การประมาณการสภาพการจราจรและเวลาในการเดินทางแบบทันกาลสำหรับการพยากรณ์เวลาในการเดินทาง

นาย ปิติ โรจน์วรรณสินธุ์

วิทยานิพนธ์นี้เป็นส่วนหนึ่งของการศึกษาตามหลักสูตรปริญญาวิศวกรรมศาสตรดุษฎีบัณฑิต

สาขาวิชาวิศวกรรมโยธา ภาควิชาวิศวกรรมโยธา

คณะวิศวกรรมศาสตร์ จุฬาลงกรณ์มหาวิทยาลัย

ปีการศึกษา 2553

DEVELOPMENT OF REAL-TIME TRAFFIC STATE AND TRAVEL TIME ESTIMATION FOR TRAVEL TIME PREDICTION

Mr. Piti Rotwannasin

A Dissertation Submitted in Partial Fulfillment of the Requirements
for the Degree of Doctor of Philosophy Program in Civil Engineering
Department of Civil Engineering
Faculty of Engineering
Chulalongkorn University
Academic Year 2010

Thesis Title	DEVELOPMENT OF REAL-TIME TRAFFIC STATE AND TRAVEL TIME ESTIMATION FOR TRAVEL TIME PREDICTION
By	Mr. Piti Rotwannasin
Field of Study	Civil Engineering
Thesis Advisor	Associate Professor Sorawit Narupiti, Ph.D.
Thesis Co-advisor	Professor Takashi Nakatsuji, D.Eng.

Accepted by the Faculty of Engineering, Chulalongkorn University in Partial Fulfillment of the Requirements for the Doctoral Degree

.... Dean of the Faculty of Engineering

(Associate Professor Boonsom Lerdhirunwong, Dr.Ing.)

THESIS COMMITTEE

.... Chairman

(Associate Professor Sompong Sirisoponsilp, Ph.D.)

Sorawit Narupiti .... Thesis Advisor

(Associate Professor Sorawit Narupiti, Ph.D.)

中辻 隆 .... Thesis Co-advisor

(Professor Takashi Nakatsuji, D.Eng.)

.... Examiner

(Associate Professor Kasem Choocharukul, Ph.D.)

.... External Examiner

(Passakorn Prathombutr, Ph.D.)

Sakda P. .... External Examiner

(Sakda Panwai, Ph.D.)

ปิติ โรจน์วรรณสินธุ์ : การประมาณการสภาพการจราจรและเวลาในการเดินทางแบบทันกาลสำหรับการพยากรณ์เวลาในการเดินทาง. (DEVELOPMENT OF REAL-TIME TRAFFIC STATE AND TRAVEL TIME ESTIMATION FOR TRAVEL TIME PREDICTION) อ. ที่ปรึกษาวิทยานิพนธ์หลัก: รองศาสตราจารย์ ดร.สรวิศ นฤปิติ, อ. ที่ปรึกษาวิทยานิพนธ์ร่วม ศาสตราจารย์ ดร.ทาคาชิ นากาซึจิ, 115 หน้า.

ในทางปฏิบัติ ผู้ปฏิบัติการด้านการจราจรต้องการข้อมูลการจราจรแบบพลวัต เพื่อใช้ในการตัดสินใจเลือกแผนการอำนวยการจราจรที่เหมาะสม ให้สามารถขับเคลื่อนการจราจรได้อย่างปลอดภัยและเกิดความล่าช้าน้อยที่สุด ความท้าทายในทางทฤษฎีและปฏิบัติคือการปรับปรุงความแม่นยำของการประมาณเวลาในการเดินทางภายใต้ข้อจำกัดของการมีสถานีตรวจนับค่าการจราจรจำนวนน้อย การศึกษานี้มีเป้าหมายในการนำเสนอแบบจำลองไมโครซิมมูเรชั่นแบบออนไลน์เพื่อเพิ่มความแม่นยำในการประมาณด้วยตัวกรองอันเซนเตทคาลมานสำหรับการประมาณสถานะของการจราจรและเวลาในการเดินทาง และใช้เป็นวิธีทางเลือกสำหรับการประมาณเวลาในการเดินทางบนทางพิเศษ แบบจำลองไมโครซิมมูเรชั่นถูกพัฒนาและปรับแก้ตัวแปรในแบบจำลองด้วยเจเนติกอัลกอริทึม เวลาในการเดินทางที่ถูกประมาณด้วยแบบจำลองไมโครซิมมูเรชั่นถูกนำมาใช้คาดการณ์เวลาในการเดินทางในอนาคตด้วยวิธีที่ไม่ซับซ้อน แต่ง่ายในการนำไปใช้ในทางปฏิบัติเพื่อให้ข้อมูลเวลาในการเดินทางกับผู้เดินทาง ข้อมูลที่ใช้ในการศึกษานำมาจากทางพิเศษในประเทศญี่ปุ่นและในประเทศไทย ผลของการศึกษาแสดงให้เห็นว่าเวลาในการเดินทางที่ประมาณจากวิธีที่เสนอมีความน่าเชื่อถือมากกว่าเวลาในการเดินทางที่ประมาณจากวิธีที่นิยมใช้ในปัจจุบันที่คำนวณจากความเร็ว ณ สถานีตรวจนับค่าการจราจร การใช้ตัวกรองอันเซนเตทคาลมานช่วยปรับปรุงความถูกต้องของเวลาในการเดินทางแต่ปรับปรุงเพียงเล็กน้อย ความถูกต้องของการประมาณและคาดการณ์เวลาในการเดินทางขึ้นอยู่กับสภาพการจราจร ทั้งสภาพการจราจรเบาบางหรือการจราจรหนาแน่น

ภาควิชา	วิศวกรรมโยธา	ลายมือชื่อนิสิต	
สาขาวิชา	วิศวกรรมโยธา	ลายมือชื่อ อ.ที่ปรึกษาวิทยานิพนธ์หลัก	
ปีการศึกษา	2553	ลายมือชื่อ อ.ที่ปรึกษาวิทยานิพนธ์ร่วม	

4971885721 : MAJOR CIVIL ENGINEERING

KEYWORDS : Dynamic Traffic Information / Point Detector / On-line Microsimulation / Expressway / Unscented Kalman Filer

PITI ROTWANNASIN: DEVELOPMENT OF REAL-TIME TRAFFIC STATE AND TRAVEL TIME ESTIMATION FOR TRAVEL TIME PREDICTION. ADVISOR: ASSOC.PROF.SORAWIT NARUPITI, Ph.D., CO-ADVISOR: PROF.TAKASHI NAKATSUJI, D.Eng., 115 pp.

In the state of practice, traffic operators require dynamic traffic information in order to make decision to choose the suitable traffic operational plan that could mobilize traffic safer and with less travel delay. The theoretical as well as practical challenges are the improvement of accuracy of estimated travel time using available or lower amount of data from point detection system. This study aimed to propose on-line microsimulation integrated with Unscented Kalman Filter for traffic state and travel time estimation to be an alternate method for estimating link travel time on expressway, which the developed microsimulation model was calibrated using genetic algorithm. Estimated travel time was further used for predicting short-term future travel time and uncomplicated and easily to implement prediction methods were evaluated. The data in the study came from Hanshin Expressway in Japan and Chalerm Mahanakorn Expressway in Thailand. The results show that travel time estimated from microsimulation is more reliable than those from speed-based conventional estimation method. The Unscented Kalman filter can further but slightly improve the accuracy of travel time. The accuracy of travel time estimation and prediction depends on traffic condition, uncongested or congestion conditions.

Department : Civil Engineering	Student's Signature
Field of Study : Civil Engineering	Advisor's Signature Sorawit Narupiti
Academic Year : 2010	Co-advisor's Signature 中辻隆

ACKNOWLEDGEMENTS

I would like to thank my advisor, Associate Professor Dr. Sorawit Narupiti for his advice and guidance throughout my doctoral study. Furthermore his encouragement and support in both academic and non-academic aspects. It was a great opportunity to study and work with him.

I would like to thank my co-advisor, Professor Dr. Takashi Nakatsuji for his advice on my dissertation and also take care of me for setting up my life in Japan during I stayed for one year at Hokkaido University. It was a great experience for me to open my vision on several approaches on intelligent transportation study.

I would like to express my thank to Associate Professor Dr. Sompong Sirisoponsilp, Associate Professor Dr. Kasem Choocharukul, Dr. Sakda Panwai, and Dr. Passakorn Prathombutr for being dissertation committees.

I would like to express my thanks to:

Associate Professor Dr. Surames Piriyawat for providing opportunity for me to get scholarship from the Office of the Higher Education Commission, Ministry of Education, Thailand and get a job as lecturer at Civil Engineering Department, Engineering Faculty, Burapha University, Thailand.

All colleagues and friends at Transportation Engineering division, Chulalongkorn University and all friends at Intelligence Transportation Laboratory at Hokkaido University, Japan for their supports.

National Electronics and Computer Technology Center (NECTEC) for the research scholarship. Expressway Authority of Thailand (EXAT) to provide a study section and comfort when setting up equipments on locations.

Finally, I would like to express my thank to my parents for their love, understanding, encouragement, and supports for everything in my life.

CONTENTS

Page

Page

LIST OF TABLES

Page

LIST OF FIGURES

Page

Page

CHAPTER I

INTRODUCTION

1.1 BACKGROUND

Uncontrollable and increasing of travel demand according to the growing of economic and several activities in everyday lives in this century has become a serious reason of many problems that widely occur especially in developing country. Traffic congestion is one of the serious problems affected by these activities that result in three main problems including congestion related, transportation safety, and environmental impact especially global warming caused by fossil energy consumption. Conventional approaches conducted to mitigate these problems are aimed to increase service capacity of infrastructures; for examples, new road construction, additional lane expansion, new transportation system, and etc. However, these approaches have been unable to respond the increasing of travel demand within the financial and environmental constraints. Unfortunately, it could not be the approach to achieve the concept of sustainable transportation development. Due to these constraints, the improvement of existing infrastructure by means of performance maximization was considered.

In recent years, growing of wireless communications, computational technologies, and sensing technologies have integrated and applied into transportation system known as intelligent transportation system (ITS) which aims to adopt additional information and communications technology to transportation infrastructure, vehicle, and users to improve transportation safety, mobility, energy consumption, and pollution. Three major applications of ITS in highway and traffic engineering are advanced traveler information system (ATIS), advanced traffic management system (ATMS), and advanced vehicle control system (AVCS). These applications are designed on the basis of existing infrastructure performance maximization using the integration of advanced technologies. In this research, ATIS application was considered in the mechanism of getting reliability of travel information disseminated to travelers especially travel time information that is suggested to be a main key information for travelers to consider for their travel options.

ATIS is one of the ITS applications which provides travel information for travelers in order to plan the shortest travel route due to their trip purpose during both pre-trip and en-route. Three main components of AITS components consist of data collection, data processing, and data dissemination. Data collection module is designed for measuring and collecting required information from the field which the required information is not only traffic parameters but also weather condition, lane closure, road maintenance section, incident, accident, special event, and etc. These kinds of field data are sent to traffic management center (TMC) to further analyze and estimate travel information which is necessary for travelers to make a decision on the best route to reach their destination. The data is arranged in suitable format and stored on efficient database at TMC. Subsequently, dissemination module is broadcast the travel information to the travelers using several kinds of user interfaces, for example traffic radio broadcasting, internet website, variable message sign board, in-vehicle car navigation device, etc. In order to accomplish ATIS application, reliable real-time traffic information is required.

Reliable real-time traffic information is required to accomplish the ATIS application especially travel time information. In order to provide reliable real-time travel time information, real-time traffic data is measured using several kinds of traffic surveillance system. Inductive loop detector is the most common point-based traffic detector that widely uses for measuring traffic data including traffic volume, occupancy, and speed. In practice, travel time information is estimated using the link length and average link speed relationship. Therefore, accuracy of traffic data using point-based detector depends on the number of detector and placement that equips on road section. More detectors are equipped; more accuracy of traffic data is measured. However, it is costly to improve accuracy of traffic data by increasing the number of detectors on road section.

Mobile-based detector is another kind of traffic surveillance system that can be used to measure traffic data, where travel time information can be directly measured. Mobile-based detectors are included automatic vehicle location (AVL) and automatic vehicle identification (AVI). The accuracy of traffic data using mobile-based detector depends on the number of probes currently running on road sections. Presently, sufficient mobile-based detector is still difficult to achieve on real road network. Low number of samples of mobile-based detector is currently provided by GPS probe which normally use GPS equipped taxis as probes. Toll tag ID can also be used to measure traffic data but most are used on toll roads or expressways. However, low number of sample traffic data can not reflect good representative traffic data during normal condition but it can provide good data during congested condition.

In the past, the estimation of real-time travel time information is a product of traffic state estimation which is further estimated from speed-based travel time information and flow-based travel time information (Vanajakshi et al., 2009). Most of past studies relied on traffic data which provided by point-based detectors with short spacing of detectors. Macroscopic traffic flow models were also proposed in order to estimate real-time traffic state and further estimate travel time information (Nanthawichit, 2003). State-space model and standard Kalman Filter (KF) and developed form for nonlinear systems such as Extended Kalman Filter (EKF) have been used as the dynamic state estimators. However, it is known that EKF provides only an approximation to optimal nonlinear estimation. Moreover, it is complicated and inflexible to adapt with a dynamic traffic state estimation such as the concept of on-line microsimulation that can parallel operated by real-time basis to estimate traffic state and also travel time information. The other filter for nonlinear system with performance superior to that of the EKF but at the same order of computational complexity and also compatible with on-line microsimulation was considered.

Unscented Kalman Filter (UKF) was first developed in the mid of 1990s by Julier et al. (1995) and has attracted a number of researchers in various fields. This filter has a number of unique advantages over the EKF such as the ability to capture the true mean and covariance accurately to second-order Taylor expansion. In contrast, the EKF only achieves first-order accuracy. The UKF also has an important inherent property that it does not require explicit computation of matrix derivative or Jacobian matrix. This property of the UKF is extremely important and provides a new way to develop on-line microsimulation framework of real-time traffic state and travel time estimation.

