

Table 7.4: Scheduling decision models for commuter cars obtained at each of the calibration iterations

Variable	Parameter	Model coefficients in each iteration						
		1	2	3	4	5	6	7
<i>ERP</i>	α_1	-0.381	-0.267	-0.227	-0.213	-0.205	-0.199	-0.199
	α_2	-0.259	-0.312	-0.348	-0.381	-0.402	-0.412	-0.413
<i>TTPK</i>	τ	+0.607	-0.299*	-0.439*	-0.494	-0.533	-0.545	-0.547
<i>SDE</i>	β_1	-0.081	-0.056	-0.053	-0.051	-0.047	-0.046	-0.046
<i>SDL</i>	β_2	-0.073	-0.070	-0.070	-0.068	-0.063	-0.061	-0.061
<i>H (at PAT)</i>	γ	+0.449	+0.688	+0.781	+0.820	+0.847	+0.853	+0.854
ρ^2		0.3254	0.4311	0.4613	0.4767	0.4909	0.4957	0.4962

Note: * Variable not significant at the 5% significance level.

Similar iteration-to-iteration changes in the model coefficient values could be seen for the categories of non-commuter cars, motorcycles, LGVs, HVs and taxis. The iterative procedure improved the goodness-of-fit of the models. Model coefficient values for these motorist categories obtained in all iterations, as well as the goodness-of-fit measures, are also included in Appendix D.

Table 7.5 shows the final calibration results of the discrete choice models (separately, denoted as models M1 – M5) for categories of commuter cars, non-commuter cars, motorcycles, LGVs and HVs. In the models, all variables are significant at the 5% significance level, except the variable *ERP* in model M5, and all the values of ρ^2 index are higher than 0.496. This implies that the models are strong, considering that the numbers of observations for these models are large (>1000). More details of the models' goodness-of-fit can be found in Appendix E, which shows the output results of model calibration from Limdep 7.0.

Some general trends emerge from the calibration results:

- (1) Consistently for all the motorist categories, the variables of *ERP*, congestion

penalty (*TTPK*) and schedule delay (*SDE* and *SDL*) have negative effects on the motorists' scheduling decisions. It means that a higher value of any of these variables corresponding to a particular time interval will lead to a lower probability for the motorists to choose this interval. The positive coefficient value of *H* variable (see its definition for model [7.7] and [7.8]) implies that motorists would like to arrive at their PATs if it does not mean extra costs in terms of the ERP fee and travel time when compared to arriving at the other time intervals.

- (2) Generally, car motorists are more sensitive to road pricing than motorists of the other vehicle types, as the relevant models have the highest absolute values of α coefficient among models M1 – M5.
- (3) Commuter cars with MAT before 8:00 AM or after 9:00 AM are more sensitive to the pricing rates than the other motorist categories, as reflected by the *ERP* coefficient (α_2) value of -0.4130 and relatively lower absolute coefficient values for the other variables.
- (4) HV motorist category is the least sensitive to road pricing — the variable of *ERP* is even insignificant in the motorists' scheduling model.
- (5) For all categories, postponing a trip is more onerous than bringing it forward, especially for LGVs the ratio is almost double (i.e., the ratio of β_2 to β_1 : $-0.0848 / -0.0438 = 1.93$).
- (6) The values of γ indicate that there is a certain threshold of utility for motorists to resist scheduling away from their PATs.
- (7) Congestion penalty is always a significant and important factor in the motorists' scheduling decisions. Although no serious congestion exists on the CTE, motorists would still prefer a time interval with light traffic.

Table 7.5: Separate discrete choice models of scheduling decision

Variable	Parameter	Model coefficients (<i>t</i> -statistics)				
		M1 Commuter cars	M2 Non-commuter cars	M3 Motorcycles	M4 LGVs	M5 HVs
<i>ERP</i>	α	–	–0.2426 (–9.75)	–0.2266 (–3.17)	–0.1202 (–2.05)	–0.0115* (–0.31)
	α_1	–0.1987 (–3.26)	–	–	–	–
	α_2	–0.4130 (–9.11)	–	–	–	–
<i>TTPK</i>	τ	–0.5469 (–2.17)	–0.9912 (–2.22)	–0.9744 (–2.06)	–1.0208 (–3.31)	–0.9683 (–2.18)
<i>SDE</i>	β_1	–0.0460 (–49.6)	–0.0386 (–25.7)	–0.0745 (–21.2)	–0.0438 (–19.6)	–0.0557 (–10.2)
<i>SDL</i>	β_2	–0.0606 (–48.3)	–0.0598 (–26.3)	–0.0791 (–21.2)	–0.0848 (–21.7)	–0.0786 (–11.1)
<i>H (at PAT)</i>	γ	+0.8536 (+31.5)	+1.6291 (+35.4)	+0.7727 (+9.94)	+1.1480 (+16.9)	+1.1790 (+8.39)
<i>Number of observations</i>		22004	7907	3365	3675	1053
<i>Log likelihood (0)</i>		–45756	–16442	–6998	–7642	–2190
<i>Log likelihood</i>		–23053	–7598	–3100	–3471	–881
ρ^2		0.4962	0.5379	0.5570	0.5458	0.5978

Note: *Log likelihood* (0) is the model's log likelihood value when all coefficients are equal to 0;

* Variable not significant at the 5% significance level.

Table 7.6 shows the calibration result of the incremental logit model for taxis. For this motorist category, the coefficients of *ERP* and *TTPK* are also negative. The coefficient values are reasonable and comparable to those of models M1 – M5. For the scheduling model of taxis, as the model inputs are volume data, no statistical tests are available for evaluating its goodness-of-fit. The model yielded a percentage RMSE value of 4.88%.

Table 7.6: Scheduling decision model of taxis

Variable	Parameter	Value
<i>ERP</i>	α_t	-0.1537
<i>TTPK</i>	τ_t	-0.4365
Percentage RMSE		4.88%

Using Equations [5.21] and [5.22], the direct and cross point elasticities of the scheduling decision models can be calculated. Table 7.7 shows the elasticity values. Note that the cross elasticities of any option time interval i with respect to ERP_m of option m are equal. Again, although these elasticities at certain degree reflect the sensitivities of the motorists to the change of road pricing, it is difficult and inadequate to apply them to predict the traffic volumes under road pricing with time-variable rates.

7.6.4. Predictions of Volume Distribution and Traffic Volumes

As presented in Section 7.2, the aim of the scheduling decision models is to predict the impacts of ERP rate adjustment on the volume distributions over time for taxis, commuter cars, non-commuter cars, motorcycles, LGVs and HVs.

Table 7.8 shows the values of travel time per unit distance before and after the ERP rate adjustment. The values did not vary significantly among the time intervals, with a COV value of 6.34% before and 5.98% after the rate adjustment. Again, it implies that the influence of congestion penalty variable on motorists' scheduling decisions may not be sufficient to alleviate congestion in the peak period without the additional cost imposed by road pricing.

Table 7.7: Direct and cross-point elasticities

Interval start time		7:30	7:45	8:00	8:15	8:30	8:45	9:00	9:15
Commuter Cars 1	Direct	-0.150	-0.165	-0.306	-0.333	-0.421	-0.394	-0.182	-0.157
	Cross	0.016	0.034	0.059	0.064	0.076	0.056	0.016	0.009
Commuter Cars 2	Direct	-0.311	-0.343	-0.635	-0.692	-0.874	-0.820	-0.379	-0.326
	Cross	0.033	0.070	0.122	0.134	0.158	0.116	0.034	0.018
Non-commuter Cars	Direct	-0.179	-0.212	-0.390	-0.428	-0.526	-0.476	-0.210	-0.178
	Cross	0.023	0.030	0.055	0.057	0.081	0.074	0.033	0.024
Motor-cycles	Direct	-0.085	-0.097	-0.182	-0.195	-0.243	-0.221	-0.099	-0.087
	Cross	0.009	0.017	0.026	0.032	0.041	0.036	0.014	0.007
Taxis	Direct	-0.009	-0.010	-0.019	-0.020	-0.025	-0.022	-0.010	-0.008
	Cross	0.001	0.001	0.002	0.003	0.004	0.004	0.002	0.001
LGVs	Direct	-0.088	-0.104	-0.190	-0.213	-0.263	-0.241	-0.101	-0.090
	Cross	0.012	0.016	0.030	0.028	0.037	0.031	0.019	0.010
HVs	Direct	-0.018	-0.021	-0.040	-0.045	-0.056	-0.051	-0.022	-0.019
	Cross	0.003	0.005	0.006	0.006	0.007	0.007	0.003	0.002

Note: 'Commuter Cars 1' are commuter cars with MAT within the period of 8:00–9:00 AM;
'Commuter Cars 2' are the other commuter cars.

Table 7.8: Travel time per unit distance

Interval start time	TTPK (minute/km)		Change (%)
	Before adjustment	After adjustment	
7:30	0.94	0.83	-11.5
7:45	0.96	0.94	-1.92
8:00	0.93	0.92	-0.99
8:15	1.05	0.97	-6.75
8:30	1.00	0.95	-4.84
8:45	0.97	0.92	-5.26
9:00	0.97	0.91	-6.71
9:15	0.84	0.83	-1.44
COV (%)	6.34	5.98	–

Figures 7.7 – 7.8 show the predicted and actual volume distributions of commuter cars, non-commuter cars, motorcycles, LGVs and HVs. It should be noted that models M1 – M5 were calibrated based on regular motorists' transaction records,

whereas the model predictions were the volume distributions of all the vehicles in each category. Therefore, it is not surprising to find that the curves of “model” fitted the curves of “regular ‘after’” better than the curves of “category ‘after’”. For instance, model M2 has a good performance in reflecting the volume distribution of regular non-commuter cars whereas its accuracy of predicting the volume distribution for all non-commuter cars is relatively low. This was due to the fact that the volume distribution of regular non-commuter cars was considerably different from that of the other non-commuter cars (see the curves of “regular ‘after’” and “category ‘after’”). On the other hand, the proportion of regular passes in this category is low (47.8%), compared to the commuter cars (75.1%). In the other motorist categories, the regular motorists can better represent the effects of ERP rate adjustment on the volume distribution of the whole category, as the responses of regular and irregular motorists are closer to each other. In general, models M1 – M5 reflected the effects of road pricing on the motorists’ scheduling decisions correctly. Figure 7.9 shows the predicted and actual volume distribution of taxis. It indicates that the incremental logit model did reflect the impacts of road pricing on taxis’ travel demand distribution over the time intervals.

Figure 7.7: Predicted and actual volume distribution of commuter cars

Figure 7.8: Predicted and actual volume distribution of non-commuter cars, motorcycles, LGVs and HVs

Figure 7.9: Predicted and actual volume distribution of taxis

Given the total number of passes and their distribution, the 15-minute volumes can now be calculated for each category (Equation [7.1]).

Table 7.9 shows the forecast and observed 15-minute volumes for 5 working days for each category. As the prediction accuracies of the total numbers of passes for these categories were considerably high (see Table 7.2), the errors in forecasting their 15-minute volumes mainly depended on the predictions of volume distributions. Overall, the volume predictions yielded the following percentage RMSE values: commuter cars 5.42%; non-commuter cars 9.93%; motorcycles 5.03%; LGVs 5.10%; HVs 7.74%; and taxis 4.92%.