In this research, the possibility and potential of UKF was investigated and developed the new frameworks for estimating real-time traffic state and travel time information on road section with have limited amount of point-based detector data. Moreover, short-term travel time estimation was also developed to enhance the dynamic traffic state and travel time estimation framework.

1.2 PROBLEM STATEMENT

In past researches on the subject of real-time traffic state and travel time estimation, the macroscopic flow models were the most popular traffic model applied to formulate dynamic traffic state estimation model, with travel time information as a byproduct of traffic state estimation model. Macroscopic model is relied on traffic data measured by traffic surveillance system such as inductive loop detector or other detector with similar performance. Traffic state estimation model using macroscopic model is formulated based on the law of conservation of traffic stream. It is known as the conservation or continuity Equation. The limitation of macroscopic model is depended on the quality of traffic data measured by traffic surveillance system. It is difficult to know accurate traffic states data in case of long length of road section which point detectors are equipped far apart. Previous studies adapted filtering techniques to develop dynamic traffic state estimator (Mihaylova et al., 2007, Nanthawichit, 2003, van Lint, 2008, Ye et al., 2006).

The EKF has been the most widely used estimation algorithm for nonlinear systems. However, the estimation community was shown that it is difficult to implement, tune, and only reliable for a system that is almost linear on the time scale of the updates. Many of these difficulties arise from its use of linearization. To overcome this limitation, the unscented transformation (UT) was developed as a method to propagate mean and covariance information through nonlinear transformations. It is more accurate, easier to implement, and uses the same order of calculations as linearization (Julier and Uhlmann, 2004).

The accuracy of traffic data measured by point-based detection system is limited by the types and amount of traffic detectors which toward affect the accuracy of traffic state estimator processed by macroscopic model. Spacing and placement are also the main factors that affect to the traffic state and travel time estimation. In practice, the extrapolation method is a simple way of estimating average travel time using point-based detection system because it assumes that a spot speed measured by traffic detector is applicable over short segments of roadway with typically less than 0.8 km. However, there are many road sections that traffic detector are equipped far apart which extrapolation method is not suitable to reflect traffic situation. Reducing the space by increased number of traffic detectors is concerned in order to improve the accuracy. However, it is costly to install detectors for retrieving reliable traffic data according to the extrapolation method. Mobile-based detection system can be used to measure traffic data especially link travel time information. Therefore, the reliability of mobile detection system is also dependent on sample size of probe vehicle that report traffic data during a time interval. It is difficult to get sufficient amount of probe samples in present operation but it should be increased in the near future.

The above two issues could be improved by adapting microscopic traffic simulation model instead of macroscopic traffic model. Moreover, the UKF can be easily implemented with microscopic simulation model. Furthermore, the modern technology of traffic surveillance systems, for example GPS probe and AVI data are introduced for measuring traffic parameters such as link speed and travel time to support real time traffic information. It is interesting to study and develop real time traffic state and travel time estimation framework based on on-line microscopic simulation integrated with feedback estimation using UKF.

Since ATIS will provide travel information such as list of the k^{th} shortest path that travelers can receive travel information from a variable message sign, portable navigator, and in-vehicle navigation system disseminated traveler information from TMC via FM radio. Travel time information on selected route is an expected travel time that travelers could reach the destination which it is estimated while travelers arrive at the origin point on selected route. In past researches, several travel time prediction methods were proposed in the case of short-term and long-term prediction for ATIS. In case of short-term prediction methods, it can be categorized under two approaches included regression methods and time series estimation methods. The third approach may be describes as combining the first two methods known as data fusion (Li et al., 2009, Yuh-Horng et al., 2005). The methodologies that were proposed such as historical data estimation method by Yanying and McDonald (2002), artificial intelligence by Bielli et al (1994) and Park and Rilett (1999), statistical techniques by Kothuri et al (2007). EKF was also proposed on prediction module in case of short-term prediction to predict traffic state and then further estimate travel time (Nanthawichit, 2003). However, a few studies integrated prediction module into real-time traveler information framework using on-line microsimulation model. Given such a few studies, it would be interesting to study prediction a method that could be applied with on-line microsimulation for predicting travel time information.

Furthermore, in order to develop on-line microsimulation model to support real-time traffic state and travel time estimation, consistency of microscopic traffic simulation model should be emphasized. The components of microscopic traffic simulation model generally include physical component of road network, traffic control system, and driver-vehicle units which driver behavior models and route choice models are associated. The complex data and numerous model parameters are required by these components. These parameters need to be calibrated for a particular study area (Mcnally and Oh, 2002). Conventional model calibration procedure adjusts parameters in driver behaviors model and route choice model until simulation outputs are corresponded with those of field observation in both qualitative and quantitative aspects. The trial-and-error method is normally employed for calibrating parameters based on engineering and experience decision, and this method is a time consuming and tedious process. Some previous studies attempted to introduce a systematic procedure to calibrate a network level simulation model for both freeways and their adjacent parallel surface streets by focusing on one component of the simulation model while assuming other components held constant at present values (Chu et al., 2004). Some studies presented calibration framework which also focused on route choice model calibration when the O-D flow was an unknown variable (Toledo et al., 2004, Toledo et al., 2003). However, with this conventional calibration procedure, calibrated traffic parameters are not guaranteed to be used in all range of various traffic system environments. The parameters may require re-adjustment which would again consume great effort based on the conventional model calibration. This limitation could improve by artificial intelligence approach such as genetic algorithm instead of conventional methods to calibrate model parameters that calibration time should be decreased. Genetic algorithm method is often introduced to reduce time on calibration process by treating parameters calibration to be an optimization problem and searching optimal combinatorial parameters values that can minimize a fitness function within defined number of generations in genetic algorithm procedure (Cheu et al., 1998, Lee and Yang, 2001, Ma et al., 2007, Park and Qi, 2006, Schultz and Rilett, 2004).

1.3 RESEARCH OBJECTIVES

The following research objectives are defined according to problems described in the previous section:

- Develop a combinatorial model parameters calibration for microscopic traffic simulation model using genetic algorithm.
- Develop a framework of real-time traffic state and travel time estimation using microsimulation.
- Apply Unscented Kalman Filter to improve the accuracy of traffic state and travel time information estimated by on-line microsimulation.
- Study short-term prediction for OD travel time information.

1.4 SCOPE AND LIMITATIONS

In this research, the real-time traffic state and travel time estimation for travel time prediction was developed and evaluated for the traffic characteristics on expressway's corridor which the route choice process was not concerned. Moreover, only existing point-based detector was the traffic data source available in practice. The proposed on-line microsimulation can not directly applied with other types of road section for example arterial road or road with traffic signal control and also route travel time for large network with multiple origins and destinations.

1.5 ORGANIZATION OF DISSERTATION

The structure of this research proposal is as follows.

Chapter 2 provides the reviews of the related literatures including the historical and fundamental background on travel time estimation, on-line simulation using microscopic traffic flow approach, the Kalman filtering technique for both linear and nonlinear problems, particle filtering technique, data fusion techniques in order to improve the reliability of travel time information, the methods to deal with short term and long term prediction.

Chapter 3 presents the methodology adopted to develop on-line micro-simulation framework for estimating dynamic OD travel time. Initially, a framework is presented to give an overview of this study. First, the step on how to develop microscopic traffic simulation model is presented. Then, the process of model parameters calibration for microscopic traffic simulation is presented which genetic algorithm is proposed instead of conventional calibration methods. Second, on-line microscopic traffic simulation model will be operated as real-time traffic state and travel time estimator, where point detector system will be used to update traffic states estimated by on-line microscopic traffic simulation. Here, the estimation algorithm with the UKF as the estimator is presented. Third, prediction algorithm is presented to be able to forecast travel time information and the prediction algorithm in case of short term prediction is presented. Finally, data fusion techniques are presented in order to combine several traffic information estimated by on-line microscopic traffic simulation model and mobile detection system if available in the future practice, GPS probe and AVI data, is presented.

Chapter 4 presents traffic data that were conducted in this research in order to evaluate the proposed method for estimating traffic state and travel time information on expressway section. Two road sections were selected which the first site is Matsubara line on Hanshin Expressway in Japan. The second site is Chalerm Mahanakhon line on Bangkok expressway in Thailand. Physical alignment of sites was explained in detail. Finally, the results of model parameter calibration using genetic algorithm of two study site were reported.

Chapter 5 presents the numerical analysis of experiments that were proposed. Finding of four main parts of this dissertation were presented and discussed. The first part is the evaluation of link speed estimation based on point detection system on expressway. The second part is the real-time traffic state and travel time estimation using microsimulation. The third part is the improvement of microsimulation by feedback estimation using Unscented Kalman Filter. The final part is the study of short-term travel time prediction.

Chapter 6 presents the conclusion of the findings in dissertation and then recommendations of future research are proposed.

CHAPTER II

LITERATURE REVIEWS

This chapter reviews related literature including overview of advanced traveler information system, traffic state estimation, filtering techniques, travel time estimation and prediction, and traffic simulation tools and model parameters calibration.

2.1 ADVANCED TRAVELER INFORMATION SYSTEM

Increasing of travel demand affects the congestion level on a road network especially during the rush hour period. Travelers intend to spend the shortest travel time possible on their trip from origin to destination. Typically, the route selection logic is based on each traveler's experience, but the proper decision using the past experience along may not yield the optimum (best) selection due to the fact that traffic condition on selected route might vary from the past and could not be predicted based on their experience without any update or current traffic condition information. The growing of advanced technologies for informing traffic condition to travelers and guiding shortest route based on their trip destination while pre-trip and en-route and a group of these technologies are called an advanced traveler information system (ATIS). In this part, the review of the advanced traveler information is described.

2.1.1 General Background

The system of advanced traveler information consists of three main parts including data collection, data processing, and data dissemination. The framework of a typical ATIS is shown in Figure 2-1.

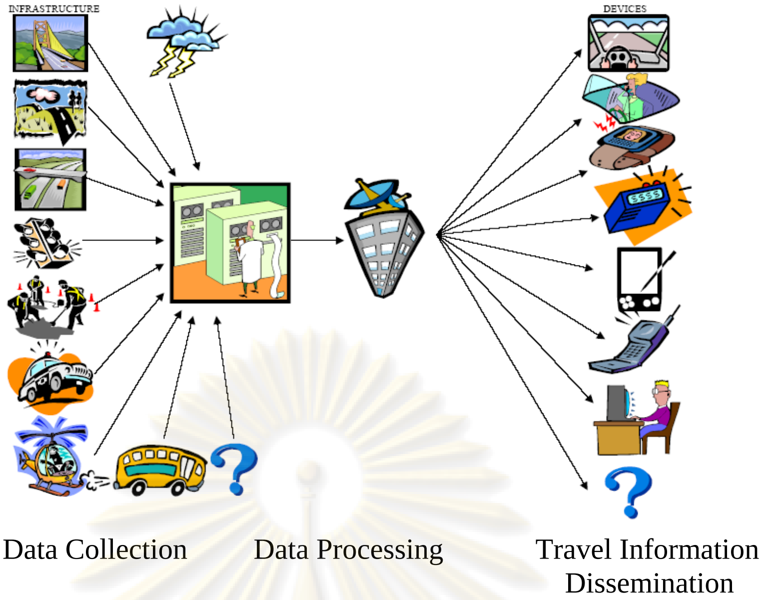


Figure 2-1 Framework of ATIS (ITS America, 2000)

From Figure 2-1, in the first component of ATIS, the data collection component collects several data such as present traffic condition, road activities, and travel environments from road network such as traffic volume, lane closure, road maintenance, incident, accident, special event, and weather condition. Traffic detection and surveillance technologies play an essential role to data collection part. There are several kinds of traffic detection such as single inductive loop detector, dual inductive loop detector, microwave, close circuit television (CCTV), infrared, video image processing, and etc. Most of existing traffic surveillance as described are called “point-based detection”.

In present practice, traffic detection and surveillance devices are typically available at specific discrete points through a freeway corridor. Most of deployed traffic sensors are single inductive loop detectors that have limited detection capabilities. The cost of large scale detection and surveillance with point-based detector is one of the biggest obstacles for implementation. Using modern traffic detection technology could widely increase traffic detection and implementation with affordable cost but high accuracy of traffic data.

States of the art in detection and surveillance replace traditional single loop detectors with sensors that provide additional types of data, merge infrastructure-based point detection techniques with a variety of newer techniques, including cellular-based geo-location, Global Positioning Systems (GPS), and move toward the Vehicle Infrastructure Integration (VII) concept. Improvements in positioning, computing, and detection technologies have also provided the potential to update and improve upon detection algorithms. Some traffic management centers (TMC) are equipped with computerized algorithms that can identify locations where significant congestion exists and trigger operators to find congestion-prone locations and reduce the delay from incident response and management.

In fact, inductive loop detectors are still the most utilized type of traffic sensor in existing traffic management system (Klein et al., 2006). They are commonly used as single loops at discrete locations on road section with only traffic volume and lane occupancy being measured while other traffic condition indicators such as traffic speed and traffic density must be inferred from algorithms that interpret the mentioned measured data. Several studies developed algorithms for detecting the onset of congestion and incident using these single loop measurements (Dailey, 1999, Coifman et al., 2003, Wang and Nihan, 2003). In order to measure traffic speed and vehicle length, inductive loops are sometimes configured as dual loops or a speed trap that is formed by two consecutive single-loop detectors placed several meters apart. Dual loop detectors are ideal for collecting speed and vehicle length data. Operators at a traffic management center (TMC) on freeway use visual surveillance from field-located cameras or closed circuit television (CCTV) to verify incidents when these take place.

In the second component of ATIS, the data processing component receives field traffic data from the data collection part. Traffic management center is the place that retrieves data and processes raw data into travel information which can be used to indicate congestion location, incident detection, traffic management, and traffic planning.

In the third component of ATIS, many channels can be used to disseminate travel information to travelers which can be divided by stage of pre-trip and en-route. The pre-trip information is essential for travelers to make decision about their route selection before the trips start. They can receive travel information from traffic information website, radio, or television while they do not depart from their origins. The en-route information can be received from dynamic message signs (DMS), traffic radio broadcast, Personal Navigation Device (PND), and in-vehicle route guidance.