Table 7.9: Observed and forecast 15-minute volumes for all the motorist categories

Interval start time		7:30	7:45	8:00	8:15	8:30	8:45	9:00	9:15
Commuter cars	Observed	2798	4886	4594	4836	4387	3494	2627	1686
	Predicted	3090	4827	4623	4894	4623	3466	2460	1563
	Error (%)	+10.4	-1.21	+0.63	+1.20	+5.38	-0.80	-6.36	-7.30
Non-commuter cars	Observed	1826	1877	1865	2049	2076	2029	2549	2282
	Predicted	2000	2187	1924	2008	2114	2110	2135	2025
	Error (%)	+9.53	+16.5	+3.16	-2.00	+1.83	+3.99	-16.2	-11.3
Motor-cycles	Observed	593	795	694	779	771	753	723	466
	Predicted	602	778	660	801	781	778	687	414
	Error (%)	+1.52	-2.14	-4.90	+2.82	+1.30	+3.32	-4.98	-11.2
LGVs	Observed	858	839	860	736	831	820	1134	712
	Predicted	869	885	909	791	830	795	1052	676
	Error (%)	+1.28	+5.48	+5.70	+7.47	-0.12	-3.05	-7.23	-5.06
HVs	Observed	276	319	256	223	212	232	250	219
	Predicted	254	360	248	230	226	207	235	205
	Error (%)	-7.97	+12.9	-3.13	+3.14	+6.60	-10.8	-6.00	-6.39
Taxis	Observed	1063	1232	1379	1828	1923	2301	2131	1919
	Predicted	1161	1133	1451	1769	1929	2266	2169	1940
	Error (%)	+9.22	-8.04	+5.22	-3.23	+0.31	-1.52	+1.78	+1.09

Note: The 15-minute volumes here are the aggregated results for 5 working days.
Prediction results for the other two categories multiple-passes and exempted vehicles are shown in Table 7.3.

As presented in Section 7.2.2, by adding the predicted 15-minute volumes for all the motorist categories (Table 7.3 and Table 7.9), traffic volume Q in each time interval after the rate adjustment can be obtained. Figure 7.10 shows the forecast and observed 15-minute volumes after ERP rate adjustment at CTE Gantry OS 31. This forecasting yielded a percentage RMSE of 4.57%.

Figure 7.10: Forecast and observed traffic volumes after ERP rate adjustment

CHAPTER EIGHT

MODEL TESTING AND VALIDATION

8.1. INTRODUCTION

Motorists were segmented into different categories, as presented in Chapter 6. Based on the segmentation, scheduling decision models for six of the eight categories were developed separately, as described in Chapter 7. Although coefficient values look different across the separate models, the significance of these differences is still unknown. This chapter will statistically test these differences and thus validate the necessity of motorist segmentation. The segmentation of car motorists based on data mining will also be tested.

In Chapter 7, the calibrated models have been partially evaluated based on their goodness-of-fits and/or prediction accuracies, such as the ρ^2 index, t -statistic test of variable significance and percentage RMSE values. In this chapter, the specifications of calibrated scheduling decision models as well as the model calibration approach will be further evaluated.

Finally, the proposed methodology for predicting the effects of ERP rate adjustment on traffic volumes, including the overall traffic forecasting framework and the calibrated models, will be systematically tested by applying them to the 15-minute volume forecasting at CTE Gantry OS 31 after the rate adjustment on 30 June 2003. This rate adjustment was different from that which has been used for model calibration.

8.2. VALIDATION OF MOTORIST SEGMENTATION

8.2.1. Taste Variations by Vehicle Type

By simply comparing the absolute coefficient values, conclusions can be drawn from the calibrated scheduling decision models which are consistent with the elasticity analysis presented in Table 4.8. For instance, car motorists are more sensitive to road pricing than other motorists, as the absolute coefficient value of *ERP* in the car model is relatively larger than those in other models.

To further test whether significant taste variations exist among the various motorists, a hypothesis test of equal vectors of coefficients across the motorist categories is suggested by Ortúzar and Willumsen (2001). This can be done by employing the asymptotic *t*-statistic test of equality of coefficients between two motorist categories (denoted as k_1 and k_2). The test statistic is:

$$t_l = \frac{\theta_l^{k_1} - \theta_l^{k_2}}{\sqrt{\left[\left(\frac{\theta_l^{k_1}}{t_l^{k_1}}\right)^2 + \left(\frac{\theta_l^{k_2}}{t_l^{k_2}}\right)^2\right]}}, \quad (\forall \theta_l \in \Theta) \quad [8.1]$$

where:

$\theta_l^{k_1}$ and $\theta_l^{k_2}$ are the coefficients of variable X_l in the scheduling decision models of motorist categories k_1 and k_2 ; and

$t_l^{k_1}$ and $t_l^{k_2}$ are the *t*-statistic values of $\theta_l^{k_1}$ and $\theta_l^{k_2}$, respectively.

Table 8.1 shows the application results of this test to the scheduling decision models presented in Table 7.5 for different vehicle types. For 25 of the 48 tests, the hypotheses of equal coefficients were rejected at the 5% significance level. Furthermore, between any two models, at least one of the coefficient values was significantly different. The model-to-model differences in the coefficient values suggest that systematic taste variations do exist across the various motorists

categories. Therefore, development of separate models for different vehicle types is justified.

Table 8.1: Tests of equal coefficients hypotheses between scheduling decision models

Models	Coefficients					
	α		τ	β_1	β_2	γ
M1 vs. M3	α_1	0.30	0.80	7.84*	4.69*	0.98
	α_2	−2.20*				
M1 vs. M4	α_1	−0.93	1.19	−0.91	5.90*	−4.03*
	α_2	−3.95*				
M1 vs. M5	α_1	−2.62*	0.83	1.76	2.51*	−2.27*
	α_2	−6.85*				
M2 vs. M3	−0.21		−0.03	9.39*	4.41*	9.48*
M2 vs. M4	−1.92		0.05	1.93	5.54*	5.87*
M2 vs. M5	−5.17*		−0.04	3.03*	2.53*	3.04*
M3 vs. M4	−1.15		0.08	−7.37*	1.05	−3.64*
M3 vs. M5	−2.67*		−0.01	−2.90*	−0.06	−2.53*
M4 vs. M5	−1.57		−0.10	2.02*	−0.77	−0.20

Note: α_1 and α_2 are the coefficients of variable *ERP* for model M1 (see Table 7.5).

* Rejected at the 5% significance level.

8.2.2. Segmentation of Car Motorists

As described in Chapter 6, the data mining discovered that motorists of commuter cars behaved differently than non-commuter cars when road pricing changed. It also found that commuter cars with MAT from 8:00 to 9:00 AM had a different sensitivity to pricing than the other commuter cars. Corresponding to these findings, two scheduling decision models M1 and M2 were developed separately for commuter and non-commuter car motorists, as described in Chapter 7. Such motorist segmentation for modelling is examined below.

Test on the Feasibility of Developing a Single Model for All Car Motorists

As argued by Ben-Akiva and Lerman (1985), a null hypothesis of no taste variations among market segments can also be statistically tested for discrete choice models. This hypothesis requires a re-estimation of the models. The likelihood ratio test statistic is given by:

$$X^2 = -2 \left[L(\boldsymbol{\theta}) - \sum_k L_k(\boldsymbol{\theta}_k) \right] \quad [8.2]$$

where, $L(\boldsymbol{\theta})$ is the log likelihood for the restricted model that is estimated on the pooled data set with a single vector of coefficients $\boldsymbol{\theta}$ and $L_k(\boldsymbol{\theta}_k)$ is the log likelihood of the separate model estimated with the data set for category k .

This test statistic is χ^2 distributed with the degrees of freedom equal to the number of restrictions:

$$\sum_k F_k - F$$

where F_k is the number of coefficients in the model of category k , and F is the number of coefficients in the restricted model.

The importance of segmenting car motorists can be validated by this statistical test. A systematic test includes the following steps: (1) building a restricted model for car motorists as one single category; (2) re-calibrating all the models based on the same datasets which have been used for modelling with segmented car categories; and then (3) calculating the value of likelihood ratio test statistic for models of cars and evaluating its significance level. The model performance after re-estimation will also be compared with those of modelling with segmented car categories.

The model calibration approach and traffic forecasting methodology are the same as those presented in Chapter 7. Volume forecasting for categories of

multiple-passes and exempted vehicles were the same as presented in Table 7.3. Re-calibration of the other models is described as follows.

In Chapter 7, the total numbers of car passes were estimated for commuter cars and non-commuter cars separately. Here the number of car passes should be re-estimated. The method also includes two steps: (1) estimating the effects of factors other than road pricing on the total number of passes, by using comparative method; and (2) estimating the effects of rate adjustment on the total number of passes, by employing the elasticity model. The number of car passes observed at Nicoll Highway was 19412 in May and 18181 in June. With the proposition that the impacts of factors other than road pricing on the traffic at CTE were the same as at Nicoll Highway, the number of car passes would decrease from 47836 to 44803 without considering the ERP rate change. Employing the elasticity model (Function [7.2]), the total number of car passes in June was estimated as 46035, which differed by 0.38% from the observed number 45861. For motorist categories other than cars, the predicted total numbers of passes were the same as those presented in Table 7.2.

With the same pre-defined threshold (0.50%, as used in Chapter 7), the model calibration procedure reached convergence at its sixth iteration. During this process, the percentage RMSE for traffic forecasting also decreased smoothly and finally became steady: it yielded values from 6.82% at the first iteration to 5.50% at the fifth iteration and finally 5.44%.

The scheduling decision models obtained from this re-calibration approach are shown in Table 8.2 for cars, motorcycles, LGVs and HVs, and Table 8.3 for taxis. The scheduling decision models of motorcycles, LGVs and HVs resulted in small changes of coefficient values from the modelling with car segmentation. When comparing Table 8.2 with Table 7.5, one can see that the goodness-of-fit indicators were worse for all the models from the re-calibration. The most significant

difference occurred in the models of cars: in Table 7.5, the value of ρ^2 is 0.4962 for commuter cars and 0.5379 for non-commuter cars, whereas in Table 8.2 its value is 0.4558 for the restricted model of all cars.

The incremental logit model of taxis has a small difference in coefficient values with that obtained in the modelling with car segmentation (compare Table 8.3 with Table 7.6). It also performs a bit worse in the distribution prediction, as the percentage RMSE value increased from 4.88% to 4.89%.

For the models of cars, the likelihood ratio test statistic:

$$X^2 = -2 \times [-33850 - (-23053 - 7598)] = 6398, \text{ with 6 degrees of freedom } (=6+5-5).$$

With this evidence, one can reject the null hypothesis of no taste variations among the car motorists at the 5% significance level ($X^2 > \chi^2_{0.05}(6) = 12.6$). This rejection of hypothesis suggests a need for further exploration of taste variations among the car motorists, rather than pooling them in a single model. That is to say, separate models for commuters and non-commuters are required according to the statistical test result.

Given the total number of passes and the volume distribution, the 15-minute pass volumes for each category can be calculated (Equation [7.1]). Table 8.4 shows the percentage RMSE values for forecasting the pass volumes for each category. When comparing the results, one can see that the percentage RMSE values with car segmentation are consistently lower for all vehicle types than those without. The most significant improvement in volume forecasting was found for car motorists, which yielded percentage RMSE values of 8.29% and 6.65%, for modelling without and with car segmentation respectively. This implies that further segmentation of car motorists let the separate models represent the motorists' scheduling decisions better. Overall, the forecasting of 15-minute traffic volume was improved from 5.44% to 4.57% with the assistance of segmentation.

Table 8.2: Discrete choice models of scheduling decision with a single car category

Variable	Parameter	Model coefficients (<i>t</i> -statistics)			
		Cars	Motorcycles	LGVs	HVs
<i>ERP</i>	α	-0.3123 (-3.21)	-0.2268 (-3.17)	-0.1197 (-2.01)	-0.0121* (-0.32)
<i>TTPK</i>	τ	-0.6449 (-3.61)	-0.9638 (-2.03)	-1.0212 (-3.32)	-0.9680 (-2.17)
<i>SDE</i>	β_1	-0.0398 (-58.4)	-0.0743 (-21.1)	-0.0435 (-19.5)	-0.0555 (-10.2)
<i>SDL</i>	β_2	-0.0601 (-63.4)	-0.0790 (-21.2)	-0.0851 (-21.8)	-0.0783 (-11.0)
<i>H (at PAT)</i>	γ	+1.0638 (+45.7)	+0.7719 (+9.93)	+1.1469 (+16.7)	+1.1785 (+8.38)
<i>Number of observations</i>		29911	3365	3675	1053
<i>Log likelihood (0)</i>		-62198	-6998	-7642	-2190
<i>Log likelihood</i>		-33850	-3162	-3526	-898
ρ^2		0.4558	0.5482	0.5386	0.5897

Note: *Log likelihood* (0) is the model's log likelihood value when all coefficients are equal to 0;

* Variable not significant at the 5% significance level.

Table 8.3: Scheduling decision model of taxis with a single car category

Variable	Parameter	Value
<i>ERP</i>	α_t	-0.1516
<i>TTPK</i>	τ_t	-0.4370
Percentage RMSE		4.89%

Table 8.4: Comparison of percentage RMSE values with and without car segmentation

Motorist category	Without segmentation	With segmentation
Cars	8.29	6.65*
Motorcycles	5.10	5.03
LGVs	5.14	5.10
HVs	7.75	7.74
Taxis	4.94	4.92
15-minute volumes	5.44	4.57

* Value calculated by adding up the volumes of commuter and non-commuter cars.

Test on the Feasibility of Developing 3 Separate Models for Car Motorists

As described in Chapter 7, model M1 was calibrated with two different coefficients (α_1 and α_2) for variable *ERP* to reflect the behavioural difference between commuter cars with MAT from 8:00–9:00 AM and the other commuter cars. To justify this model specification, two scheduling decision models were calibrated separately for these two groups of commuter cars to make a comparison.

Table 8.5 shows the model calibration results. In both models M1a and M1b, the parameters have signs consistent with model M1 (Table 7.5). The variable of *TTPK* in model M1b is not significant at the 5% significance level.

Table 8.5: Separate scheduling decision models for commuter cars

Variable	Parameter	Model coefficients (<i>t</i> -statistics)	
		M1a MAT within 8:00–9:00	M1b The other commuter cars
<i>ERP</i>	α	–0.2073 (–4.41)	–0.4163 (–5.02)
<i>TTPK</i>	τ	–0.4945 (–2.09)	–0.5990* (–1.89)
<i>SDE</i>	β_1	–0.0467 (–39.5)	–0.0487 (–24.0)
<i>SDL</i>	β_2	–0.0595 (–40.9)	–0.0608 (–31.8)
<i>H (at PAT)</i>	γ	+0.8478 (+27.2)	+0.8527 (+12.1)
<i>Number of observations</i>		13764	8240
<i>Log likelihood (0)</i>		28621	–17135
<i>Log likelihood</i>		–15992	–7058
ρ^2		0.4413	0.5881

* Variable not significant at the 5% significance level.

Models M1a and M1b, together with model M2 which had been calibrated for non-commuter cars, were tested with the hypotheses of equal coefficients. Again, the asymptotic *t*-statistic test (Equation [8.1]) was applied.

As shown in Table 8.6, the test results show that the coefficient values between models M1a and M1b have no significant differences at the 5% significance level, except for α — on which the equal coefficients hypothesis was rejected. This implies that development of separate models for further segmentation of commuter cars is not necessary, as the separate coefficients for variable *ERP* in model M1 are able to reflect the behavioural difference among these motorists. Half of the equal coefficients hypotheses for models M2 versus M1a and M2 versus M1b were rejected at the 5% significance level. Again, these differences in the coefficient values imply that systematic taste variations do exist between commuter and non-commuter car motorists. Therefore, the segmentation of car motorists for developing separate models M1 and M2 is justified.

Table 8.6: Tests of equal coefficient hypotheses for three separate models of cars

Models	Coefficients				
	α	τ	β_I	β_2	γ
M1a vs. M1b	2.19*	0.26	0.85	0.54	-0.06
M1a vs. M2	0.66	0.98	-4.24*	-0.11	-14.0*
M1b vs. M2	-2.01*	0.72	-4.00*	-0.34	-9.21*

* Rejected at the 5% significance level.

8.3. ASSESSMENT OF THE SCHEDULING DECISION MODELS

8.3.1. Correlations of the Parameter Estimates

In the calibrated discrete choice model for motorist category k , the vector of estimated coefficients (parameters) θ_k , found by the method of maximum likelihood, is asymptotically normally distributed with its expected values and a covariance matrix Ω_k . The estimated variances of parameters S^2 are on the matrix diagonal. With the estimated coefficient value θ_k and its variance S^2_k , the significance level of each variable can be evaluated by the t test statistic (Equation [2.12]). The correlation between any two of the parameters is also presented in the covariance matrix Ω_k . By scaling the matrix to unit diagonals, the correlation coefficients of the estimates are derived.

Tables 8.7 and 8.8 show the correlation matrices of parameter estimates for the discrete choice models presented in Table 7.5. An element of the matrix describes the degree of correlation between the parameters listed in the row and the column respectively. For example, in Table 8.7, the correlation coefficient between variables τ and β_I is -0.0237, which implies that there exists a negative and low degree of linear relationship between the estimations of τ and β_I . Consistently for all the models, the highest correlations are found among the variables of β_I , β_2 and γ . This is expected as these three parameters are related to the variable of PAT.

However, even for these parameters the absolute values of correlation coefficients are all less than 0.3. The values of correlation coefficient imply that there is no problem of multi-colinearity among the parameters.

Table 8.7: Correlation of parameter estimates for model M1

	α_1	α_2	τ	β_1	β_2	γ
α_1	1.0000					
α_2	0.2630	1.0000				
τ	0.1024	0.1448	1.0000			
β_1	0.2745	0.0699	-0.0237	1.0000		
β_2	-0.1419	-0.2763	-0.1020	0.2986	1.0000	
γ	0.0296	0.0064	-0.0388	0.2082	0.2683	1.0000

Table 8.8: Correlation of parameter estimates for models M2 – M5

Model		α	τ	β_1	β_2	γ
M2	α	1.0000				
	τ	0.0548	1.0000			
	β_1	0.1155	-0.1063	1.0000		
	β_2	0.1216	0.1487	0.2536	1.0000	
	γ	0.0028	-0.0120	0.2328	0.2993	1.0000
M3	α	1.0000				
	τ	0.1504	1.0000			
	β_1	0.1052	0.0814	1.0000		
	β_2	0.0146	-0.0145	0.2532	1.0000	
	γ	0.0035	0.0166	0.2822	0.2831	1.0000
M4	α	1.0000				
	τ	-0.1872	1.0000			
	β_1	-0.0082	-0.0040	1.0000		
	β_2	0.0247	-0.0284	0.2625	1.0000	
	γ	0.0008	-0.0226	0.2855	0.2632	1.0000

Note: Table 8.8 is to be continued at next page.

Table 8.8 (continued):

Model		α	τ	β_1	β_2	γ
M5	α	1.0000				
	τ	0.1487	1.0000			
	β_1	-0.0375	0.0246	1.0000		
	β_2	-0.0910	-0.0146	0.2090	1.0000	
	γ	-0.0246	-0.0649	0.2810	0.2309	1.0000

8.3.2. Model Prediction Accuracy at Individual Level

As presented in Chapter 7, the ρ^2 index describes the goodness-of-fit of a model to the calibration data, and the percentage RMSE value describes how accurately is the travel behaviour of motorists predicted by the model at an aggregate level.

At the individual level, the prediction accuracy of a discrete choice model can also be estimated. In discrete choice modelling theory, the basic concept is that an individual selects the maximum-utility alternative from his choice-set (see Chapter 2). With the calibrated utility function, the time interval related to the maximum-utility is predicted as the scheduling choice for each pass. Table 8.9 shows the cross tabulation of actual versus predicted choices for the scheduling decision model of commuter cars. Numbers on the diagonal are the time choices of motorist predicted correctly by the model. By adding up these numbers, it can be found that the rate of correct predictions of this model is 53.2% (= 11695 / 22004).

Cross tabulations of actual versus predicted choices for the other calibrated discrete choice models are shown in Appendix E. According to the tabulations, the rates of correct predictions are: 58.4% for model M2 (= 4619 / 7907); 56.3% for model M3 (= 1894 / 3365); 57.0% for model M4 (= 2093 / 3675); and 57.3% for model M5 (= 603 / 1053).

Table 8.9: Cross tabulation of actual versus predicted choices for model M1

Time choices		Predicted (Interval start time)							
		7:30	7:45	8:00	8:15	8:30	8:45	9:00	9:15
Actual (Interval start time)	7:30	1318	383	144	123	94	44	18	7
	7:45	699	2142	513	215	94	40	19	7
	8:00	134	630	1864	619	219	53	17	6
	8:15	69	244	561	1794	609	175	83	29
	8:30	36	117	218	572	1703	483	170	73
	8:45	26	50	92	227	544	1340	325	128
	9:00	10	19	34	67	130	329	914	294
	9:15	9	10	17	28	50	117	286	620

It is noted that the number of alternatives in the model choice-sets is eight, which implies that the prediction correct rate will be 12.5% ($= 100\% / 8$) if all of the model parameters were 0. From this perspective, the above prediction correct rates indicate good performance of the models at an individual level.

8.3.3. Convergence of the Model Calibration Process

As shown in Figure 7.4 in Chapter 7, the iterative model calibration procedure has smoothly improved the forecasting accuracy of the 15-minute traffic volumes. This trend can also be found by tracing the performance of each of the separate models during the calibration iterations.