2.1.2 State of Practice

Three zones in the world including several states in the United States of America and North America, countries in Europe, and countries in Asia were explored on the state of practice. State of practice is summarized as follows.

- **In United State of America and North America**

A number of states in the United States of America and North America have provided travel time information or have plans to provide such information in the near future. The summary of the state of practice is shown in Table 2-1 (Kothuri et al., 2007b).

Table 2-1 State of Practice on ATIS in United State of America

States	State of Practice
Portland, Oregon	The Oregon Department of Transportation currently provides travel times on three DMS along the I-5 corridor. Travel times are provided in a 2-3 minutes range. These times are estimated from speeds reported by dual loop detectors embedded in the pavement. Currently approximately data from 500 loop detectors are reported every 20 seconds to the TMC. The midpoint algorithm which uses a ratio of distance to speed is used to estimate travel times.
Seattle, Washington	Travel times are estimated using occupancy measurements from single loop detectors which are spaced 0.25 – 0.5 mile apart. The speeds and segment lengths are used to estimate travel time for different links. These current travel times are compared to the historical travel times and are adjusted if the historical travel times report a higher value. These travel times are disseminated through DMS as well as internet and are updated approximately every two minutes. Tests show accuracy greater than 90%.
Minneapolis-St.Paul, Minnesota	Travel time are estimated based on speeds which are calculated from volume and occupancy measurements from single loop detectors spaced approximately 0.5 mile apart. A modified midpoint algorithm is used to estimate travel times based on the calculated speeds. These travel times are reported on DMS and software developed by the Minnesota DOT's (MnDOT) Traffic Management Center is used to control the signs and post messages. Estimated travel times have been found accurate in most of the time except when traffic conditions are changing.
Chicago, Illinois	Illinois DOT operates the un-tolled highway network where loop detectors are present every 0.5 mile. Travel times are calculated as a simple ratio of distance to speed with the algorithms including a fudge factor to account for extremely congested conditions where occupancy is greater than 95%. Travel times are posted on DMS as well as on the website.
San Francisco-Bay Area	Travel times are estimated from data obtained by a variety of sources included loop detectors, AVI toll tag readers and spot speed loop sensors. The travel time algorithms are employed for calculating travel time using data from all three sources to predict travel times and display them on DMS. The travel time estimation errors are less than 20%.
Milwaukee, Wisconsin	Loop detectors are spaced every 0.25 miles in the urban area and be greater in the suburban areas. In some cases, microwave detectors are also employed to supplement additional data. Travel time is calculated as the ratio of distance to speed. Travel time is not reported if more than 33% of the detectors are not available. Travel times information is updated on the website every three minutes and the DMS is updated every minute.

Table 2-1 State of Practice on ATIS in United State of America (con't)

States	State of Practice
Houston, Texas	Travel times are primarily derived from AVI toll tag transponders. Over 200 toll tag readers are present in addition to the toll plazas. Travel times are posted automatically onto the DMS every ten minutes. Public response to the posting of travel times has been highly favorable and the travel times are generally considered accurate. Based on the information provided, users were observed to change routes.
Nashville, Tennessee	RTMS sensors form the primary source of data collection which are spaced 0.25 mile apart and subjected to periodic maintenance to ensure optimal performance. Travel times are calculated knowing the distance and average speed that is obtained from the RTMS sensors. Travel times are posted to destinations that are not more than 5 miles away from the DMS.
Atlanta, Georgia	Video Detection System cameras are present on the highways in Atlanta and continuously record speed and volume and transmit these data to the TMC, where travel times are generated and posted onto the DMS. Travel times are calculated from average speeds obtained from the VDS cameras.
San Antonio, Texas	Travel times in San Antonio are obtained from speeds measured by loop detectors and video detection systems. These sensors are placed 0.5 mile apart. The travel time algorithm assumes that a segment is bounded by detector stations on either end, and the speed for the segment is chosen as the lower of the speed displayed by the upstream or downstream station. The ratio of the distance covered by each method of detection to the speed generates the travel times. The posting of travel times on the website as well as on DMS has been well received by the public.
Toronto, Canada	Loop detectors are placed every one third mile to provide speeds that are used to calculate travel times. The initial travel time algorithm is used to generate times using distance over speed to compute the estimated travel time. Travel times are displayed on the DMS in ranges of times. When travel times exceed 40 minutes, the DMS does not display travel times information but display "stop and go conditions" instead. Public reaction has been positive.

- **In European Countries**

There are many projects on ATIS implemented in European countries. They are summarized as shown in Table 2-2 (Bob Rupert, 2003).

Table 2-2 State of Practice on ATIS in European Countries

Countries	State of Practice
Barcelona, Spain	The Catalan Traffic Service is responsible for regional and interregional traffic management and operates the TMC. 300 detector stations both inductive loops and vision processing collected and sent traffic data every minute in which travel information is displayed on DMS.
Munich, Germany	The detection system on motorway has 58 weather stations, 120 visibility (fog) meters, 452 sensor loops, and 93 video cameras. Data are collected every minute. Traveler information can be viewed on the internet and also personnel travel assistants such as cell phones, PDAs, and etc.
Berlin, Germany	Radio Data System-Traffic Message Channel (RDS-TMC) and DMS are the main channel to disseminate travel information to traveler.
Stockholm, Sweden	ITS plays a major role in network operations which focus on traffic information in winter condition. However, traffic congestion is not the major focus but road weather data are provided every half an hour at 700 stations.
Glasgow, Scotland	The core functions of the system include a monitoring network (CCTV, loop detectors, incident detection, etc), traffic control, and informing users (DMS, lane signals).
Newcastle, England	The system by highways agency is considered a video information highway. Twenty police control center have a CCTV system. RDS-TMC is also available.

- **In Asian Countries**

In Asian countries, there are few countries that comprehensively implemented ATIS. Japan is the leader of using ATIS and also other ITS s. Vehicle Information and Communication System (VICS) is the most popular system which users can receive traffic information using their own in-vehicle car navigation system. VICS center gather traffic data from expressway using radio wave beacons and ordinary trunk roads using infrared beacons. After that, VICS center processes data and then disseminates travel information using NHK local FM multiplex broadcasting stations. VICS provides information including traffic congestion, travel time, location of accidents and roadwork, speed limits and lane regulations, and parking lot locations and availability. Other expressway operators also measure traffic data and display traffic information on their DMS and also transfer data to VICS. Hanshin Expressway Company limited is a company that provides travel time information to motorists. The information gatherings are provided by vehicle detectors that are installed at entrances and exits and above the thruways to measure traffic volume, speed, and time occupancy ratio. There are also monitoring cameras that visually check traffic conditions on the road. Some cameras on sharp curb sections can automatically detect accidents and disabled vehicles with special image processing technology. The detectors are placed every 500 meters in order to measure volume, occupancy, and speed then derived for travel time information (VICS, 1995).

In Thailand, there are 40 traffic information sign boards installed in Bangkok in order to provide traffic information to road users. Three congestion levels consisting of red, yellow, and green are displayed as the colors represent high, medium, and low congestion respectively. Occupancy ratio is measured using video image processing camera and additional CCTV for monitoring real-time situation.

2.2 TRAFFIC STATE ESTIMATION

Traffic state is required by traffic operators in order to perceive traffic condition on roadway. Common traffic state includes traffic flow, speed, and density. Traffic state can be measured or approximated using traffic detector and also estimated using traffic flow model that is presented as follows.

2.2.1 Field Measurement and Approximation

In practice, most of traffic operators attempt to estimate traffic state based on existing traffic detectors which are installed on their road section. Single inductive loop detector is a typical traffic detector that is normally selected by most of traffic operators. The mechanism of single inductive loop detector is illustrated in Figure 2-2 which the single inductive loop detector is turned on when vehicle passing over the detection area and turned off when no vehicle passing over the detection area (Sisiopiku et al., 1994).

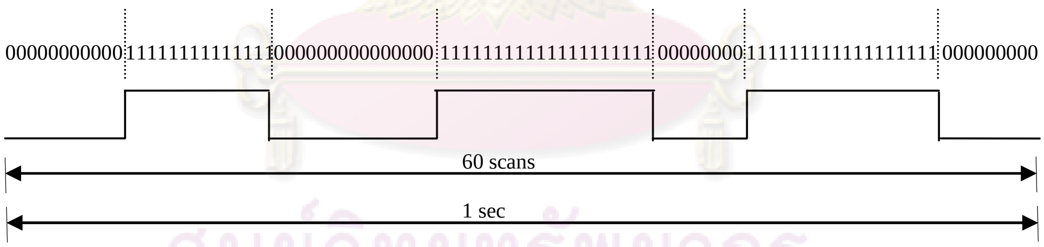


Figure 2-2 Output Signal from Presence Type Detector

However, traffic data consists of only traffic volume and occupancy can be provided by a single inductive loop detector. Traffic speed is a good traffic state that reflects what the level of convenience for traveling on road section and also used to estimate travel time. However, speed can be directly measured by a single inductive loop detector.

Speed can be approximated from a single loop detector but needs to rely on predefined vehicle length and occupancy. Total number of scanning intervals "ON" over a time period of T seconds is referred to as occupancy and denoted as OCC (in scans). Given that the scanning frequency is 60 scans/sec, T_{ON} in seconds is equal $\frac{OCC}{60}$ and $\%OCC = 100\left(\frac{T_{ON}}{T}\right)$, the average speed over a detector in m/sec is shown in Equation (2-1) where $\bar{L}_V$ is average vehicle length (m) which is assumed 4.72 m and L_D is detection zone (m) which is assumed 1.83 m.

$$\bar{\mu} = \frac{VOL}{T_{ON}}\left(\bar{L}_V + L_D\right) \tag{2-1}$$

Substitute $T_{ON} = \left(\frac{OCC}{60}\right)$ into Equation (2-1), and then Equation (2-2) is shown where $\bar{\mu}$ is average speed (in m/sec), VOL is volume (in veh/5-min), and OCC is occupancy (in scans/5-min)

$$\bar{\mu} = 60\left(\frac{VOL}{OCC}\right)\left(\bar{L}_V + L_D\right) \tag{2-2}$$

Note that $\bar{\mu}$ is space mean speed since they are based on the average of vehicle occupancy times not on an average of individual vehicle speeds. The speed estimate is calculated on each influence section due to detection zone as shown in Figure 2-3.

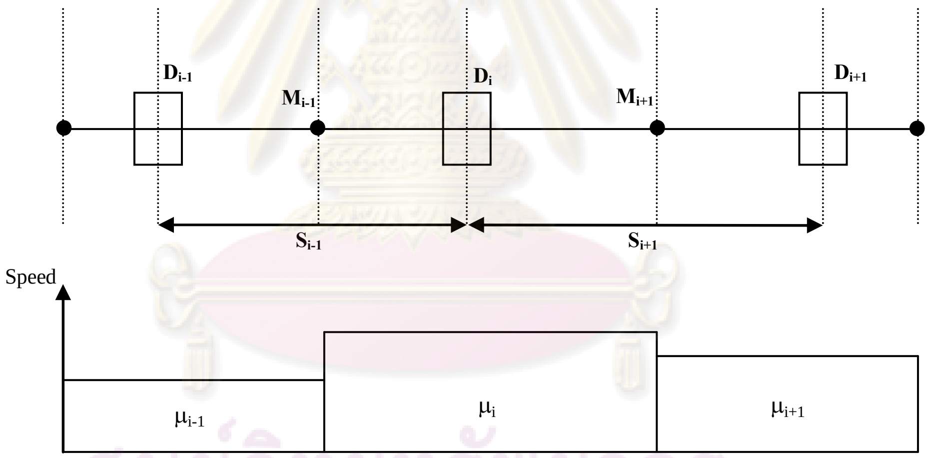


Figure 2-3 Influence Area of Detection Zone

Speed is also indirectly estimated from other traffic data obtained from a single loop detector, which are flow and occupancy, without heavily relying on the flawed speed calculation. Previous studies on speed (travel time) estimation based on single loop detectors can be broken into two broad classes. The first class is to use one detector data to determine the speed at that detector and then extrapolates it to get a link travel time. The speed estimation is derived using flow and occupancy as shown in Equation (2-3): where g is the average effective vehicle length (EVL); the sum of the vehicle length and the width of the loop detector (EVL ~vehicle length + detector length). The g factor is simply converted occupancy into density. The second class is to use information from two single loop detectors, one at either end of the link to estimate the link travel time directly (Petty et al., 1998).

$$\text{speed} = \frac{\text{flow}}{\text{occupancy} \times g} \tag{2-3}$$

Several studies present a different approach, using a new aggregation methodology to estimate speed and to reduce the impact of long vehicles in the original traffic measurement. In contrast to conventional practice, the new estimate significantly reduces velocity estimation errors when it is not possible to control for a wide range of vehicle lengths (Coifman, 2003). Many researchers investigated techniques to reduce the influence of long vehicles (Coifman, 2001, Dailey, 1999, Pushkar et al., 1994, Wang and Nihan, 2000). All of these studies used aggregated flow (q) and occupancy (occ) to estimate mean velocity. Rather than manipulating aggregate data, Coifman (2003) examined new aggregation methods to reduce the estimation errors. Provided that vehicle lengths and vehicle velocities are uncorrelated, harmonic mean velocity (mean v) and arithmetic mean vehicle length (L) for a given sample are related as shown in Equation (2-4).

$$\text{mean } v = \frac{q \cdot L}{occ} \tag{2-4}$$

Note that, two variables in this Equation cannot be measured independently with a single loop. Typically, an operating agency will set L to a constant value and use this Equation to estimate a velocity from the single loop measurement. For this fact, this approach fails to account for a percentage of long vehicles which may change during the day or this value may not be included in typical vehicle length. Particularly during low traffic flow, when the number of vehicles in a sample is small, a long vehicle can skew occupancy simply because it takes more time to pass the detector. For example, approximately 85 percent of the individual vehicle lengths observed at one detector station are between 15 and 22 feet but some vehicle are as long as 85 feet or roughly four times the median length (Coifman, 2001).

However, traffic state especially speed as previously presented reflects the traffic condition only on the location that a detector is equipped, not the traffic state that occur along the length of road segment. In order to approximate average speed on road segment, several detector stations have to be installed in practice. Three simple methods of conventional segment speed estimation that are normally used in practice (Kothuri et al., 2007), namely average speed, weighted average speed, and San Antonio, which are described as follows.