Figure 8.1 shows the percentage RMSE values yielded by the scheduling decision model of taxis and Figures 8.2 – 8.3 show the values of the ρ^2 index obtained during the calibration iterations for models M1 – M5. Consistently for all the models, the calibration process increased the accuracy and finally became steady when the process reached convergence. These iteration-by-iteration performance improvements further justify the iterative model calibration approach.

Figure 8.1: Percentage RMSE for the scheduling decision model of taxis at each iteration

Figure 8.2: Improvement of the value of ρ^2 index for model M1 during calibration

Figure 8.3: Improvement of the value of ρ^2 indices for models M2 – M5 during calibration

8.4. MODEL VALIDATION

As presented in Sections 3.5.3 and 7.2.2, to forecast the traffic volumes after a rate adjustment, a historical ERP transaction dataset captured at the site of interest is required for: (1) identifying the motorists and segmenting them into eight categories; (2) knowing a “before adjustment” situation, i.e., observing the total traffic volume and the volume distribution over the time intervals for each category; (3) initialising the values of congestion penalty. Furthermore, with the utility functions of scheduling decision model, MLPAT for each motorist in the categories of commuter cars, non-commuter cars, motorcycles, LGVs and HVs are also estimated based on this historical dataset.

For testing the calibrated models and the proposed overall framework in traffic forecasting with respect to rate adjustment, one-week transaction dataset collected at CTE OS 31 before the rate adjustment on 30 June 2003 was used here as the historical dataset. Another week of transaction data collected after the rate adjustment was used to evaluate the forecasting. These data are called June and July datasets (details were described in Chapter 6).

8.4.1. Multiple-passes and Exempted Vehicles

The constant volume assumption regarding volumes of multiple-passes and exempted vehicles was tested by comparing their 15-minute pass volumes in July to the volumes observed in June.

This prediction yielded percentage RMSE values of 8.48% and 6.50% respectively. The differences between the observed and forecast pass volumes in July as well as the percentage forecasting error for each time interval are shown in Table 8.10.

Table 8.10: Observed and forecast 15-minute volumes of multiple-passes and exempted vehicles at CTE

Interval start time		7:30	7:45	8:00	8:15	8:30	8:45	9:00	9:15
Multiple-passes	Observed	44	38	24	21	24	36	32	44
	Predicted	40	34	25	21	21	34	28	46
Exempted vehicles	Observed	104	85	76	102	90	119	89	93
	Predicted	94	86	75	106	89	102	93	92
Percentage error (%)		-9.46	-2.44	0.00	+3.25	-3.51	-12.3	0.00	+0.73

Note: The 15-minute volumes here are the aggregated results for 5 working days.

8.4.2. Total Number of Passes

For categories of commuter cars, non-commuter cars, motorcycles, LGVs, HVs and taxis, the prediction of total number of passes includes two steps for separately estimating the effects of road pricing and other factors (see Section 7.3 for details).

Table 8.11 shows the observed changes in the total number of passes from June to July at Nicoll Highway OS 2, where the ERP charges were kept constant during the data collection period. Using the same change ratios, the total numbers of passes for the different motorist categories were estimated for CTE and the results are shown in Table 8.11. It was assumed that these numbers of passes would be observed if the charging rates had not been adjusted at CTE between June and July 2003.

Table 8.11: Number of passes estimated for CTE in July with the assumption of no change in ERP rates

Motorist category	Nicoll Highway OS 2			CTE OS 31	
	June	July	Change (%)	June	Q_k^a #
Commuter cars	11714	13045	+11.4	29308	32638
Non-commuter cars	6467	5849	-9.56	16553	14971
Motorcycles	2158	2386	+10.6	5574	6163
LGVs	1354	1460	+7.83	6790	7322
HVs	850	986	+16.0	1987	2305
Taxis	4081	4857	+19.0	13776	16396

Estimated number of passes before rate adjustment.

Table 8.12 shows the results estimated by the elasticity models [7.2]. The prediction of total numbers of passes yielded errors within the range from 0.31% to 4.92% for the six motorist categories. This confirms that the 2-step approach of travel demand prediction is effective and reliable.

Table 8.12: Predicted and observed number of passes for CTE in July

Motorist category		Commuter cars	Non-com-muter cars	Motor-cycles	LGVs	HVs	Taxis
Q_k^a		32638	14971	6163	7322	2305	16396
C_k^0 (S\$)		1.533	1.533	0.767	1.533	2.465	1.533
C_k (S\$)		1.763	1.763	0.881	1.763	2.833	1.763
E_{Ak}		-0.195	-0.195	-0.134	-0.044	-0.109	-0.112
Q_k	Observed	31875	15324	6149	7617	2385	16093
	Predicted	31765	14571	6049	7277	2270	16143
	Error (%)	-0.35	-4.91	-1.63	-4.46	-4.82	+0.31

8.4.3. Convergence of the Traffic Forecasting Process

The convergence threshold for model application was also set at 0.50%. The process of traffic volume forecasting reached this convergence level in its fourth iteration. As shown in Figure 8.4, from the 3rd to 4th iteration, the convergence indicator value for the first time dropped to below 0.50% and thus the forecasting process was stopped.

During the iterative procedure, the forecasting accuracy of 15-minute traffic volumes was improved: the values of percentage RMSE in the traffic forecasting decreased from 6.36% in the first iteration to 5.27% in the final iteration. As indicated by Figure 8.5, the traffic forecasting performance increased smoothly and finally became steady. The results confirm that this approach is convergent and it is helpful in improving the traffic forecasting.

Figure 8.4: Convergence indicator values in the forecasting process

Figure 8.5: Percentage RMSE values in the forecasting iterations

8.4.4. Predictions of Volume Distribution and Traffic Volumes

The calibrated models M1 – M5 were used separately to predict the time choice

probability after the rate adjustment for each observed motorist captured in the historical dataset belonging to categories of commuter cars, non-commuter cars, motorcycles, LGVs and HVs. Then the volume distributions for these motorist categories under the new charging rates were predicted by using Equation [7.10]. The input value of WTF D_n for each of these motorists under the new charging rates was assumed unchanged from June, as the average WTF for these motorist categories were found stable across the months (see Section 6.3.3).

The travel demand distribution of taxis under the new charging rates was predicted by the calibrated incremental logit model. After that, with the predicted total numbers of passes (as shown in Table 8.12), the 15-minute pass volumes for each category of the above six categories were calculated using Equation [7.1].

The comparison of forecast and observed 15-minute volumes for these categories is shown in Table 8.13. The predictions yielded the following percentage RMSE values: commuter cars 6.66%; non-commuter cars 10.03%; motorcycles 6.57%; LGVs 6.18%; HVs 8.72%; and taxis 7.26%.

Table 8.13: Observed and forecast 15-minute pass volumes for July

Interval start time		7:30	7:45	8:00	8:15	8:30	8:45	9:00	9:15
Commuter cars	Observed	3601	4764	4803	5363	4425	3898	3323	1698
	Predicted	3295	4490	5195	5481	4853	3710	3132	1608
	Error (%)	-8.50	-5.74	+8.16	+2.20	+9.68	-4.82	-5.74	-5.28
Non-commuter cars	Observed	2612	1624	1502	1792	1773	1808	2137	2076
	Predicted	2176	1420	1540	1872	1666	2039	1957	1900
	Error (%)	-16.7	-12.6	+2.56	+4.48	-6.02	+12.8	-8.43	-8.45
Motorcycles	Observed	791	818	735	890	815	799	817	484
	Predicted	744	753	761	905	766	890	778	451
	Error (%)	-5.88	-7.93	+3.50	+1.69	-5.99	+11.4	-4.76	-6.73
LGVs	Observed	1004	907	918	969	868	906	1114	931
	Predicted	910	861	944	983	808	873	1058	840
	Error (%)	-9.37	-5.12	+2.85	+1.42	-6.90	-3.59	-5.05	-9.75

Note: Table 8.13 is to be continued at next page.

Table 8.13 (continued):

Interval start time		7:30	7:45	8:00	8:15	8:30	8:45	9:00	9:15
HVs	Observed	349	383	270	304	256	281	280	262
	Predicted	306	345	276	322	274	258	254	234
	Error (%)	-12.3	-9.92	+2.40	+5.98	+7.10	-8.12	-9.42	-10.6
Taxis	Observed	1651	1487	1574	1882	2314	2518	2430	2237
	Predicted	1469	1685	1463	1989	2229	2640	2456	2211
	Error (%)	-11.0	+13.3	-7.07	+5.70	-3.66	+4.86	+1.05	-1.15

Note: The 15-minute volumes here are the aggregated results for 5 working days.
Prediction results for the other two categories multiple-passes and exempted vehicles are shown in Table 8.10.

By adding up the predicted pass volumes for all motorist categories (shown in Table 8.10 and Table 8.13), the total traffic volume Q in each time interval after rate adjustment can be obtained. Figure 8.6 shows the forecast and observed 15-minute volumes at CTE Gantry OS 31 after the rate adjustment on 30 June 2003. The overall percentage RMSE value was 5.27%.

Figure 8.6: Forecast and observed traffic volumes for July

CHAPTER NINE

CONCLUSIONS AND RECOMMENDATIONS

9.1. CONCLUSIONS

This study has demonstrated the feasibility of forecasting the effects of road pricing on traffic at a single charging point, which can be practically used in the ERP system planning. Modelling methods were developed for two purposes: one is using traffic volume data to forecast the traffic response to a new single ERP gantry and the other is using ERP transaction data to forecast the impacts of rate adjustment on motorists and consequently on traffic volumes at existing gantry points. The experimental testing of the proposed methodologies yielded the following accuracies in traffic predictions: for introduction of a new gantry, the best model yielded percentage RMSE values of 3.91% in calibration and 8.25% in validation; for ERP rate adjustment, the best set of models yielded percentage RMSE values of 4.57% in calibration and 5.27% in validation.

This study faced some new challenges in modelling travel responses based on traffic volume data and ERP transaction data. For planning a new charge point, observations of individual motorist's behaviour at the site are difficult to capture and assemble. This situation calls for a new modelling methodology for using traffic volume data in both of model calibration and application, as the volume data are much more readily available. For planning rate adjustments at existing charging points, the ERP transaction records provide an ample and valuable source of actual data for model development and traffic forecasting. However, the specific structure of transaction data dictates that the methodology needed for this modelling requires a novel approach.

To deal with the challenges, several new features were incorporated in the proposed methodology. Some of these features are:

- (1) an MNL-based scheduling decision model for using traffic volume data to forecast the impacts of ERP introduction on traffic volumes;
- (2) motorist segmentation based on elasticity analysis and data mining techniques, for modelling based on ERP transaction data;
- (3) model specifications of scheduling decision in terms of the characteristics of transaction records of individual motorists;
- (4) a maximum likelihood method for estimating the unknown PAT;
- (5) an integrated framework with iterative approach for using ERP transaction data to model and forecast the effects of rate adjustment on traffic volumes, which combines different model techniques for various motorist categories.

In conclusion, this study has developed a practical modelling methodology, specifically for the ERP system planning and forecasting traffic volumes with respect to road pricing change. With increasing worldwide interest in urban road pricing, more and more automatic charging schemes like the ERP system in Singapore are expected to be implemented. Therefore, a common question of great interest would be how to make use of the readily available data or system-recorded transaction data for expediently and accurately predicting the effects of road pricing change on traffic. This research can be seen as the first attempt to solve this problem.