- **Average Speed**

The average speed is one of the simplest methods to estimate segment speed based on spot speed measurement using point detector data. Spot speeds are measured at upstream and downstream end of the segment in every time step. Then the average speed is calculated using simple arithmetic mean as shown in Equation (2-5). Traffic speed on a segment is assumed to be uniformly distributed under short time interval and short segment length.

$$v_s(k) = \frac{v_u(k) + v_d(k)}{2} \tag{2-5}$$

where $v_s(k)$ is the estimated segment speed at time k, $v_u(k)$ and $v_d(k)$ is the measured spot speed at upstream and downstream detector at time k respectively.

- **Weighted Average**

The weighted average method is proposed to estimate segment speed using spot speed data measured by upstream and downstream detector. This method takes account of traffic flows (volumes) that are also simultaneously measured with spot speeds in each time interval. Estimated segment speed is calculated as shown in Equation (2-6).

$$v_s(k) = \frac{q_u(k)v_u(k) + q_d(k)v_d(k)}{q_u(k) + q_d(k)} \tag{2-6}$$

where $q_u(k)$ and $q_d(k)$ are traffic flow (volume) on upstream and downstream detector station respectively.

- **San Antonio**

This method has been used according to San Antonio Transguide project which employs the minimum spot speed value between upstream and downstream detector station to represent link speed as illustrated in Equation (2-7).

$$v_s(k) = \min\left(v_{up}(k), v_{down}(k)\right) \tag{2-7}$$

As seen from these three simple methods for estimating segment speed, it is obvious shown that these methods just attempt to approximate segment speed based on what happens at the detection station. It is necessary that traffic state on the segment must be reflected by the traffic data at the detection points and hence a requirement for short span detector stations limits the applicability of these methods.

2.2.2 Traffic Flow Model

In previous studies, macroscopic traffic flow model was introduced to estimate dynamic traffic state on road section which relies on traffic flow conservation equation, dynamic speed equation, and stationary speed equation. The macroscopic model represents in discrete space-time frame which consists of four main traffic values including traffic density, space mean speed, traffic flow, and on-ramp inflow and off-ramp outflow. The dynamic macroscopic model equations are shown as follows.

$$\rho_i(k+1) = \rho_i(k) + \frac{T}{\Delta_i \lambda_i}\left[q_{i-1}(k) - q_i(k) + r_i(k) - s_i(k)\right] \tag{2-8}$$

$$s_i(k) = \beta_i(k) \cdot q_{i-1}(k) \tag{2-9}$$

$$\begin{aligned} v_i(k+1) = v_i(k) + \frac{T}{\tau}\left[V\left(\rho_i(k) - v_i(k)\right)\right] + \frac{T}{\Delta_i} v_i(k)\left[v_{i-1}(k) - v_i(k)\right] \\ - \frac{\nu T}{\tau \Delta_i} \frac{\left[\rho_{i+1}(k) - \rho_i(k)\right]}{\rho_i(k) + \kappa} - \frac{\delta T}{\Delta_i \lambda_i} \frac{r_i(k) v_i(k)}{\rho_i(k) + \kappa} + \xi_i^v(k) \end{aligned} \tag{2-10}$$

$$V(\rho) = v_f \exp\left[-\frac{1}{a}\left(\frac{\rho}{\rho_{cr}}\right)^a\right] \tag{2-11}$$

$$q_i(k) = \rho_i(k) \cdot v_f(k) \cdot \lambda_i + \xi_i^q(k) \tag{2-12}$$

A road section is subdivided into a number of N segments with lengths Δ_i (i = 1,.., N) while the discrete time is based on a time step T with the discrete time index k = 0, 1, 2,… From Equation (2-8), it is the conservation equation where $\rho_i(k)$ (veh/km/lane) is the number of vehicles in the segment i at time instant kT, divided by the segment Δ_i and lane number λ_i. $v_i(k)$ (km/h) is the average speed of all vehicles included in segment i at time instant kT. $q_i(k)$ (veh/h) is the number of vehicles leaving segment i during the time period [kT, $(k+1)T$], divided by T. The $r_i(k)$ and $s_i(k)$ are on-ramp inflow and off-ramp outflow respectively at segment i (if any). From Equation (2-9), $\beta_i(k)$ is the dimensionless denoted the exiting rate at the off-ramp in segment i (if any). The τ, ν, κ, δ, v_f, ρ_{cr}, and a are model parameters which need to be calibrated, subject to individual case, which v_f and ρ_{cr} are the free speed and critical density respectively. The ξ_i^v and $\xi_i^q(k)$ denote zero mean noise acting on the empirical speed equation as shown in Equation (2-10) and the approximate flow equation as shown in Equation (2-12) to reflect the modeling inaccuracies (Nanthawichit, 2003, Wang et al., 2007)

2.3 TRAVEL TIME ESTIMATION

In this part, the reviews of previous studies that proposed several methods in order to estimate travel time information are presented. Travel time estimation and prediction are described as follows.

2.3.1 Travel Time Estimation

Travel time has been identified by Austroads as an important system performance measure (Cunningham et al., 1995). Travel time information is applied in various usage and purposes. In Advanced Traveler Information System (ATIS) application, travel time information is used as an index to indicate traffic situation of road network and helps travelers to save trip time through better path selection. Accurate travel time estimation could help reduce transport costs by avoiding congested sections and increase the service quality of commercial delivery goods.

One of the most important issues, before the travel time information begins to be provided for ATIS, is the acquirement of travel time data. Due to practical operation, travel time data can be obtained from both indirect and direct measurement. The indirect measurement is the basic method that several traffic agencies have conducted in their own system using traffic data measured on site-based detector, which normally is an inductive loop detector. The travel time information is derived due to simple traffic parameters measured by these existing inductive loop detectors, which measured traffic data are volume, speed, and occupancy. The direct measurement is the method that directly measures travel time data from the field which several applications can be applied, for example license plate matching, floating vehicle testing, AVI, and location tracking by GPS and cellular probe. The review of indirect and direct travel time measurement is described as follows.

- **Indirect Travel Time Measurement**

The indirect measurement is based on the field traffic data collected using inductive loop detectors or any kind of point-based detectors that can measure volume, speed, and occupancy. Travel time on a road section is composed of running time, or time in which the mode of transport is in motion, and stopped delay time (Turner et al., 1998) as shown in Figure 2-4.

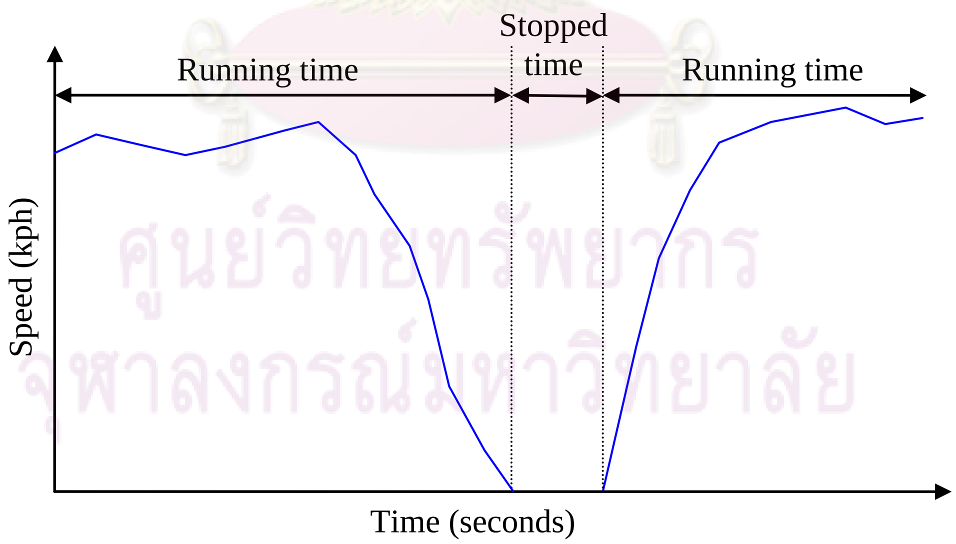


Figure 2-4 Illustration of running time and stopped time

According to the definition of travel time, it can be simply estimated as shown in Equation (2-13) and Equation (2-14).

$$TT_s = \text{Running Time} + \text{Stopped Time} \qquad (2\text{-}13)$$

$$TT_s = \frac{d_s}{v_s} + \text{Stopped Time} \tag{2-14}$$

where TT_s is segment travel time, d_s is the segment length, and v_s is an average segment speed. Due to simplified travel time definition, the average segment speed is an important parameter to estimate travel time that vehicles transverse on road segment. In practice, approximated average segment speed discussed in previous part appeared in Equation (2-5), Equation (2-6), and Equation (2-7) are conducted to estimate segment travel time.

In transportation planning, one of the several travel time estimation methods is proposed by United States Bureau of Public Roads which later becomes the Federal Highway Administration. This method of travel time estimation uses travel time function is known as BPR function (Bureau of Public Road, 1964). The function can estimate travel time based on the relationship of volume to capacity ratio and ideal travel time as shown in Equation (2-15); where TT is the estimated travel time, TT_0 is an ideal travel time (distance/speed), V/C_P is volume to capacity ratio, and a and b is coefficient. Note that this travel time estimation is good only for planning purpose and requires only traffic volume at a given time and a basic (ideal) travel time in the function TT_0, which is basically the travel time at free flow speed.

$$TT = TT_0 \left[1 + a \left(\frac{V}{C_P} \right)^b \right] \tag{2-15}$$

The other travel time function is introduced by the use of the conversion of occupancy and traffic volume passing loop detector during time interval into travel time information as shown in Equation (2-16): where TT_i is the travel time of section i, Occ_i is the occupation rate of the section, Q_i is the flow, TT_{fi} is the travel time prevailing at free flowing condition, and $N_{\max}$ is a maximum number of vehicles within the section (Nour-Eddin, 2005).

$$TT_i = \frac{(Occ_i \cdot N_{\max})}{Q_i} + (1 - Occ_i) TT_{fi} \tag{2-16}$$

However, travel time can be directly measured using simple methods and also modern applications which were continuous presented.

- **Direct Travel Time Measurement**

Travel time data may be recorded through a wide variety of methods. An individual traveler may register his/her time using a stop watch. More generally applicable methods, which do not involve the individual travelers to determine the travel time, make use of for instance license plate recognition, toll gates, in-car systems (Grol et al., 1999, Taylor et al., 2000a). The measurement methods can be simply divided to two types; the first, logging the passage of vehicles from selected points along a road section or route, and the second, using moving observation platforms traveling in the traffic stream itself and recording information about their progress. The site-based methods include registration plate matching, remote or indirect tracking and input-output methods and so on. The stationary observer techniques include loop detectors, transponders, radio beacons, video surveillance, etc (D'Este et al., 1999). Meanwhile, the moving observer methods (vehicle-based methods) include the floating car, volunteer driver and probe vehicle methods. The following sections introduce the main techniques of travel time measurements in there two method groups included site-based measurement and vehicle-based measurement.

For site-based measurement, registration plate matching techniques consist of collecting vehicle license plate characters and arrival times at various checkpoints, matching the license plates between consecutive checkpoints, and computing travel times from the difference between arrival times (Turner et al., 1998). The essential survey method is manual transcription of paper or tape records. Nowadays, the license plate can be recorded by speech and video and then transfer to digital data by speech recognition and image recognition techniques (Taylor et al., 2000a, Yu, 2002). It has been shown in the previous research, using automatic vehicle identification (AVI) data that travel time prediction error decreased by fifty percent when forecasting fifteen minutes into the future. It is shown that the usefulness of the real time AVI data, as compared to average historical information, is extended from approximately fifteen to thirty minutes (Kisgyorgy and Rilett, 2002).

Remote or indirect tracking uses the vantage points to observe vehicle movements. Travel times of individual vehicles along relatively short stretches of road can be obtained by monitoring them from a vantage point which has a view start and end of the route (Taylor et al., 2000a).

Signpost based system, typically used by transit agencies for tracking bus locations, relies on transponders attached to roadside signposts. Automatic vehicle identification (AVI) transponders are located inside vehicles and are used in electronic toll collection applications. A practical case of signpost based system in Sydney is ANTTS (Automatic Network Travel Time System). Moreover, the development and application of Radio Frequency Identification (RFID) might extend to the real time goods tracking in freight transport and the travel time measurement in transport research in the near future.

Cellular phone systems are one of the potential techniques to provide travel time information. In a survey of 2000 in France, 80% of drivers carried at least one mobile telephone and 60% carried at least one switched on mobile. The information shows the high density of on-trip cellular phone, providing an environment to build a 24-hours travel time monitoring system. However the preliminary results show the location accuracy that 30% of positioning is better than 30 meters and 100% is better than 500 meters (Remy, 2001). The accuracy of position might satisfy the survey of travel time in a long section. For short sections, the accuracy is not enough to estimate to high random variation (Lum et al., 1998).

For vehicle-based measurement, floating car is the most common travel time collection method. The technique utilizes one or more vehicles that are specifically dispatched to travel with the traffic stream for the purpose of data collection (Turner et al., 1998). The simplest method to perform the survey is the manual record on travel times at when traveling on designated links using a clipboard and stopwatch, or computer instrumentation may be used to record vehicle speed, travel times or distance at preset checkpoints or intervals. By fitting a GPS receiver to a vehicle, it is possible to obtain time stamped location information which can be used to track location and determine travel times (Zito and Taylor, 1994). Furthermore the GPS-GIS combination form contributes the efficiency in both data collection and results analysis (Zito and Taylor, 1994, Taylor et al., 2000b).

Volunteer drivers and fleets of probe vehicles can help to collect traffic data more comprehensively, not only travel time but also geographic data and travel behavior (Hawkins et al., 2004). The cooperation with commercial fleet such as taxis and delivery companies can get huge number of data set with a reasonable survey cost.

GPS can be used for collecting historical travel time data including link travel time and intersection signal delay information for an arterial road network. A study by Pan et al. (2008) used two GPS data sets with different GPS accuracy from Shanghai in China, and Aachen in Germany to calibrate and verify the post-trip map matching algorithm. Travel time and intersection delay information was extracted from the GPS data sets. When a vehicle traveled through an arterial roadway link, there would be three types of delay included acceleration delay (D1), deceleration delay (D2), and time in queue delay (D3) which summation of D1, D2, and D3 were total link delay.

AVI data is also used to predict average roadway travel time with a low pass adaptive filtering algorithm. The algorithm is unique in three aspects. First, it is designed to handle both stable (constant mean) and unstable (varying mean) traffic conditions,. Second, the algorithm can be successfully applied for low levels of market penetration (less than 1%), and third the algorithm works for both freeway and signalized arterial roadways. The proposed algorithm utilizes a robust data filtering procedure that identifies valid data within a dynamically varying validity window. The size of the validity window varies as a function of the number of observations within the current sampling interval, the number of observations in the previous intervals, and the number of consecutive observations outside the validity window (Dion and Rakha, 2006).

Moreover, emerging and non-traditional techniques are currently researched or developed or may be considered non-traditional when compared to existing methods. These techniques use a variety of methods such as inductance loops, weigh in motion stations, or aerial video to estimate or calculate travel time. Most of the emerging techniques are currently in developmental or testing and have not been extensively field-tested or applied (Taylor et al., 2000).

However, accurate travel time estimation and prediction is difficult and complex and needs a lot of necessary traffic data. In order to understand the effect of traffic factors to the travel time information, the related traffic factors and accuracy improving approaches are reviewed. Human, vehicles, and infrastructure are the main components of traffic environment. Various factors affect three main components and finally influence travel time information. Different drivers and road conditions could cause large differences in travel time. Even in the same time interval and on the same link, different vehicles can have quite different travel times. One of the factors affecting travel time is free flow travel speed not only on road geometry but also on the traffic flow characteristics and traffic signal coordination (Lum et al., 1998).

2.3.2 Travel Time Prediction

In a view point of time period, current travel time information might help for a short term travel decision, but for long term scheduling predicted travel time information is essential. In the other viewpoint of traffic condition in area with rapidly changing conditions, a travel time prediction is essential because the travel time is a sensitive element and affected by various factors. A single incident on roadway might impact traffic stream that will consume long time periods to recover and it can cause a great amount of delay to travelers not only who travel at the time incident takes place but also who travel during the affected time periods. In the near future, travel time prediction is essential for ATIS that operates in real time for disseminating travel information to travelers at both pre-trip and en-route (Ishak and Al-Deek, 2002).

The methods of travel time prediction are proposed using several methodologies in which most of the conventional short-term prediction techniques can be categorized under two approaches; regression methods and time series estimation methods (Anderson and Bell, 1998). The third approach may be described as combining the first two methods known as data fusion. Other proposed methodologies are for examples historical data estimation method (Yanying and McDonald, 2002), artificial intelligence (Billi et al., 1994), statistical techniques (Grol et al., 1999).

Other main factors related to travel time prediction, that have also been referred in previous studies, include holiday and special incidents (Karl and Trayford, 1999), signal delay (Wu, 2001), weather conditions (Chien and Kuch, 2003), traffic operation (level of disturb), and congestion level. The greater the period is predicted, the higher the prediction error is (Kisgyorgy and Rilett, 2002). The adoption of specific variables for prediction would determine the efficiency and accuracy of the travel time prediction model.

Linear model is proposed to predict freeway travel time in which the coefficients vary as smooth functions of the departure time. The method is straight forward to implement, computationally efficient, and applicable to widely available freeway sensor data. For the first test by Zhang and Rice (2003), the method was implemented with data from I-880 which was small scale but very high in quality, containing information from probe vehicles and double loop detectors. The results indicate that, using this data set, the prediction error ranged from 5% for a trip leaving immediately to 10% for a trip leaving 30 min or more in the future. For the second test, the method was applied with a larger scale from Caltrans district 12 in Los Angeles.

Using this data set, the errors ranged from about 8% at zero lag to 13% at a time lag of 30 min or more.

Another study by Wei et al. (2007) used a linear model for forecasting short-term travel time information based on Hanshin expressway data. Hanshin Expressway Corporation has provided travel time information in some major segments using Variable Message Sign (VMS). Travel time information are only so called instantaneous travel time, as it is a simple accumulation of link travel times calculated from the length of a link divided by the current velocity of that link in the segment. If traffic flow is stable and the link travel time is constant, the instantaneous travel time is equal to real travel time. However, the link travel time may change due to traffic conditions. Therefore the instantaneous travel time is not equal to the real travel time. Traffic condition information is updated every 5-minute interval. *time* is the moment of traffic condition detected by detectors. This study by Wei et al. was carried out on 6 km of Hanshin Expressway from Osaka city to Kobe city. The section was equipped 12 pairs of supersonic detector stations spaced approximately every 500 meters. The information of volume, occupancy, and speed at every 5 min interval from this monitoring system was collected by Hanshin Expressway control center. In this study, the prediction of travel time under extremely abnormal traffic condition (for bad weather or accident) was not considered.

V-support vector machines were proposed to forecast short-term freeway volume. Traffic volume in the near future was often estimated based on historical volumes that many previous studies used neural networks to predict short-term traffic volume. The v-support vector machine (v-SVM) model was proposed by Zhang and Xie (2008) and the results were compared with a widely used multilayer feed-forward neural network (MLFNN). Testing results show that, for both one-step and two-step forecasting, the v-SVM model outperforms the MLFNN for all data sets in term of mean absolute percentage error and root-mean-square error. Most short-term traffic volume forecasting studies are based on data aggregated into 5 min or 15 min intervals; 3 min, 9 min, and 30 min interval have also been used but less frequently. From the previous study, 15 minute interval is appropriate and thus adopted in this study.

Modeling future travel time using real time and historical data, the Kalman filter algorithm is applied for travel time prediction. Results of the study by Chien and Kuch (2003) reveal that, during peak hours, the prediction based on historical path-based data are better than the prediction with link-based data due to smaller travel time variance and larger sample size. An interval of 5 min is chosen, for instance, there would be 288 intervals (in a 24 hour time period). The path-based travel time is recorded when a vehicle finished a particular path, which can be determined based on the difference between the recorded times when the vehicle was entering and exiting the path. The link-based travel time is the sum of travel times of vehicles in the consecutive individual links that constitute the whole path.

An online short-term prediction of point-to-point freeway travel time using the integration of statistical forecasting techniques and traffic simulation was proposed by Juri et al. (2007). VISSIM was used to generate traffic volume at detector locations.

At every freeway entrance point, a time series analysis model based on traffic detector counts was used to predict traffic demands whose flow through the freeway segment was simulated by a cell transmission model (CTM). This CTM, which first introduced by Daganzo, simulated traffic behaviors at a mesoscopic level.

Most of travel time prediction models in the literature fall into one of two broad categories: Statistical models and Heuristic models. Statistical approach uses regression techniques or time series analysis to compute future travel time based on historical and/or time information. In general, purely statistical techniques have been found to perform poorly during abnormal traffic condition. Vehicle inflows are predicted using auto regressive integrated moving average (ARIMA) time series model. Another approach is the Heuristic model. Neural network is one of popular heuristic techniques. However, choosing the method for predicting travel time data using time series is not appropriate when actual travel time is unavailable from field measurement but statistical models could be applied for short-term prediction.

2.4 ACCURACY AND RELIABILITY OF TRAVEL TIME INFORMATION

There are several effects on accuracy and reliability of travel time information described as follows.

2.4.1 Effect of Effective Vehicle Length on Single Loop Detector

The occupancy variance obtained from single loop data can be used to estimate long vehicle percentage and how a log linear regression model for mean vehicle length estimation based on single loop outputs can be developed. The previous study, Wang and Nihan (2000), has used the fitness of the relationship based on the theoretical derivation of the occupancy and effective vehicle length relationship, and a log linear model for mean effective vehicle length estimation is employed. The estimated mean effective vehicle lengths (LV) are used to calculate a conversion factor, *g* value, of each time interval in order to get more accurate speed estimation. Typically, to calculate space mean speed, a constant *g* is often adopted to convert lane occupancy to traffic density. Hence, the speed estimation with fixed g value is biased when the LV percentage is higher than the average; it means that speed is underestimated. In the other hand, it becomes an overestimated speed when LV percentage is lower than the average. However, it is shown in their study that the formulae consistently under estimates speed whenever a significant number of trucks and/or other longer vehicles are present. This is due to the fact that the *g* value is actually not a constant; g value varies with occupancy. A cuspcatastrophe theory model was proposed by Pushkar et al. (1994) to estimate speed and indicated that the cuspcatastrophe theory model gives more reasonable results. Random errors were considered in the measurement and a Kalman filter was used to estimate speed. The estimation results were basically consistent with the observed speeds, but with a smaller variance. To apply the aforementioned models, several parameters must be calibrated, and the calibrations require information beyond the measurement of single loops. Such estimation bias may be corrected using the proper g value for each time interval (Dailey, 1999).

The applicable method was proposed by Hellinga (2002) for freeway traffic management system (FTMS) that contained both single and dual loop detector stations. It does not require modification to field hardware or additional field equipment. It is argued that the proposed method can reduce root mean square speed estimation error by 23% on average over the traditional speed estimation method of using a constant average divided by an effective vehicle length for the entire day. The proposed method did not show that the regression model was transferable to other FTMS or even to other detector locations within the same FTMS although their results indicated a 41% increase in the speed estimation accuracy when compared with a constant g value for entire day. Speed estimation methodologies were proposed in this study, including base case, direct correlation, filtered correlation, and bias correction. For the base case, the study assumed the case consisting of estimating single loop speeds on the basis of average effective vehicle length measured at a dual loop station over the entire 24 hour period. This assumed base case is likely to provide speed estimates that are more accurate than what would normally be obtained for FTMS with only single loop detector, as in these systems an average vehicle length must be assumed as it cannot be measured.

For the direct correlation, when some of the FTMS loop detectors are dual loop detectors, it is possible to estimate average speed for each single station on the basis of $\bar{S}_i = \dfrac{V_i L_i}{O_i}$ and the average effective vehicle length measured at a nearby dual loop station during the same polling interval. This method is used by COMPASS system in Toronto. Of course, when $\bar{L}_i$ is taken from a nearby dual loop station for use in above Equation, the implicit assumption is that the average effective vehicle length computed during the polling interval at the dual loop station is highly correlated with the unknown average effective vehicle length at the single loop station for the same time period. If the average effective vehicle length at the single loop station is not highly correlated with the average effective vehicle length at the dual loop station, then additional error is introduced into the calculation of speed at the single loop detector station.

For filtered correlation, it is shown that the direct correlation method does not perform well, primarily as a result of the lack of correlation between the average effective vehicle length at the single loop detector station and nearby dual loop detector station. During the short time period of 20 seconds time interval, the average vehicle length measured from each station is likely to be different, because the vehicles passing each station represent different samples from the population of vehicles. The average length of vehicles passing a detector station during a polling interval is the result of a random sampling process in which the variation of the sample mean vehicle length is a function of the sample size and the variation of vehicle lengths within the population. If the population mean vehicle length is not constant but varies with time of day, then averaging over a long period of time will result in estimates that do not adequately reflect these temporal trends. One way to avoid the problem of having to select a fixed sampling period duration is to use an exponentially weighted moving average

(EWMA). Exponential smoothing is an average technique that can be used when the appropriate averaging period duration is not known (Hellinga, 2002).

2.4.2 Effect of Data Collection Time Interval

Typically, Highway Capacity Manual (HCM) suggests data collection time interval of 15 minutes to aggregate flow data for getting the stable flow rate measures. Guo et al (2008) tested spectrum of data collection time intervals with an online forecasting algorithm based on the SARIMA+GARCH (Stochastic seasonal Autoregressive Integrated Moving Average plus Generalized Autoregressive Conditional Heteroscedasticity) structure to determine the applicable data collection time intervals. With respect to flow rate aggregation, the data collection time interval is a key determinant of the discrete traffic flow data series characteristics and the corresponding forecasting approach. Clearly, an understanding of the impact of data collection time interval is crucial in short-term traffic forecasting, because different applications will require different data collection time intervals. For example, incident detection based on short-term traffic condition prediction will require a short forecasting horizon, while a predictive route guidance application will likely require a longer forecasting horizon. The investigation by Smith and Ulmer (2003) quantitatively demonstrated the effects of the data collection time interval on traffic flow rate measurement series. It is shown that with the increase of the data collection time interval, the traffic flow rate measures tend to become more stable. However, for shorter data collection time intervals, the number of lags within the seasonality period (usually 1 week) increases. For example, there are 2016 lags per week for a 5 min interval and 10080 lags per week for 1 min intervals. From this study, it is shown that forecasting accuracy improves with the increasing data collection time interval length. This follows the expectation that the increase of the data collection time interval will reduce the embedded traffic flow series noise, thereby improving the signal-to-noise ratio and making the series more stable and thus more predictable.

There is a strong, priori expectation that the observed association of increased forecast accuracy with increased data collection time interval length will be a consistent feature for other valid forecasting methods, such as nonparametric regression and neural network models. In other words, this finding is not considered to be unique to the SARIMA based forecast model. A sharp increase of forecast accuracy is observed for all the measures and all the stations when the data collection time interval is increased from 1 to 5 min. At time intervals of 10 min and longer, the forecast accuracy is fairly consistent with a pronounced flattening of the rate of increase in accuracy versus interval length. The performance for data collection time intervals between 5 and 10 min may be considered acceptable for certain applications.

The impact of the time interval was proposed by Smith and Ulmer (2003) to quantify the impact and usage of freeway traffic flow measurement. It is found that stable freeway flow rate may be calculated using measurement intervals as short as 10 min, and that statistical significant improvement in stability can be achieved by adding 2 min to any measurement interval.