In addition to the main conclusions presented above, some of the salient research findings are summarised in the next sections.

9.1.1. Analysis of Travel Demand Elasticity

Analyses of travel demand elasticity highlighted the differences among the

motorists in their responses to road pricing. These provided a basic understanding of the impacts of road pricing and some evidence for motorist segmentation in further behavioural modelling. The findings are summarised below:

- (1) Drivers of different vehicle types have different sensitivity to the charges – elasticity is the highest for cars and much lower for goods vehicles.
- (2) Elasticity on expressways and the other roads where ERP is applied only during the morning peak is higher than at the city RZ cordon.
- (3) The long-term effects of road pricing on travellers are much more complex than the short-term.
- (4) For the RZ cordon, elasticity is lower during the morning peak and higher in the late afternoon.

9.1.2. Modelling Based on Traffic Volume Data

Scheduling decision models were developed and calibrated for one expressway and two arterial roads using traffic volume data collected before and after ERP introduction on these roads. Some of the model specifications and findings are as follows:

- (1) The motorists' responses to a new ERP gantry include rescheduling decisions, or changing travel mode and/or route.
- (2) The proposed discrete choice MNL-based model expresses the choice of time period of travel as a function of utility which depends on ERP rate, travel time on the road segment affected by pricing and the length of trip rescheduling from the preferred arrival time.
- (3) Although the calibrated parameter values of the utility function vary somewhat from site to site, they all have correct signs and reasonable magnitudes.

- (4) Postponing travel is generally more onerous than bringing it forward.
- (5) A positive utility is associated with travelling at one's habitual time.
- (6) More possibilities for re-routing to avoid charges correspond to a higher sensitivity to charging rates.

9.1.3. Analysis of ERP Transaction Data

Analyses of the ERP transaction data highlighted the data characteristics and revealed the traffic composition under road pricing, as well as identified the motorist segmentation that one should consider in modelling travel behaviour. Selected findings are presented below:

- (1) The electronic system captures the time of entry and the ERP transaction value of each vehicle using the system. By tracking vehicle's daily transaction records with its unique IU number, scheduling responses of the individual motorists subjected to ERP rate revisions can be observed. These transaction data provide a possibility to develop discrete choice models and apply them to forecast traffic changes under the system.
- (2) Cars contribute a much higher proportion to the total traffic volume than the other vehicle types.
- (3) Multiple-passes are a difficult problem. Transaction records related to these passes cannot be incorporated into the calibration of discrete choice models because their scheduling decisions are not unique.
- (4) The application of advanced data mining techniques led to the finding that the responses of commuter cars to ERP rate adjustment are different from non-commuter cars. It also discovered that commuter cars with median arrival time within the period 8:00–9:00 AM in general have a different sensitivity to road pricing than the other commuter cars.

9.1.4. Modelling Based on ERP Transaction Data

A modelling framework as well as the individual models to forecast the effects of rate adjustment on peak traffic were developed and calibrated using two sets of ERP transaction data. Some of the model specifications and main findings of this research are given below:

- (1) For motorists of cars, motorcycles, LGVs, HVs and taxis, the effects of rate adjustment on their total traffic volumes as well as on their volume distributions over time should be considered.
- (2) Volume of multiple-passes and exempted vehicles are not affected much by the rate adjustment and can be assumed constant.
- (3) Elasticity model can be used to predict the effects of rate adjustment on the total traffic volumes of cars, motorcycles, LGVs, HVs and taxis.
- (4) Incremental logit model can be employed to predict the effects of rate adjustment on the taxi volume distribution over time intervals.
- (5) A maximum likelihood estimation of individual's PAT makes it possible to construct and apply a discrete choice model of scheduling decision based on ERP transaction records.
- (6) MNL model can be employed to predict the effects of rate adjustment under a time-variable pricing system on the volume distribution over time intervals, separately for the categories of commuter cars, non-commuter cars, motorcycles, LGVs and HVs.
- (7) Iterative calibration and forecasting approach improves the model calibration results as well as the traffic forecasting accuracy. This iterative approach is one of the main features of the overall framework for modelling and forecasting based on ERP transaction data.
- (8) Model calibration process yielded a convergent result, with a fairly high

accuracy of 15-minute traffic volume forecasting. Acceptable performance was observed for the goodness-of-fit tests for all models incorporated in the overall framework.

- (9) Correct signs and expected magnitudes of coefficients were obtained in model calibration. Conclusions which can be drawn from the calibrated models are consistent with those from the modelling based on aggregate data and the analysis of travel demand elasticity.

9.1.5. Model Testing and Validation

The calibrated models as well as the overall traffic forecasting framework were systematically examined and validated by applying them to forecasting the effects of a rate adjustment on traffic. This part of the study revealed the following results:

- (1) Validation showed that the motorist segmentation based on elasticity analysis and data mining is necessary. The segmentation made the separate models detect properly the taste variations across the motorist categories and thus improved the overall traffic forecasting results.
- (2) Model evaluation results showed that the selection of modelling techniques for different motorist categories and the specifications of scheduling decision models are appropriate. The iterative procedure was found effective in improving both of the model calibration and traffic forecasting results.
- (3) Model application yielded a percentage RMSE value 5.27% in forecasting the 15-minute traffic volumes after a rate adjustment. All of the calibrated models for the categories of commuter cars, non-commuter cars, motorcycles, LGVs, HVs and taxis, as well as the assumptions of no change for the other motorist categories, showed acceptable performance in predictions. The iterative process of the overall traffic forecasting framework was found to be convergent.

9.2. LIMITATIONS OF THE MODELLING

Some limitations of the modelling and traffic forecasting methodology developed in this study can be described as follows:

- (1) The developed models are limited to forecast the short-term impacts of road pricing on traffic. As argued in the chapter on elasticity analysis, the long-term effects of road pricing on motorists are much more complex than the short-term. As the ERP system is being updated every 3 months, a prediction of its short-term effects would be more useful in practice. Hence, this study did not focus on the long-term effects of road pricing.
- (2) The actual travel time involved in motorists scheduling decisions was unavailable in this study. Firstly, the definition of the travel time taken into individuals' scheduling considerations is in question: it is unknown whether only the travel time on the road directly affected or the total journey time of the trip should be included. Secondly, the speed-flow relationship is more applicable to the estimation of average traffic speed on a segment of road with control of access. It is more difficult to use it for arterial roads, and also infeasible to use separately for different vehicle types. This caused certain limitations of the calibrated models. However, how accurate are the travel times (or the travel times per unit distance involved in the discrete choice models) computed is not crucial to the models, because the model calibration relies on the relative disutility values of travel time that the motorists would consider. As the speed-flow relationship can correctly reflect the relative ratios and trends of these disutility values over the choice options, it is recommended to be used in the models until a more reliable method for travel time estimation is available. However, one should be careful in interpreting the calibrated model parameters. For instance, it may not be possible to estimate the value of travel time for a particular category of motorists based

on the coefficient value of variable *TTPK*.

- (3) In the modelling based on traffic volume data, it was assumed that before the ERP was introduced there was no congestion serious enough to stimulate the motorists to reschedule their trips away from their preferred times. This assumption was justified by evaluating the traffic situation before ERP on the studied sites. However, this would not always be the case, especially as road pricing is meant to alleviate congestion and therefore should be introduced on congested roads. Furthermore, methods for statistical evaluation of the aggregate model are not available. This makes it difficult to further refine the model.
- (4) In the modelling based on ERP transaction data, the models focus on the prediction of traffic volumes within the charging hours only. For practical reasons, the modelling did not involve data other than transaction records as this would cause difficulties in models' application to the ERP system planning. The discrete choice models were calibrated based on the transaction data of regular motorists and used to predict the behaviour of the entire categories of motorists. Although the regular motorists do not constitute a fully representative random sample, only they can be used for model calibration as their choices both before and after rate adjustment are observed. This can be seen as a limitation of the modelling although the forecasting results showed that it did not cause a significant bias.
- (5) Drivers' socio-economic characteristics were ignored in this modelling. Inclusion of these variables into the models may be helpful for understanding the impacts of a road pricing policy on a particular category of motorists. However, models involving these variables would be difficult to apply to the quarterly ERP system planning as the required input values of the socio-economic variables would not be available.
- (6) The proposed modelling methodology was specially designed for a single

charging point. To forecast the impacts of road pricing on traffic in a wider area, an OD based study would be needed with detailed information about the road network, motorists' origins and destinations as well as their travel preferences. As the first attempt to provide a practical forecasting method for the ERP system planning, this study did not aim to develop such an area-wide traffic forecasting model.

9.3. RECOMMENDATIONS FOR FURTHER STUDY

Although this study has addressed a number of issues and provided a useful methodology for traffic forecasting under the ERP system, there are some areas in this field which require further research. These include:

- (1) Further evaluation of the reliability of the methodology is recommended if more sets of data become available. It is likely that use of more sets of historical transaction data collected under different charging situations would improve the maximum likelihood estimation of PAT. It is also suspected that the model calibration results might be better if school holidays did not occur during the data collection periods. However, these hypotheses need additional ERP transaction data to examine.
- (2) The maximum likelihood estimation of PAT made the development of scheduling decision models possible. However, this estimation method has not been evaluated by comparing its results with the actual PAT of motorists. It needs to be validated in the future studies if such data are available for use.
- (3) Using a mix of SP and transaction data in investigating the effects of road pricing on motorists is recommended. SP data can provide additional information on motorists and their scheduling considerations, e.g., their preferred travel times, decision constraints and socio-economic characteristics. Relating the stated information with the motorists' actual times of entry that

can be observed from their daily ERP transaction records would be helpful for further understanding the effects of road pricing on the motorists.

- (4) The accuracy of the proposed method of modelling scheduling decisions can possibly be improved by using a mixed logit model to account for possible correlations as several observations of the same motorists are used. The mixed logit modelling technique can also resolve the issue of possible correlated errors existing among scheduling alternatives. A practical method needs to be developed for applying a series of calibrated mixed logit models to the use of ERP transaction data in predicting the effects of road pricing on traffic volumes. This is an interesting and challenging research topic.
- (5) Transportation policy makers are also concerned with the long-term impacts of road pricing. Some possible long-term impacts on motorists may include: change of destination, travellers' habit adjustment, carpool formation, and so on. Thus, it is also important to study the effects of ERP in the long-term.
- (6) At a network level, modelling motorists' scheduling decisions in a framework of dynamic flow assignment under road pricing is a challenging research topic. A comprehensive study of motorists' scheduling, route and mode choices are also very useful as it would provide a systematic evaluation of the effects of road pricing. Overall, this field remains an important research area, with significant potential benefits for both theory and practice.