Different aggregation time intervals was examined by Oh et al. (2005) to characterize various levels of traffic dynamics representations and to investigate their effects on prediction accuracy. They employed three techniques including adaptive exponential smoothing (AES), adaptive autoregressive model using Kalman filtering (AAR), and recurrent neural network (RNN) with genetically optimized parameters. There are various prediction methodologies used in existing studies: historical and real time profiles, statistical modeling, Kalman filtering and artificial intelligence techniques including artificial neural network (ANN) and fuzzy logic. The study by Oh et al. (2005) also summarized the previous studies in this matter. It shows that the ANN based prediction approaches provide better prediction performance than the others. However, the drawbacks of the ANN based approach should not be disregarded. ANN requires not only huge efforts for establishing network architecture and training network parameters but also large data storage. The main results from this study indicate that AES and RNN outperform the AAR in short-term period such as less than 5 minutes. The purpose of short term travel time prediction the RNN can be a viable candidate, providing the highest accuracy in regard to Mean Absolute Percentage Error (MAPE). The RNN shows the best performance with aggregation interval of 4 minutes.

2.4.3 Probe Vehicle Percentage Requirement

A study by Long Cheu et al. (2002) investigated speed estimation on arterial network in Clementi town area in Singapore using INTEGRATION traffic simulation package. The study varied traffic volumes and percentages of probe vehicles (PV), which were taxis in this case. The study was conducted on 216 simulation runs with INTEGRATION model. Three parameters were varied with different levels; 6 levels of OD volumes which based OD in morning peak (60%, 70%, 80%, 90%, and 110%), 6 levels of PV (3%, 6%, 9%, 12%, 15%, and 18%), and 6 levels of randomness in vehicle headway (0.5, 0.6, 0.7, 0.8, 0.9, and 1.0). Runs had a warm up period of 500 sec followed by a data collection interval of 700 sec. They argued that this setup would lie within the practical range of pooling frequency for communication between vehicles and management center and it is a multiple of signal cycle time of 140 sec.

The result showed that estimated link speed error was less than 5 km/hr at least 95 % of the time, and the network needed to have active probe vehicles of 4 % to 5 % or at least ten probe vehicles must passed through a link within the sampling period. By the way, the problem arose that probe vehicles might not be distributed onto the overall network. It might be concentrated in some areas, and some link might not be passed by probes or passed with small number of probes.

Equation (2-17) shows the formulation for estimating sample size of probe vehicles derived from central limit theorem, where n is the number of probe, ε_a is allowable error in estimated speed (use 5.0 km/hr), and s is sample standard deviation of speed.

$$n \geq \left(\frac{t_{\alpha/2,n-1} s}{\varepsilon_a} \right)^2 \tag{2-17}$$

A slightly different approach, but still based on the standard deviation that is used the relative speed error ε_r instead of ε_a (Chen and Chien, 2000) as shown in Equation (2-18) where $\bar{x}$ is average speed computed from n samples.

$$n \geq \left(\frac{t_{\alpha/2,n-1} s}{\varepsilon_r \bar{x}} \right)^2 \tag{2-18}$$

In order to evaluate the feasibility of using probe vehicles to collect real time traffic information, it is necessary to determine the number of vehicles that should be equipped as "Probe". Vanajakshi et al (2009) studied using CORSIM to generate traffic data for freeway segment with 5 minutes time interval, which has been widely regarded as an appropriate interval for real time traffic parameter. The statistical sampling methodology to find the minimum required number of probe vehicles is shown in Equation (2-19), where n_{lt} represents the number of probe vehicles required, μ_{lt} represents the "true" mean of link travel time, σ_{lt} represents the "true" variance in link travel time, $\varepsilon_{\max}$ represents the maximum relative error, r represents the percentage of time that the absolute value of relative error is less than $\varepsilon_{\max}$, and $\Phi(x)$ represents the cumulative distribution function evaluated at x and Φ^{-1} is the inverse.

$$n_{lt} = \left[\frac{\Phi^{-1}\left(\frac{1+r}{2}\right)\left(\frac{\sigma_{lt}}{\mu_{lt}}\right)}{\varepsilon_{\max}} \right]^2 \tag{2-19}$$

The statistical principle behind Equation (2-19) is the central limit theorem, which is based on sample size is large enough. $\frac{\sigma_{lt}}{\mu_{lt}}$ is obtained from historical data. It is commonly assumed that vehicle travel time on a link is normally distributed which justifies the use of Equation (2-19) for small sample size cases. Distribution of link travel time is considered as it is affected by many factors including both geometric and traffic conditions. A heuristic method by Chen and Chien (2000) was developed to find the minimum number of probe vehicles on a freeway segment which consists of link will both normally and non-normally distributed travel times. Vehicle travel time distribution could affect the required minimum number of probe vehicles for a statistically accurate estimation in several ways. First, the method to be used in obtaining the minimum number of required probe vehicles is determined by the type of travel time distribution. If it is normally distributed, the minimum number of probe vehicles under a given significance level can be determined using Equation (2-19) based on a pre-specified permitted error and historical coefficient of variation. Secondly, the variance of the distribution would affect the minimum number of probe vehicle requirement despite the type of distribution. It is observed that when link traffic volume is very light or very heavy, the minimum percentage of probe vehicles that should be sampled tends to be higher than that the number of probes obtained when link traffic volume is at the medium level. The stability of the distribution would also affect the minimum number of probe vehicles necessary. In this study, 5-minute time interval was selected since it was generally regarded as an appropriate time interval for real time traffic parameter estimation. This presumed that the travel time distribution would not change in this time frame. However, in real world applications, this assumption needed to be examined and validated for each specified case.

The sample of probe vehicles was conducted to detect freeway incident detection. PARAMICS microscopic traffic simulation model was used to simulate incidents and to collect section travel time data from probe vehicles for evaluating the sampling strategies. The simulation was modeled based on a 8.6-km southbound segment of the central expressway (CTE) in Singapore. Three different methods were tested including fixed sample size (FSS), fixed time interval (FTI), and rolling interval. Incident detection performance was analyzed in terms of detection rate (DR), false alarm rate (FAR), mean time to detection (MTTD), number of algorithm applications, and number of false alarms. It was found that the FTI data aggregation method outperformed other methods for all the indicators when the probe vehicle percentage was less than 20. When the probe vehicle percentage exceeded 30 and both FSS and FTI data aggregation methods had high DR, the FSS method gave the lowest number of false alarm cases and fastest mean time detection. All three data aggregation methods showed similar performance when the probe-vehicle percentage ranged between 20 and 30. MOSES Algorithm detected incidents on the basis of the change in average travel time of probe vehicles in a freeway section.

The MOSES algorithms uses a one-tail hypothesis test on the difference between two mean section travel times from two sets of sample as shown in Equation (2-20) where n_1 is the number of most recently observed probe vehicles, n_2 is the number of probe vehicles that had exited the section just before the n_1 probe vehicles, t_{α,n_1+n_2-2} is the t-statistic with tail-end probability of α and n_1+n_2-2 degree of freedom.

$$\frac{\overline{T}_1-\overline{T}_2}{\sqrt{\frac{(n_1-1)s_1^2+(n_2-1)s_2^2}{n_1+n_2-2}\left(\frac{1}{n_1}+\frac{1}{n_2}\right)}}\ge t_{\alpha,n_1+n_2-2} \qquad (2\text{-}20)$$

When an incident has occurred in a section of the freeway, $\overline{T}_1$ is expected to be significantly higher than $\overline{T}_2$ when Equation (10) is true, the MOSES algorithm will declare an incident in that particular freeway section.

In the study by Cheu and Tay (2004), using FSS data aggregation method, the values of $\overline{T}_2$=10 and n_2=30 were retained, and the algorithm was applied for every n_1=10 probe vehicle observed on a different freeway. The FSS method controlled the sample size n_1 and n_2 such that the estimated $\overline{T}_1$ and $\overline{T}_2$ were more reliable. FTI Data

Aggregation Method was time based. Here n_1 was the number of probe vehicles that had passed the freeway section every 60 sec and n_2 was the number of probe vehicles in the previous 180 sec. In this case, the algorithm was applied every 60 sec. The 180 sec sampling of n_2 was to make n_2 about three times n_1, to be consistent with the ratio of sample sizes in the FSS method. With FTI data aggregation method, the value of n_1 and n_2 varied for every algorithm application, but the frequency of application over a 1 hour period remained constant.

This method of aggregating probe vehicle data is similar to the confidence limit algorithm (CLA). However, the two studies are different in that Equation(2-20) assumes the probe-vehicle travel time follows a normal distribution whereas the CLA assumes a log normal distribution, and the hypothesis test is conducted using t-statistics, whereas the CLA uses log normal statistics.

There was a study on arterial speed estimation using taxi equipped with global positioning receivers as probe vehicles. 100 GPS receivers were equipped on taxis in Guangzhu city, China. The accuracy of travel time increases with the sample size. It was conclude that, if the absolute error in the estimated average link speed is to be less than 5.0 km/h at least 95% of the time. It should be at least 10 probe vehicles within a sampling period (Liang et al., 2005).

There was a feasibility study on the use of probe in order to collect traffic information in an advantage city in term of cost efficiency. There are several problems to use probe vehicles instead of detectors for traffic information collection e.g. coverage area and frequency per each link and requirement of number of probe vehicles to collect traffic information with high reliability. In their study, 5 taxis were equipped GPS as probe vehicle and compared the travel time data obtained by a probe vehicle and license plate matching survey, the travel time estimated by probe vehicles seem to be statistically accurate. They argued that 5 second interval was found suitable to record location of probe vehicles and found that vehicle running frequency is high only on main roads connected to central area (Ishizaka et al., 2005).

2.5 FILTERING TECHNIQUES

In 1960, R.E. Kalman published his famous paper describing a recursive solution to the discrete-data filtering on linear dynamics system problem. During that time, the technique was employed in large part in digital computation. Kalman filter has been the subject of extensive research and application particularly in the area of autonomous or assisted navigation (Welch and Bishop, 2006). Kalman filter is the most popular filtering technique that is widely used in military and engineering field. Kalman filter is an efficient recursive filter that estimates the state of linear and nonlinear dynamic system from a series of noisy measurements. In this section, four filtering techniques are reviewed including Kalman filter (KF), extended Kalman filter (EKF), unscented Kalman filter (UKF), and particle filter described as follows.

2.5.1 Kalman Filter (KF)

Kalman filter is a recursive estimator which the only estimated state from the previous time step and the current measurement are required to estimate the current state. It assumes that the true state at time *k* is evolved from the state at *k*-1 which is formulated as shown in Equation (2-21).

$$\mathbf{X}_k = \mathbf{F}_k \mathbf{X}_{k-1} + \mathbf{B}_k \mathbf{u}_k + \mathbf{w}_k \tag{2-21}$$

where $\mathbf{F}_k$ is the state transition model which is applied to the previous state $\mathbf{X}_{k-1}$, $\mathbf{B}_k$ is the control input model which is applied to the control vector $\mathbf{u}_k$, and $\mathbf{w}_k$ is the process noise which is assumed to be drawn from a zero mean multivariate normal distribution with covariance $\mathbf{Q}_k$. At time *k*, an observation or measurement $\mathbf{z}_k$ of the true state $\mathbf{X}_k$ is made as shown in Equation (2-22)

$$\mathbf{z}_k = \mathbf{H}_k \mathbf{X}_k + \mathbf{v}_k \tag{2-22}$$

where $\mathbf{H}_k$ is the observation model which maps the true state space into the observed space and $\mathbf{v}_k$ is the observation noise which is assumed to be zero mean Gaussian white noise with covariance $\mathbf{R}_k$. The initial state and the noise vectors at each time step are assumed to be mutually independent. The Kalman filter has two distinct phases; predict and update. The predict phase uses the state estimate from the previous time step to produce an estimate of the state at the current time step, and then the update phase uses measurement information at the current time step to refine predicted state to arrive a more accurate state. The process is shown as follow.

<u>Predict Phase:</u>

Predicted state

$$\hat{\mathbf{X}}_{k|k-1} = \mathbf{F}_k \hat{\mathbf{X}}_{k-1|k-1} + \mathbf{B}_{k-1} \mathbf{u}_{k-1} + \mathbf{w}_k \tag{2-23}$$

Predicted estimate covariance

$$\mathbf{P}_{k|k-1} = \mathbf{F}_k \mathbf{P}_{k-1|k-1} \mathbf{F}_k^{\mathrm{T}} + \mathbf{Q}_{k-1} \tag{2-24}$$

<u>Update Phase:</u>

Measurement residual

$$\tilde{\mathbf{y}}_k = \mathbf{z}_k - \mathbf{H}_k \hat{\mathbf{X}}_{k|k-1} \tag{2-25}$$

Covariance

$$\mathbf{S}_k = \mathbf{H}_k \mathbf{P}_{k|k-1} \mathbf{H}_k^{\mathrm{T}} + \mathbf{R}_k \tag{2-26}$$

Optimal Kalman gain

$$\mathbf{K}_k = \mathbf{P}_{k|k-1} \mathbf{H}_k^{\mathrm{T}} \mathbf{S}_k^{-1} \tag{2-27}$$

Updated state estimate

$$\hat{\mathbf{X}}_{k|k} = \hat{\mathbf{X}}_{k|k-1} + \mathbf{K}_k \tilde{\mathbf{y}}_k \tag{2-28}$$

Updated estimate covariance

$$\mathbf{P}_{k|k} = \left(I - \mathbf{K}_k \mathbf{H}_k\right) \mathbf{P}_{k|k-1} \tag{2-29}$$

However, the basic Kalman filter was developed for linear system and it was claimed to be inefficiently performed when it is adopted with nonlinear system. Nevertheless, this drawback can be optimized using EKF which will be described in the next part.

2.5.2 Extended Kalman Filter (EKF)

In the estimation theory, EKF is the nonlinear version of the KF which current mean and covariance are linearized. To do so, a Jacobian matrix is conducted to transform nonlinear system into KF form as shown in Equation (2-30) and Equation (2-31).

$$\mathbf{F}_{k-1} = \left.\frac{\partial f}{\partial \mathbf{X}}\right|_{\hat{\mathbf{X}}_{k-1|k-1}, \mathbf{u}_{k-1}} \tag{2-30}$$

$$\mathbf{H}_{k-1} = \left.\frac{\partial h}{\partial \mathbf{X}}\right|_{\hat{\mathbf{X}}_{k|k-1}} \tag{2-31}$$

However, EKF is difficult to implement, difficult to tune, and only reliable for systems that are almost linear on the time scale of the updates. It has a number of serious limitations, which are (1) linearization transformations are only reliable if the error propagation can be well approximated by a linear function, (2) linearization and be applied only if the Jacobian matrix exists, and (3) calculating Jacobian matrix can be a very difficult and error-prone process as the Jacobian Equations frequently produce many pages of dense algebra that must be converted to code (Julier and Uhlmann, 2004).