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APPENDIX A

LOCATION OF ERP GANTRIES

Table A1: Location of ERP Gantries in Singapore (as of April 2006)

Restricted Zone	Code	Expressways	Code	Arterial Roads	Code
Victoria St.	OS 1	Into ECP from Ophir Rd.	OS 29	Thomson Rd.	OS 39
Nicoll Highway	OS 2			Bendemeer Rd.	OS 40
Eu Tong Sen St.	OS 3	ECP after Fort Rd.	OS 30	Kallang Rd.	OS 41
Orchard Link	OS 4	CTE after Braddell Rd.	OS 31	Dunearn Rd. before Wayang Satu Flyover	OS 43
Lim Teck Kim Rd.	OS 5				
Anson Rd.	OS 6	PIE after Kallang Rd. Exit	OS 32	Dunearn Rd. before Stevens Rd. / Whitley Rd. junction	OS 44
Tanjong Pagar Rd.	OS 7				
Prince Edward Rd.	OS 8	Into CTE from Serangoon Rd.	OS 33		
Bencoolen Rd.	OS 9				
Queen St.	OS 10	Into CTE from Balestier Rd.	OS 34		
North Bridge Rd.	OS 11				
Oxley Rd.	OS 12	CTE before Braddell Rd.	OS 35		
Orchard Rd.	OS 13				
Orchard Turn	OS 14	AYE before Alexandra Rd.	OS 36		
Killiney Rd.	OS 15				
Beach Rd.	OS 16	PIE after Adam Rd.	OS 37		
Temasek Boulevard	OS 17	Into PIE from Mt Pleasant Rd.	OS 38		
Republic Boulevard	OS 18				
Havelock Rd. / Clemenceau Avenue	OS 19	Into CTE from PIE	OS 42		
Havelock Rd. / CTE Exit		Into Bendemeer Rd. from PIE	OS 45		
Buyong Rd.	OS 20	CTE Northbound after PIE	OS 46		
Kramat Rd.	OS 21				
River Valley Rd.	OS 22				
Merchant Rd. / Clemenceau Ave	OS 23				
Merchant Rd. / CTE Exit	OS 24				
Clemenceau Avenue	OS 25				
Cairnhill Rd.	OS 26				
Crawford St.	OS 27				
Orchard after YMCA	OS 28				
Orchard Rd. after Handy Rd.	OS 29

Figure A1: Location of ERP Gantries in RZ A and B (as of August 2006)
(Source: LTA, 2006)

Figure A2: Location of ERP Gantries in RZ Orchard Cordon (as of August 2006)
(Source: LTA, 2006)

Figure A3: Location of ERP Gantry on AYE (as of August 2006)
(Source: LTA, 2006)

Figure A4: Location of ERP Gantries on CTE (as of August 2006)
(Source: LTA, 2006)

Figure A5: Location of ERP Gantries on ECP (as of August 2006)

(Source: LTA, 2006)

Figure A6: Location of ERP Gantries on PIE (as of August 2006)

(Source: LTA, 2006)

Figure A7: Location of ERP Gantries in Outer Ring Road Area (as of August 2006)
(Source: LTA, 2006)

Figure A8: Location of ERP Gantries on Dunearn Road (as of August 2006)

(Source: LTA, 2006)

APPENDIX B

CALIBRATION OF BPR TRAVEL TIME-FLOW

RELATIONSHIP FUNCTION

— Curve-fitting results from the Fan et al. (1995) speed-flow
relationship function (Output of SAS 8.0)

The SAS System 15:20 Saturday, March 20, 2005 12

The NLIN Procedure
Travel Time per Unit Distance
Method: Gauss-Newton

Iterative Phase			
Iter	P-alpha	P-beta	Sum of Squares
0	0.4000	5.3000	1.0752
1	0.5064	4.3488	0.2394
2	0.4980	4.4106	0.2324
3	0.4987	4.4265	0.2324
4	0.4989	4.4301	0.2324
5	0.4989	4.4309	0.2324
6	0.4989	4.4311	0.2324
7	0.4989	4.4312	0.2324

NOTE: Convergence criterion met.

Estimation Summary

Method	Gauss-Newton
Iterations	7
R	6.589E-6
PPC(Palpha)	2.199E-6
RPC(Pbeta)	9.664E-6
Object	1.029E-9
Objective	0.232396
Observations Read	410
Observations Used	410
Observations Missing	0

NOTE: An intercept was not specified for this model.

Source	DF	Sum of Squares	Mean Square	F Value	Approx Pr > F
Regression	2	342.4	171.2	300563	<.0001
Residual	408	0.2324	0.000570		
Uncorrected Total	410	342.6			
Corrected Total	409	4.6582			

Parameter	Estimate	Approx Std Error	Approximate 95% Confidence Limits	
P-alpha	0.4989	0.00489	0.4893	0.5085
P-beta	4.4312	0.0732	4.2872	4.5751

APPENDIX C

ERP CHARGING PERIODS AND RATES DURING THE DATA COLLECTION PERIOD

Table C1: ERP charging periods in 2003

Charging point	May 19–23		June 23–27		June 30–July 04	
	From	To	From	To	From	To
AYE to City before Alexandra Road	8:00	9:29	8:30	9:29	8:00	9:29
Bendemeer Road	7:30	9:29	8:00	8:29	7:30	9:29
CTE after Braddell Road *	7:30	9:29	7:30	9:29	7:30	9:29
CTE before Braddell Road	7:30	9:29	7:30	8:59	7:30	9:29
Into CTE from Balestier Road	No Charge		7:30	9:29	7:30	9:29
Into CTE from Serangoon Road	No Charge		7:30	9:29	7:30	9:29
Dunearn Road before Wayang Satu Flyover	8:00	8:59	8:30	8:59	8:00	8:59
Dunearn Road before Stevens Rd. / Whitley Rd. junction	8:00	8:59	8:30	8:59	8:00	8:59
ECP after Fort Road	7:30	9:29	8:00	8:59	7:30	9:29
Kallang Road	8:30	9:29	No Charge		8:30	9:29
Into ECP from Ophir Road	8:00	8:59	8:00	8:29	8:00	8:59
PIE after Kallang Rd. Exit	7:30	9:29	8:00	8:59	7:30	9:29
Into CTE from PIE *	7:30	9:29	7:30	9:29	7:30	9:29
Into Bendemeer Road from PIE	No Charge		8:01	8:59	7:30	9:29
Into PIE from Mt Pleasant Road	No Charge		8:00	8:59	7:30	8:59
PIE after Adam Road	7:30	8:59	8:00	8:59	7:30	8:59
Thomson Road	7:30	9:29	7:30	8:59	7:30	9:29
CBD (27 sites, except Nicoll Highway) **	8:00	18:59	8:00	18:59	8:00	18:59
Nicoll Highway **	7:30	18:59	7:30	18:59	7:30	18:59

* Charging points where the ERP charging period did not change;

Charging points where the morning ERP rates did not change in these months.

Table C2: Passenger car equivalent (PCE) values for different vehicle types

Vehicle type	PCE value
Cars, LGVs and taxis	1.00
Motorcycles	0.50
HGV and small buses	1.50
Very HGV and big buses	2.00

Table C3: ERP rates (S\$) for cars at AYE OS 36 in 1999

Time period	September	October
7:30–8:00	1.00	1.00
8:00–8:30	1.50	1.00
8:30–9:00	2.00	1.50
9:00–9:30	0.50	0.00

Note: The rates for the other vehicle types were set as their PCE values (see Table C2) multiplied by the rates for cars.

Table C4: ERP rates (S\$) for cars at CTE and Nicoll Highway in 2003

Time period	CTE after Braddell Road (Gantry OS 31)			Nicoll Highway
	May 19–23	June 23–27	June 30–July 04	May – July
7:30–7:35	0.80	0.50	0.80	0.50
7:35–8:00	1.50	1.00	1.50	
8:00–8:05	2.00	1.50	2.00	1.50
8:05–8:30	2.00	2.00	2.00	2.50
8:30–8:35	2.50	2.50	2.50	
8:35–8:55	3.00	2.50	3.00	
8:55–9:00	2.00	1.80	2.00	
9:00–9:25	1.00	1.00	1.00	2.00
9:25–9:30	0.50	0.50	0.50	1.50

Note: 1. The ERP charging period at Nicoll Highway Gantry OS 2 was 7:30 AM–7:00 PM. Here it shows the charging rates relevant to the data used in this study only.

2. The rates for the other vehicle types were set as their PCE values (see Table C2) multiplied by the rates for cars.

APPENDIX D

CALIBRATION RESULTS OF THE

SCHEDULING DECISION MODELS

Table D1: Calibration results of Model M1 (for category of commuter cars) obtained at each of the iterations

Variable	Parameter	Model coefficients (<i>t</i> -statistics)						
		Iteration 1	Iteration 2	Iteration 3	Iteration 4	Iteration 5	Iteration 6	Iteration 7
<i>ERP</i>	α_1	-0.3809 (-6.29)	-0.2674 (-4.46)	-0.2267 (-3.83)	-0.2127 (-3.64)	-0.2045 (-3.32)	-0.1991 (-3.31)	-0.1987 (-3.26)
	α_2	-0.2586 (-5.97)	-0.3116 (-6.91)	-0.3478 (-7.80)	-0.3810 (-8.45)	-0.4017 (-9.02)	-0.4118 (-9.09)	-0.4130 (-9.11)
<i>TTPK</i>	τ	+0.6073 (+2.49)	-0.2991* (-1.25)	-0.4390* (-1.78)	-0.4939 (-1.99)	-0.5327 (-2.14)	-0.5450 (-2.16)	-0.5469 (-2.17)
<i>SDE</i>	β_1	-0.0806 (-56.2)	-0.0556 (-53.8)	-0.0534 (-52.6)	-0.0506 (-51.0)	-0.0473 (-50.6)	-0.0462 (-49.9)	-0.0460 (-49.6)
<i>SDL</i>	β_2	-0.0728 (-54.1)	-0.0701 (-53.9)	-0.0698 (-53.6)	-0.0682 (-52.9)	-0.0630 (-50.2)	-0.0607 (-48.3)	-0.0606 (-48.3)
<i>H (at PAT)</i>	γ	+0.4491 (+16.3)	+0.6883 (+24.9)	+0.7808 (+28.8)	+0.8201 (+29.3)	+0.8473 (+30.7)	+0.8526 (+31.5)	+0.8536 (+31.5)
<i>Log likelihood</i>		-30867	-26031	-24650	-23945	-23294	-23076	-23053
ρ^2		0.3254	0.4311	0.4613	0.4767	0.4909	0.4957	0.4962
<i>Number of observations:</i> 22004		<i>Log likelihood (0):</i> -45756						

Note: * Variable not significant at the 5% significance level.