2.5.3 Unscented Kalman Filter (UKF)

An improvement to the EKF has led to the development of the Unscented Kalman filter (UKF) which also a nonlinear filtering technique. In the UKF, the probability density is approximated by the nonlinear transformation of a random variable which returns much more accurate results than the first-order Taylor expansion of the nonlinear functions in the EKF. The approximation utilizes a set of sample points, which guarantees accuracy with the posterior mean and covariance to the second order for any nonlinearity (Julier and Uhlmann, 2004).

When predict and update functions ($f\left(\bullet\right)$ and $h\left(\bullet\right)$) are highly nonlinear, EKF can give particularly poor performance because mean and covariance are propagated through linearization of the underlying nonlinear model. UKF uses a deterministic sampling technique known as the unscented transform to pick a minimal set of sample points as called sigma points around the mean. These sigma points are propagated through the nonlinear functions which the mean and covariance of the estimate are then recovered. The result is a filter which captures more accurate true mean and covariance. In addition, this technique removes the requirement to explicitly calculate Jacobian Equation. The process of UKF also consists of predict phase and update phase which are described as follows.

Predict Phase:

As with the EKF, the UKF prediction can be used independently from the UKF update. The estimated state and covariance are augmented with the mean and covariance of the process noise as shown in Equation (2-32) and Equation (2-33).

$$\mathbf{X}^a_{k-1|k-1} = \begin{bmatrix} \hat{\mathbf{X}}^T_{k-1|k-1} & E\left[\mathbf{w}^T_k\right] \end{bmatrix}^T \tag{2-32}$$

$$\mathbf{P}^a_{k-1|k-1} = \begin{bmatrix} \mathbf{P}_{k-1|k-1} & 0 \\ 0 & \mathbf{Q}_k \end{bmatrix} \tag{2-33}$$

A set of $2L+1$ sigma points is derived from the augmented state and covariance where L is the dimension of the augmented state.

$$\boldsymbol{\chi}^0_{k-1|k-1} = \mathbf{X}^a_{k-1|k-1} \tag{2-34}$$

$$\boldsymbol{\chi}^i_{k-1|k-1} = \mathbf{X}^a_{k-1|k-1} + \left(\sqrt{(L+\lambda)\mathbf{P}^a_{k-1|k-1}}\right)_i \quad \text{for } i = 1 \ldots L \tag{2-35}$$

$$\boldsymbol{\chi}^i_{k-1|k-1} = \mathbf{X}^a_{k-1|k-1} - \left(\sqrt{(L+\lambda)\mathbf{P}^a_{k-1|k-1}}\right)_i \quad \text{for } i = L+1, \ldots 2L \tag{2-36}$$

where $\left(\sqrt{(L+\lambda)\mathbf{P}^a_{k-1|k-1}}\right)_i$ is the i th column of the matrix square root of $(L+\lambda)\mathbf{P}^a_{k-1|k-1}$ using the definition: square root A of matrix B satisfies $\left(B = AA^T\right)$. The matrix square root should be calculated using numerically efficient and stable methods such as the Cholesky decomposition. The sigma points are propagated through the transition function $f(\bullet)$.

$$\boldsymbol{\chi}^i_{k|k-1} = f\left(\boldsymbol{\chi}^i_{k-1|k-1}\right) \quad \text{for } i = 0.2L \tag{2-37}$$

The weighted sigma points are recombined to produce the predicted state and covariance:

$$\hat{\mathbf{X}}_{k|k-1} = \sum_{i=0}^{2L} W^i_s \boldsymbol{\chi}^i_{k|k-1} \tag{2-38}$$

$$\mathbf{P}_{k|k-1} = \sum_{i=0}^{2L} W^i_c \left[\boldsymbol{\chi}^i_{k|k-1} - \hat{\mathbf{X}}_{k|k-1}\right]\left[\boldsymbol{\chi}^i_{k|k-1} - \hat{\mathbf{X}}_{k|k-1}\right]^T \tag{2-39}$$

where the weights for the state and covariance are given by:

$$W_s^0 = \frac{\lambda}{L+\lambda} \tag{2-40}$$

$$W_c^0 = \frac{\lambda}{L+\lambda} + \left(1-\alpha^2+\beta\right) \tag{2-41}$$

$$W_s^i = W_c^i = \frac{1}{2\left(L+\lambda\right)} \tag{2-42}$$

$$\lambda = \alpha^2\left(L+\kappa\right) - L \tag{2-43}$$

α and κ control the spread of the sigma points. β is related to the distribution of x. Normal values of α and κ are 10^{-3} and 0 respectively. The optimal value of β is equal to 2, if the true distribution of x is Gaussian.

Update Phase:

The predicted state and covariance are augmented as before, except now with the mean and covariance of the measurement noise:

$$\mathbf{X}^a_{k|k-1} = \left[\hat{\mathbf{X}}^T_{k|k-1} \quad E\left[\mathbf{v}_k^T\right]\right]^T \tag{2-44}$$

$$\mathbf{P}^a_{k|k-1} = \begin{bmatrix} \mathbf{P}_{k|k-1} & 0 \\ 0 & \mathbf{R}_k \end{bmatrix} \tag{2-45}$$

As earlier mentioned, a set of 2L + 1 sigma points is derived from the augmented state and covariance where L is the dimension of the augmented state:

$$\boldsymbol{\chi}^0_{k|k-1} = \mathbf{X}^a_{k|k-1} \tag{2-46}$$

$$\boldsymbol{\chi}^i_{k|k-1} = \mathbf{X}^a_{k|k-1} + \left(\sqrt{\left(L+\lambda\right)\mathbf{P}^a_{k|k-1}}\right)_i \quad \text{for } i = 1 \ldots L \tag{2-47}$$

$$\boldsymbol{\chi}^i_{k|k-1} = \mathbf{X}^a_{k|k-1} - \left(\sqrt{\left(L+\lambda\right)\mathbf{P}^a_{k|k-1}}\right)_{i-L} \quad \text{for } i = L+1, \ldots 2L \tag{2-48}$$

Alternatively if the UKF prediction has been used the sigma points themselves can be augmented along the following lines.

$$\boldsymbol{\chi}_{k|k-1} := \left[\boldsymbol{\chi}^T_{k|k-1} \quad E\left[\mathbf{v}_k^T\right]\right]^T \pm \sqrt{\left(L+\lambda\right)\mathbf{R}^a_k} \tag{2-49}$$

where

$$\mathbf{R}^a_k = \begin{bmatrix} 0 & 0 \\ 0 & \mathbf{R}_k \end{bmatrix} \tag{2-50}$$

The sigma points are projected through the observation function h.

$$\boldsymbol{\gamma}_k^i = h\left(\boldsymbol{\chi}_{k|k-1}^i\right) \text{ for } i = 0...2L \tag{2-51}$$

The weighted sigma points are recombined to produce the predicted measurement and predicted measurement covariance.

$$\hat{\mathbf{z}}_k = \sum_{i=0}^{2L} W_s^i \boldsymbol{\gamma}_k^i \tag{2-52}$$

$$\mathbf{P}_{z_k z_k} = \sum_{i=0}^{2L} W_c^i \left[\boldsymbol{\gamma}_k^i - \hat{\mathbf{z}}_k\right]\left[\boldsymbol{\gamma}_k^i - \hat{\mathbf{z}}_k\right]^T \tag{2-53}$$

The state-measurement cross-covariance matrix,

$$\mathbf{P}_{x_k z_k} = \sum_{i=0}^{2L} W_c^i \left[\boldsymbol{\chi}_{k|k-1}^i - \hat{\mathbf{x}}_{k|k-1}\right]\left[\boldsymbol{\gamma}_k^i - \hat{\mathbf{z}}_k\right]^T \tag{2-54}$$

$\mathbf{P}_{z_k z_k}$ and $\mathbf{P}_{x_k z_k}$ are used to compute the UKF Kalman gain.

$$\mathbf{K}_k = \mathbf{P}_{x_k z_k} \mathbf{P}_{z_k z_k}^{-1} \tag{2-55}$$

As with the KF, the updated state is the predicted state plus the innovation weighted by the Kalman gain,

$$\hat{\mathbf{x}}_{k|k} = \hat{\mathbf{x}}_{k|k-1} + \mathbf{K}_k \left(\mathbf{z}_k - \hat{\mathbf{z}}_k\right) \tag{2-56}$$

And the updated covariance is the predicted covariance, minus the predicted measurement covariance, weighted by the Kalman gain.

$$\mathbf{P}_{k|k} = \mathbf{P}_{k|k-1} - \mathbf{K}_k P_{z_k z_k} \mathbf{K}_k^T \tag{2-57}$$

2.6 TRAFFIC SIMULATION TOOLS AND MODEL PARAMETER CALIBRATION

2.6.1 Traffic Simulation Tools

In recent years, microscopic traffic simulation model is widely employed for analyzing transportation problems which cannot be carried out by conventional analysis methods, especially when network-wide study is conducted. The high performance of computer technology has been developed to analyze complicated problems with less time consuming. Computational performance of microscopic traffic simulation modeling makes it possible to analyze individual travelers' behaviors. Microscopic traffic simulation is used to enhance the capability of operation, control, and management for both freeway and surface street traffic. There are many commercial suites; for example PARAMICS, MITSIM, VISSIM, and AIMSUN.

Fries et al. (2007) conducted a feasibility study on using the traffic simulation as a decision support in real-time regional traffic management. The result shows that microscopic traffic simulation programs can help the operator in regional traffic management center. It makes an operational decision by predicting future traffic conditions caused by traffic incidents. The speed for traffic data processing is a key factor to determine the viability of using simulation in real time decision support. There are several commercial software packages in the market. However, PARAMICS microscopic traffic simulation is one of the software that is widely used because it has a flexible application programming interface and can be integrated with traffic control and simulate special cases, for example toll plaza operation and ramp metering. PARAMICS Modeler is the preferred simulation tool because it offers advantages over other decision support tools by providing traffic management personnel with visual representative of the traffic impacts.

On-line simulation can be used to provide real time traffic information and to select the best control and management strategies according to the interpretation of results from simulation runs of candidate control strategies using predicted traffic demands. Chu and Recker (2004) performed a study to enhance the capabilities of PARAMICS to enable its application for on-line simulation. The study established the connection between real world loop detector data and simulation. A simple Origin Destination (OD) estimation method was developed for the estimation of dynamic OD demand matrices for a freeway network based on real world loop detector data. A Kalman filtering based traffic flow prediction algorithm was also developed. The predicted traffic flows served for the prediction of future demand matrices.

2.6.2 Model Parameters Calibration

The components of microscopic traffic simulation model generally include physical component of road network, traffic control system, and driver-vehicle units which driver behavior models and route choice models are associated. The complex data and numerous model parameters are required by these components. These parameters need to be calibrated for a particular study area (Mcnally and Oh, 2002).

Car following behavior, in particular, has a significant impact on the accuracy of the simulation model in replicating traffic behavior on the road. Car following considers the situation of one vehicle following another in a single lane. In general, the trailing vehicle of a two-car following pair in the same lane will respond to observed stimulus from the leading driver according to the relationship of response and λ stimulus. The stimulus is composed of factors such as speed, relative speed, inter-vehicle spacing, accelerations, vehicle performance, and driver thresholds. A proportionality factor λ equates the stimulus function to the driver response. This relationship forms the basic philosophy behind the car following theories. Other critical parameters that govern car following models include mean headway and mean reaction time, which are assigned random values for each individual vehicle according to a predefined distribution function. A number of studies have suggested using headway values in the range of 1.65 – 2.0 sec and reaction times in the range of 0.3 – 2.0 sec (Ma and Abdulhai, 2002).

Conventional model calibration procedure adjusts parameters in driver behavior model and route choice model until simulation output is corresponded with field observation in both qualitative and quantitative aspects. The trial-and-error method is normally employed for calibrating parameters based on engineering and experience decision, and this method is a time consuming and tedious process. Some previous studies attempted to introduce a systematic procedure to calibrate a network level simulation model for both freeways and their adjacent parallel surface streets by focusing on one component of the simulation model while assuming others component held constant at present values (Chu et al., 2004). Some studies presented calibration framework which also focused on route choice model calibration when the O-D flow was an unknown variable (Toledo et al., 2004, Toledo et al., 2003). However, with this conventional calibration procedure, calibrated traffic parameters are not guaranteed to be used in all range of various traffic system environments. The parameters may require re-adjustment which would again consume great effort based on the conventional model calibration.

Another calibration approach is artificial intelligence approach in which genetic algorithm method was often introduced to reduce time of calibration process by treating parameters calibration to be an optimization problem and searching optimal combinatorial parameters values that can minimize a fitness function within defined number of generations in genetic algorithm procedure (Cheu et al., 1998, Lee and Yang, 2001, Ma et al., 2007, Park and Qi, 2006, Schultz and Rilett, 2004). A study introduced pilot software which was a genetic optimizer for traffic microscopic traffic simulation models (Ma and Abdulhai, 2002). However, those studies used different calibration frameworks and fitness functions according to their purposes of microscopic traffic simulation model applications.

Several optimization methods are available to find some suitable solutions; for example, hill climbing, tabu search, simulated annealing, and genetic algorithm. These methods are often considered for searching a good solution though it might not be the real optimal solution. As a matter of fact, in many cases it is not possible to verify what the real optimum is.

Genetic algorithm is a stochastic search space method based on the principle of natural evolution theory of Charles Robert Darwin. The algorithm initiates a set of solutions that are represented as “chromosomes” called population. Solutions included in one population are selected and used to produce a new population if the new population performs better than the previous population. The previous population is selected according to their fitness which means the more chance it will be selected to produce a new population.