Table D2: Calibration results of Model M2 (for category of non-commuter cars) obtained at each of the iterations

Variable	Parameter	Model coefficients (<i>t</i> -statistics)						
		Iteration 1	Iteration 2	Iteration 3	Iteration 4	Iteration 5	Iteration 6	Iteration 7
<i>ERP</i>	α	-0.2634 (-10.9)	-0.2586 (-10.2)	-0.2575 (-10.3)	-0.2525 (-10.1)	-0.2459 (-9.92)	-0.2431 (-9.82)	-0.2426 (-9.75)
<i>TTPK</i>	τ	-0.5965* (-1.47)	-0.8674* (-1.94)	-0.8728* (-1.95)	-0.9646 (-2.15)	-0.9823 (-2.21)	-0.9901 (-2.22)	-0.9912 (-2.22)
<i>SDE</i>	β_1	-0.0708 (-33.9)	-0.0523 (-29.8)	-0.0483 (-29.1)	-0.0403 (-26.6)	-0.0392 (-26.1)	-0.0388 (-25.8)	-0.0386 (-25.7)
<i>SDL</i>	β_2	-0.0674 (-33.47)	-0.0680 (-31.6)	-0.0647 (-29.9)	-0.0630 (-28.4)	-0.0615 (-27.6)	-0.0599 (-26.4)	-0.0598 (-26.3)
<i>H (at PAT)</i>	γ	+0.7823 (+17.55)	+1.2333 (+26.9)	+1.3750 (+30.6)	+1.5175 (+32.7)	+1.6008 (+34.9)	+1.6255 (+35.3)	+1.6291 (+35.4)
<i>Log likelihood</i>		-10346	-8585	-8422	-7785	-7673	-7609	-7598
ρ^2		0.3708	0.4779	0.4878	0.5265	0.5333	0.5372	0.5379
<i>Number of observations:</i> 7907		<i>Log likelihood (0):</i> -16442						

Note: * Variable not significant at the 5% significance level.

Table D3: Calibration results of Model M3 (for category of motorcycles) obtained at each of the iterations

Variable	Parameter	Model coefficients (<i>t</i> -statistics)						
		Iteration 1	Iteration 2	Iteration 3	Iteration 4	Iteration 5	Iteration 6	Iteration 7
<i>ERP</i>	α	-0.1406 (-1.99)	-0.1993 (-2.79)	-0.2110 (-2.93)	-0.2136 (-2.98)	-0.2223 (-3.12)	-0.2260 (-3.16)	-0.2266 (-3.17)
<i>TTPK</i>	τ	-0.1043* (-0.23)	-0.8325* (-1.75)	-0.9207* (-1.93)	-0.9546 (-2.01)	-0.9669 (-2.04)	-0.9721 (-2.06)	-0.9744 (-2.06)
<i>SDE</i>	β_1	-0.1074 (-23.7)	-0.0798 (-22.2)	-0.0731 (-20.8)	-0.0716 (-20.4)	-0.0730 (-20.7)	-0.0744 (-21.3)	-0.0745 (-21.2)
<i>SDL</i>	β_2	-0.0920 (-22.9)	-0.0804 (-21.6)	-0.0787 (-21.1)	-0.0770 (-20.1)	-0.0781 (-21.0)	-0.0790 (-21.2)	-0.0791 (-21.2)
<i>H (at PAT)</i>	γ	+0.1786 (+2.17)	+0.6260 (+8.06)	+0.7360 (+9.49)	+0.7463 (+9.61)	+0.7645 (+9.85)	+0.7712 (+9.93)	+0.7727 (+9.94)
<i>Log likelihood</i>		-4441	-3647	-3296	-3241	-3153	-3108	-3100
ρ^2		0.3654	0.4789	0.5290	0.5369	0.5494	0.5559	0.5570
<i>Number of observations:</i> 3365		<i>Log likelihood (0):</i> -6998						

Note: * Variable not significant at the 5% significance level.

Table D4: Calibration results of Model M4 (for category of LGVs) obtained at each of the iterations

Variable	Parameter	Model coefficients (<i>t</i> -statistics)						
		Iteration 1	Iteration 2	Iteration 3	Iteration 4	Iteration 5	Iteration 6	Iteration 7
<i>ERP</i>	α	-0.2778 (-4.71)	-0.1620 (-2.76)	-0.1356 (-2.32)	-0.1237 (-2.10)	-0.1212 (-2.07)	-0.1205 (-2.06)	-0.1202 (-2.05)
<i>TTPK</i>	τ	-0.2701* (-0.93)	-0.6186 (-2.01)	-0.8308 (-2.68)	-0.9543 (-3.11)	-1.0030 (-3.25)	-1.0192 (-3.31)	-1.0208 (-3.31)
<i>SDE</i>	β_1	-0.0733 (-23.1)	-0.0592 (-22.5)	-0.0503 (-21.5)	-0.0459 (-20.3)	-0.0443 (-19.7)	-0.0439 (-19.6)	-0.0438 (-19.6)
<i>SDL</i>	β_2	-0.0662 (-23.1)	-0.0714 (-20.3)	-0.0750 (-20.9)	-0.0806 (-21.1)	-0.0838 (-21.4)	-0.0846 (-21.6)	-0.0848 (-21.7)
<i>H (at PAT)</i>	γ	+0.7486 (+11.0)	+0.8938 (+13.2)	+1.0066 (+14.7)	+1.1052 (+16.2)	+1.1330 (+16.8)	+1.1451 (+16.9)	+1.1480 (+16.9)
<i>Log likelihood</i>		-4907	-4012	-3816	-3620	-3503	-3478	-3471
ρ^2		0.3579	0.4750	0.5007	0.5263	0.5416	0.5449	0.5458
<i>Number of observations:</i>		3675	<i>Log likelihood (0):</i>					
								-7642

Note: * Variable not significant at the 5% significance level.

Table D5: Calibration results of Model M5 (for category of HVs) obtained at each of the iterations

Variable	Parameter	Model coefficients (<i>t</i> -statistics)						
		Iteration 1	Iteration 2	Iteration 3	Iteration 4	Iteration 5	Iteration 6	Iteration 7
<i>ERP</i>	α	-0.0851 (-2.39)	-0.0435* (-1.17)	-0.0293* (-0.77)	-0.0203* (-0.55)	-0.0177* (-0.49)	-0.0126* (-0.34)	-0.0115* (-0.31)
<i>TTPK</i>	τ	-0.0216* (-0.05)	-0.5137* (-1.14)	-0.8440* (-1.91)	-0.9215 (-2.08)	-0.9522 (-2.14)	-0.9670 (-2.18)	-0.9683 (-2.18)
<i>SDE</i>	β_1	-0.0970 (-12.4)	-0.0778 (-13.8)	-0.0672 (-13.3)	-0.0590 (-10.9)	-0.0567 (-10.5)	-0.0559 (-10.2)	-0.0557 (-10.2)
<i>SDL</i>	β_2	-0.0802 (-12.5)	-0.0795 (-11.9)	-0.0804 (-11.6)	-0.0797 (-11.3)	-0.0790 (-11.2)	-0.0787 (-11.1)	-0.0786 (-11.1)
<i>H (at PAT)</i>	γ	+0.4711 (+3.31)	+0.8430 (+6.00)	+1.0378 (+7.39)	+1.1353 (+8.09)	+1.1705 (+8.34)	+1.1781 (+8.38)	+1.1790 (+8.39)
<i>Log likelihood</i>		-1296.2	-1063.0	-996.8	-921.7	-902.7	-883.5	-880.6
ρ^2		0.4080	0.5145	0.5448	0.5791	0.5877	0.5965	0.5978
<i>Number of observations:</i>		1053	<i>Log likelihood (0):</i>					
			-2189.6					

Note: * Variable not significant at the 5% significance level.

Table D6: Calibration results of the model for category of taxis obtained at each of the iterations

Variable	Parameter	Model coefficients (<i>t</i> -statistics)						
		Iteration 1	Iteration 2	Iteration 3	Iteration 4	Iteration 5	Iteration 6	Iteration 7
<i>ERP</i>	α_{τ}	-0.1643	-0.1595	-0.1569	-0.1543	-0.1539	-0.1537	-0.1537
<i>TTPK</i>	τ_{τ}	-0.3668	-0.4152	-0.4310	-0.4355	-0.4359	-0.4364	-0.4365
Percentage RMSE (%)		5.822	5.270	5.166	5.023	4.912	4.880	4.883

APPENDIX E

OUTPUT OF DISCRETE CHOICE

MODEL CALIBRATION

(Limdep 7.0)

Model M1

→ DISCRETECHOICE
 ; Lhs = DECISION
 ; Choices = TI_1, TI_2, TI_3, TI_4, TI_5, TI_6, TI_7, TI_8
 ; Rhs = ERP1, ERP2, TTPK, SDE, SDL, H
 ; Crosstab
 ; Start = -0.3, -0.3, -0.3, -0.1, -0.1, 0.3\$
 Normal exit from iterations. Exit status = 0.

```

+-----+
| Discrete choice (multinomial logit) model |
| Maximum Likelihood Estimates |
| Model estimated: Oct 14, 2005 at 02:05:36PM. |
| Dependent variable Choice |
| Weighting variable None |
| Number of observations 22004 |
| Iterations completed 11 |
| Log likelihood function -23053.00 |
| Log-L for Choice model = -23053.00475 |
| R2=1-LogL/LogL* Log-L fncn R-sqrd RsqAdj |
| No coefficients -45756.0317 .49618 .49616 |
| Constants only -44446.4723 .48133 .48131 |
| Response data are given as ind. choice. |
| Number of obs. = 22004, skipped 0 bad obs. |
+-----+

```

Variable	Coefficient	Standard Error	b/St.Er.	P[Z >z]
ERP1	-.1986708924	.60909624E-01	-3.262	.0011
ERP2	-.4129991948	.45349818E-01	-9.107	.0000
TTPK	-.5469090533	.25231068	-2.168	.0302
SDE	-.4602441191E-01	.92769138E-03	-49.612	.0000
SDL	-.6061952416E-01	.12552390E-02	-48.293	.0000
H	.8535982226	.27143446E-01	31.448	.0000

(Note: E+nn or E-nn means multiply by 10 to + or -nn power.)

Matrix: Las
 [6,4]

+ -----+
 | Cross tabulation of actual vs. predicted choices. |
 | Row indicator is actual, column is predicted. |
 | Predicted total is $F(k, j, i) = \text{Sum}(i = 1, \dots, N) P(k, j, i)$. |
 | Column totals may be subject to rounding error. |
 + -----+

Matrix: Crc
 [9,9]

Time choices		Predicted (Interval start time)								
		7:30	7:45	8:00	8:15	8:30	8:45	9:00	9:15	Total
Actual (Interval start time)	7:30	1318	383	144	123	94	44	18	7	2131
	7:45	699	2142	513	215	94	40	19	7	3729
	8:00	134	630	1864	619	219	53	17	6	3542
	8:15	69	244	561	1794	609	175	83	29	3564
	8:30	36	117	218	572	1703	483	170	73	3372
	8:45	26	50	92	227	544	1340	325	128	2732
	9:00	10	19	34	67	130	329	914	294	1797
	9:15	9	10	17	28	50	117	286	620	1137
	Total	2301	3595	3443	3645	3443	2581	1832	1164	22004

Note: Enclosed cross tabulation of actual versus predicted choices (Matrix [9.9])

Model M2

→ DISCRETECHOICE
 ; Lhs = DECISION
 ; Choices = TI_1, TI_2, TI_3, TI_4, TI_5, TI_6, TI_7, TI_8
 ; Rhs = ERP, TTPK, SDE, SDL, H
 ; Crosstab
 ; Start = -0.3, -0.3, -0.3, -0.1, -0.1, 0.3\$
 Normal exit from iterations. Exit status = 0.

```
+-----+
| Discrete choice (multinomial logit) model |
| Maximum Likelihood Estimates |
| Model estimated: Oct 14, 2005 at 03:27:05PM. |
| Dependent variable          Choice |
| Weighting variable          None |
| Number of observations      7907 |
| Iterations completed        8 |
| Log likelihood function     -7598.125 |
| Log-L for Choice    model = -7598.12477 |
| R2=1-LogL/LogL*    Log-L fcn    R-sqrd    RsqAdj |
| No coefficients      -16442.1443    .53789    .53785 |
| Constants only      -16428.0522    .53749    .53745 |
| Response data are given as ind. choice. |
| Number of obs. = 7907,   skipped 0 bad obs. |
+-----+
```

```
+-----+ +-----+ +-----+ +-----+ +-----+
| Variable | Coefficient | Standard Error | b/St.Er. | P[|Z|>z] |
+-----+ +-----+ +-----+ +-----+ +-----+
| ERP      | -.2426413984 | .24888337E-01 | -9.749 | .0000 |
| TTPK     | -.9911681321 | .44548505 | -2.225 | .0261 |
| SDE      | -.3861670265E-01 | .15018057E-02 | -25.714 | .0000 |
| SDL      | -.5984947587E-01 | .22722096E-02 | -26.340 | .0000 |
| H        | 1.629064362 | .46014462E-01 | 35.403 | .0000 |
```

(Note: E+nn or E-nn means multiply by 10 to + or -nn power.)

Matrix: Las
 [6,4]

+ ----- +
 | Cross tabulation of actual vs. predicted choices. |
 | Row indicator is actual, column is predicted. |
 | Predicted total is $F(k, j, i) = \text{Sum}(i = 1, \dots, N) P(k, j, i)$. |
 | Column totals may be subject to rounding error. |
 + ----- +

Matrix: Crc
 [9,9]

Time choices		Predicted (Interval start time)								
		7:30	7:45	8:00	8:15	8:30	8:45	9:00	9:15	Total
Actual (Interval start time)	7:30	662	86	59	45	35	14	11	5	917
	7:45	141	595	95	51	36	32	22	16	988
	8:00	59	189	479	107	55	41	25	16	971
	8:15	30	71	117	498	108	40	33	30	927
	8:30	22	40	74	108	563	136	74	39	1056
	8:45	25	38	58	79	111	560	121	67	1059
	9:00	13	19	22	46	64	125	619	154	1062
	9:15	6	10	18	28	41	63	118	643	927
	Total	958	1048	922	962	1013	1011	1023	970	7907

Note: Enclosed cross tabulation of actual versus predicted choices (Matrix [9.9])

Model M3

→ DISCRETECHOICE
 ; Lhs = DECISION
 ; Choices = TI_1, TI_2, TI_3, TI_4, TI_5, TI_6, TI_7, TI_8
 ; Rhs = ERP, TTPK, SDE, SDL, H
 ; Crosstab
 ; Start = -0.3, -0.3, -0.3, -0.1, -0.1, 0.3\$
 Normal exit from iterations. Exit status = 0.

```

+-----+
| Discrete choice (multinomial logit) model |
| Maximum Likelihood Estimates |
| Model estimated: Oct 14, 2005 at 04:47:56PM. |
| Dependent variable Choice |
| Weighting variable None |
| Number of observations 3365 |
| Iterations completed 5 |
| Log likelihood function -3099.688 |
| Log-L for Choice model = -3099.68764 |
| R2=1-LogL/LogL* Log-L fncn R-sqrd RsqAdj |
| No coefficients -6997.3208 .55702 .55692 |
| Constants only -6934.1314 .55298 .55289 |
| Response data are given as ind. choice. |
| Number of obs. = 3365, skipped 0 bad obs. |
+-----+

```

Variable	Coefficient	Standard Error	b/St.Er.	P[Z >z]
ERP	-.2266363243	.71574875E-01	-3.166	.0015
TTPK	-.9743886254	.47285577	-2.061	.0393
SDE	-.7445783623E-01	.35140757E-02	-21.188	.0000
SDL	-.7906945116E-01	.37358366E-02	-21.165	.0000
H	.7726911816	.77727403E-01	9.941	.0000

(Note: E+nn or E-nn means multiply by 10 to + or -nn power.)

Matrix: Las
[6,4]

+ ----- +
 | Cross tabulation of actual vs. predicted choices. |
 | Row indicator is actual, column is predicted. |
 | Predicted total is $F(k, j, i) = \text{Sum}(i = 1, \dots, N) P(k, j, i)$. |
 | Column totals may be subject to rounding error. |
 + ----- +

Matrix: Crc
 [9,9]

Time choices		Predicted (Interval start time)								
		7:30	7:45	8:00	8:15	8:30	8:45	9:00	9:15	Total
Actual (Interval start time)	7:30	233	65	22	9	3	2	0	1	335
	7:45	93	296	67	26	8	4	2	0	496
	8:00	29	73	205	73	23	12	6	3	424
	8:15	7	29	67	269	71	22	6	3	474
	8:30	3	5	21	76	259	78	27	13	482
	8:45	2	3	10	25	71	261	75	28	475
	9:00	1	3	7	8	22	66	240	74	421
	9:15	0	2	5	4	21	31	64	131	258
	Total	368	476	404	490	478	476	420	253	3365

Note: Enclosed cross tabulation of actual versus predicted choices (Matrix [9.9])

Model M4

→ DISCRETECHOICE
 ; Lhs = DECISION
 ; Choices = TI_1, TI_2, TI_3, TI_4, TI_5, TI_6, TI_7, TI_8
 ; Rhs = ERP, TTPK, SDE, SDL, H
 ; Crosstab
 ; Start = -0.3, -0.3, -0.3, -0.1, -0.1, 0.3\$
 Normal exit from iterations. Exit status = 0.

```

+-----+
| Discrete choice (multinomial logit) model |
| Maximum Likelihood Estimates |
| Model estimated: Oct 14, 2005 at 05:31:41PM. |
| Dependent variable          Choice |
| Weighting variable          None |
| Number of observations      3675 |
| Iterations completed        8 |
| Log likelihood function     -3470.644 |
| Log-L for Choice    model = -3470.64420 |
| R2=1-LogL/LogL*    Log-L fncn    R-sqrd    RsqAdj |
| No coefficients      -7641.9477    .54584    .54575 |
| Constants only      -7606.2405    .54371    .54362 |
| Response data are given as ind. choice. |
| Number of obs. = 3675,   skipped 0 bad obs. |
+-----+

```

Variable	Coefficient	Standard Error	b/St.Er.	P[Z >z]
ERP	-.1202202048	.58698420E-01	-2.048	.0406
TTPK	-1.020751320	.30880795	-3.305	.0009
SDE	-.4381887294E-01	.22399372E-02	-19.563	.0000
SDL	-.8480819578E-01	.39038273E-02	-21.724	.0000
H	1.148019625	.67805544E-01	16.931	.0000

(Note: E+nn or E-nn means multiply by 10 to + or -nn power.)

Matrix: Las
[6,4]

+ ----- +
 | Cross tabulation of actual vs. predicted choices. |
 | Row indicator is actual, column is predicted. |
 | Predicted total is $F(k, j, i) = \text{Sum}(i = 1, \dots, N) P(k, j, i)$. |
 | Column totals may be subject to rounding error. |
 + ----- +

Matrix: Crc
 [9,9]

Time choices		Predicted (Interval start time)								
		7:30	7:45	8:00	8:15	8:30	8:45	9:00	9:15	Total
Actual (Interval start time)	7:30	316	48	21	10	6	8	15	12	436
	7:45	76	287	75	23	9	8	6	1	485
	8:00	34	75	259	90	27	11	8	2	506
	8:15	25	31	66	194	76	19	9	2	422
	8:30	9	18	39	61	226	67	27	11	458
	8:45	4	10	16	26	58	217	65	28	424
	9:00	4	7	12	17	33	72	364	79	588
	9:15	1	2	3	6	13	27	74	230	356
	Total	469	478	491	427	448	429	568	365	3675

Note: Enclosed cross tabulation of actual versus predicted choices (Matrix [9.9])

Model M5

→ DISCRETECHOICE
 ; Lhs = DECISION
 ; Choices = TI_1, TI_2, TI_3, TI_4, TI_5, TI_6, TI_7, TI_8
 ; Rhs = ERP, TTPK, SDE, SDL, H
 ; Crosstab
 ; Start = -0.3, -0.3, -0.3, -0.1, -0.1, 0.3\$
 Normal exit from iterations. Exit status = 0.

```

+-----+
| Discrete choice (multinomial logit) model |
| Maximum Likelihood Estimates |
| Model estimated: Oct 14, 2005 at 06:18:57PM. |
| Dependent variable          Choice |
| Weighting variable          None |
| Number of observations      1053 |
| Iterations completed        7 |
| Log likelihood function     -880.5706 |
| Log-L for Choice    model = -880.57061 |
| R2=1-LogL/LogL*    Log-L fncn    R-sqrd    RsqAdj |
| No coefficients      -2189.6519    .59785    .59758 |
| Constants only      -2172.5851    .59469    .59441 |
| Response data are given as ind. choice. |
| Number of obs. = 1053,  skipped 0 bad obs. |
+-----+

```

Variable	Coefficient	Standard Error	b/St.Er.	P[Z >z]
ERP	-.1150403754E-01	.36640638E-01	-.314	.7535
TTPK	-.9682987440	.44509492	-2.175	.0296
SDE	-.5569102916E-01	.54438565E-02	-10.230	.0000
SDL	-.7861868424E-01	.70767115E-02	-11.109	.0000
H	1.179040506	.14051497	8.391	.0000

(Note: E+nn or E-nn means multiply by 10 to + or -nn power.)

Matrix: Las
[6,4]

+ ----- +
 | Cross tabulation of actual vs. predicted choices. |
 | Row indicator is actual, column is predicted. |
 | Predicted total is $F(k, j, i) = \text{Sum}(i = 1, \dots, N) P(k, j, i)$. |
 | Column totals may be subject to rounding error. |
 + ----- +

[Matrix: Crc](#)
 [9,9]

Time choices		Predicted (Interval start time)								
		7:30	7:45	8:00	8:15	8:30	8:45	9:00	9:15	Total
Actual (Interval start time)	7:30	94	28	6	2	1	1	1	0	133
	7:45	30	113	33	8	4	1	2	1	192
	8:00	7	34	60	23	8	4	1	0	137
	8:15	3	11	20	58	18	5	4	2	121
	8:30	1	3	5	16	63	17	4	4	113
	8:45	1	3	5	11	16	63	18	6	123
	9:00	0	1	2	3	8	13	78	23	128
	9:15	0	0	2	2	3	7	18	74	106
	Total	136	193	133	123	121	111	126	110	1053

Note: Enclosed cross tabulation of actual versus predicted choices (Matrix [9.9])

**Thank you for reading my thesis. Please feel free to contact me
for any comments or questions you may have.**

Xie Litian

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08 February 2007