One string element in the genetic algorithm is the chromosome that is encoded as a single solution which means one set of combinatorial parameters prepared for simulation model. Standard genetic algorithm is based on binary representative characterized by zero and one. Real value is also proposed to represent genes (Wright, 1991). There are many types of genetic algorithm; for example, simple GA, steady-state GA, and crowding-based GA. The simple GA is a very common method that is based on non-overlapping population in each generation. If the elitism mechanism is enumerated, the best fitness of each population will be carried over from parent to child without reproduction. Steady-state GA is another standard genetic algorithm based on overlapping population in each generation in which a portion of the population is substituted by the new generated. If only one or two members may be substituted in each generation, it is called incremental GA but it will become a simple GA when entire population is substituted. Crowding-based GA is a generalization of pre-selection which selection and reproduction are the same as steady-state but the new generation will perform a comparison with population individually using a distance function as a similarity measurement before replacement. The most similar member in the population between parent and child is substituted by the child.

The reproduction process consists of selection, crossover, and mutation in order to produce new generation. There are many selection methods for choosing members from a parent for example, roulette wheel, Boltzmen, tournament, rank, and steady state. After choosing a parent, a child will be produced using a simplest way, called crossover, by randomly choosing everything before chosen point from a father and then everything after a crossover point copied from a mother. After the crossover is performed, mutation process randomly changes child in order to prevent falling all solutions in population into a local optimum of solved problem.

The genetic algorithm is performed by iterative loop basis until the final result meets predefined criteria on the number of generations and fitness function. The number of generation is defined in order to constrain the genetic algorithm optimizer to repeat reproduction loops. The fitness function is defined to check the matching between model output from several configurations and observed data.

2.7 CONCLUSION REMARKS

According to the review of general background and the state of practice of travel time estimation, travel time saving is the first priority concerned in transport and logistics. For travel time information in travelers' points of view, it can help travelers to achieve the traffic situation in advance and to save travel time based on shortest route guidance system during pre-trip and en-route. Several approaches for estimating traffic sate and travel time information have been proposed and tested with different algorithms and frameworks so that the resulting travel time is obtained with accuracy and reliability. In general, the provision of travel times has called a positive response from the public in almost all places where the information has been provided. Most states in the United States have been providing travel times and maintain them with high quality standards of data by periodic checks on accuracy. The accuracy of travel time information is the most important that should highly concerned.

Traffic state and travel time estimation have usually been constrained by traffic data sources. Most of studies estimated traffic state and travel time based on only data from one traffic surveillance system, which typical detector is point detection system. Normally, existing installation of detectors on road sections is unable to provide sufficient data to represent actual traffic situation. Even a well equipped area still encounters difficulties in providing enough traffic data in both quality and quantity aspects. Other studies attempted to estimate traffic state and travel time information using mobile detection system such as GPS probes. Unfortunately, GPS probes provide poor traffic data especially in urban areas due to the potential for high obstruction of GPS signals and the amount of probe vehicle data. Moreover, getting sufficient (minimum) requirement of probe vehicle data in a particular estimation time step is quite difficult in practice.

Currently, microscopic traffic simulation modeling has been improved and validated in various projects. This provides the opportunity to adopt simulation model as a real-time traffic state and travel time estimator. However, calibration process is the important process when microscopic traffic simulation model is adopted. Conventional model parameter calibration has consumed much time and is inflexibly operated when applying the simulation with real-time estimation framework. Genetic algorithm could be adopted to develop model parameters calibration module instead of conventional methods. It should be flexible for multiple model parameters consideration which several sets of model parameters combination can be generated and evaluated.

Unless using microscopic traffic simulation model only, feedback estimation could be improved the accuracy of traffic state and travel time. Furthermore, short-term and long term prediction would be developed to solve time lag of estimation due to the time spent on data collection and processing procedure. As mentioned above, there are only few studies on the development of traffic state and travel time estimation using microscopic traffic simulation model as an estimator and enhance traffic state and travel time's accuracy by feedback estimation using Unscented Kalman Filter. Moreover, short-term prediction is also required to inform traveler in advance which the concept of statistical model should be concerned in case of real-time travel time data is unavailable. It is necessary to study and develop the estimation and prediction framework for ATIS.

CHAPTER III

RESEARCH METHODOLOGY

In this chapter, methods for developing real-time traffic state and travel time estimation using microsimulation with feedback estimation are presented. The study framework consisted of three main components which included the development of real-time traffic state and travel time estimation, the development of feedback estimation with microsimulation, and the development of traffic state and travel time prediction. The organization of this chapter starts with an overview of study framework. Secondly, real-time microscopic traffic simulation for traffic state estimation toward travel time estimation is described. It contains details mainly on the development of microsimulation using microscopic traffic model and model parameters calibration. Thirdly, the development of feedback estimation with microsimulation using Unscented Kalman Filter is described in order to improve accuracy of travel time information. Finally, the development of traffic state and travel time prediction is presented.

3.1 OVERVIEW OF STUDY FRAMEWORK

A framework of the study was specified in order to develop comprehensive real-time traffic state and travel time estimation toward travel time prediction. An overview of this study framework was illustrated in Figure 3-1.

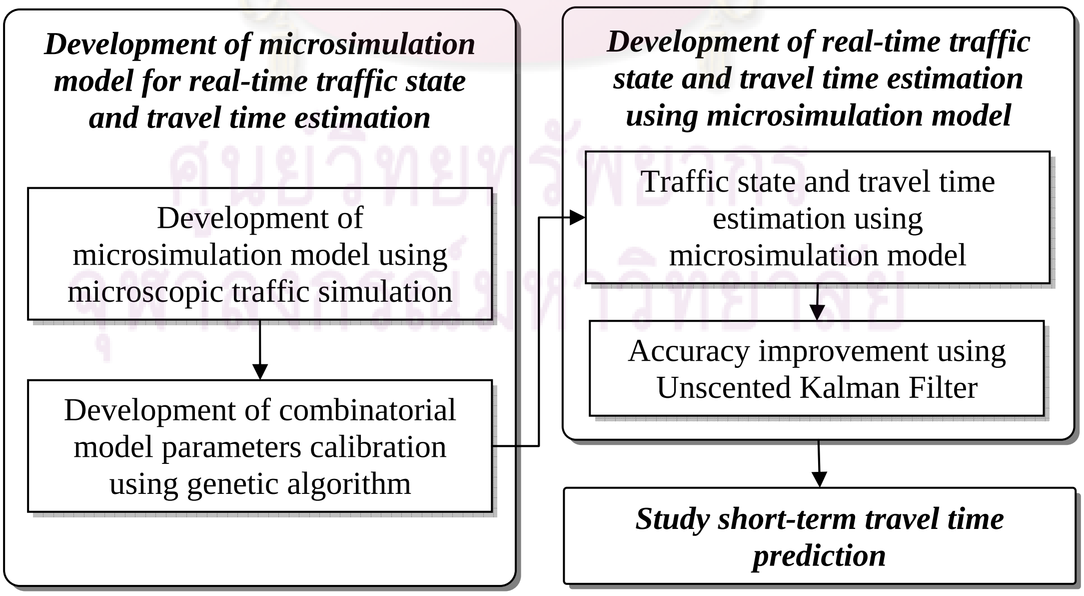


Figure 3-1 Study Framework

From Figure 3-1, the framework consists of three main components. First, the development of real time traffic state and travel time estimation which is subdivided into three processes. They are 1) the development of microsimulation using microscopic traffic simulation model, 2) the development of combinatorial model parameters calibration using GA, and 3) the development of traffic state and travel time estimation using microsimulation. For the first subsection, the process of microsimulation modeling was presented. The second subsection, in the process of microsimulation modeling, the procedure of several model parameters calibration was described that was aimed to get output data from simulation model close to the actual traffic data. Genetic algorithm was conducted in this step for calibrating combinatorial model parameters instead of conventional calibration methods. Third subsection, calibrated microsimulation model was further processed in order to estimate traffic state and travel time information.

Second, the development of feedback estimation with microsimulation was carried out by introducing a filtering techniques namely Unscented Kalman Filter. It was introduced in order to improve the accuracy of traffic state and travel time information which prior estimated by microsimulation model.

Third, the development of traffic state and travel time prediction aimed to increase the capability of ATIS in order to predict future traffic condition and also travel time information in short-term basis.

The above three main components are successively described in the following sections.

3.2 DEVELOPMENT OF REAL-TIME TRAFFIC STATE AND TRAVEL TIME ESTIMATION

Microscopic traffic simulation model was used as a traffic state and travel time estimator instead of using macroscopic traffic estimators which were mostly proposed in previous studies. In order to develop microsimulation model, commercial simulation software package was selected in this study for developing traffic state and travel time estimator which focus on expressway section. Firstly, development of microsimulation model was explained. Secondly, development of combinatorial model parameters calibration using genetic algorithm was described. Finally, development of traffic state and travel time estimation using on-line microsimulation model was described.

3.2.1 Development of Microsimulation Model

A commercial package of microscopic traffic simulation model was selected in this study, namely PARAMICS, in order to model an artificial expressway corridor. Several aerial photos which covered the whole section of site study needed to be captured and then imported and scaled in the program. In the concept of traffic simulation, artificial expressway sections on the study site are denoted as nodes and links which are digitized according to road section on aerial photos which nodes and links are layout as same as actual geometry relied on scaled aerial photos. The process of microscopic traffic simulation modeling is illustrated as shown in Figure 3-2.

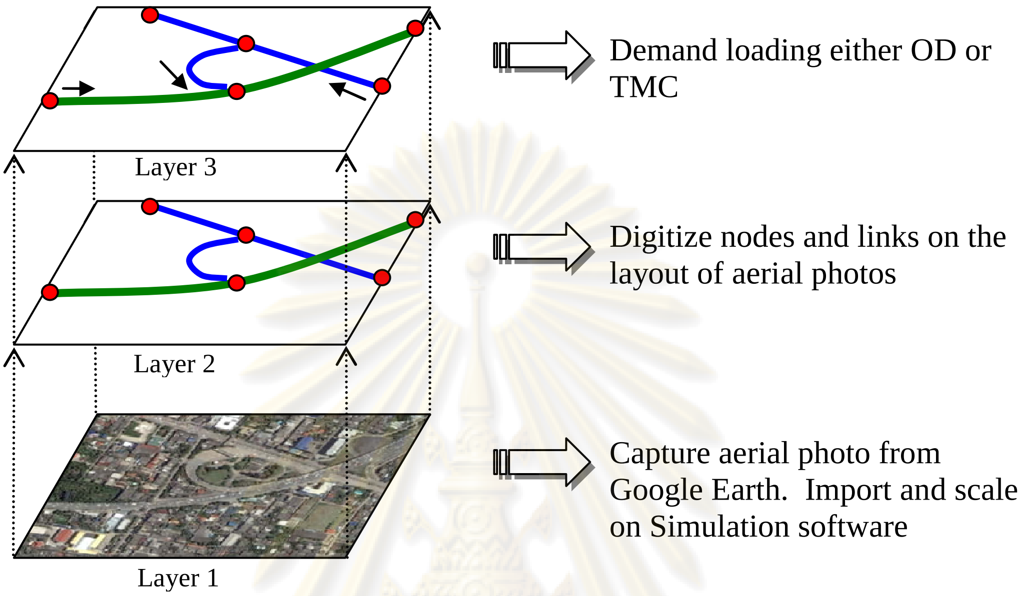


Figure 3-2 Development of Microsimulation Model

Figure 3-2 illustrates the main three layers on the process of microscopic traffic simulation modeling. As described above, the first layer shows the aerial photo that import and scale. The second layer shows a road network which build by a concept of node and link. It is digitized based on the geometry of roadway on aerial photos. The third layer shows a travel demand on road network which is normally represented by either OD flow or traffic movement count data. However, microsimulation model needs to be calibrated before implementation which the process of model parameters calibration is described in next part.

3.2.2 Development of Combinatorial Model Parameters Calibration using Genetic Algorithm

In this study, the calibration of combinatorial model parameters was concerned because of several model parameters jointly affected a simulation result. The practical procedure such as trial and error is widely used but this study conducted a genetic algorithm in the calibration procedure which is illustrated the procedure as shown in Figure 3-3. The on-line model calibration was concerned in this study which genetic algorithm can be operated. However, only off-line calibration was analyzed in this part but the consideration of using predefined control definition was relied on the performance when on-line calibration could be implemented. The optimal result could received with in limited of calculation time.

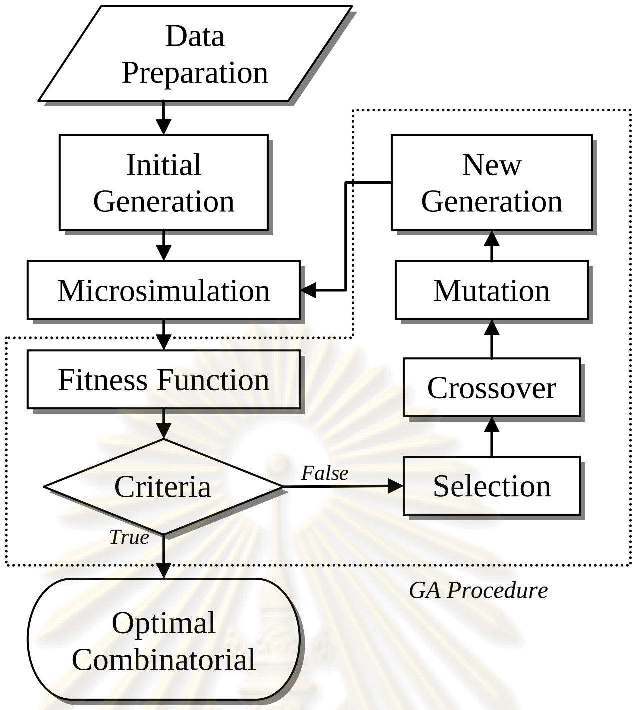


Figure 3-3 Calibration Process using GA

From Figure 3-3, calibration process using GA begins with data preparation and then subsequent initial generation of first set of combinatorial model parameters. After that the process of GA is operated. Finally, the optimal combinatorial model parameters under predefined criteria are received. The calibration processes using Genetic Algorithm is described in detail as follows.

3.2.2.1 Data Preparation

Basic input data include network geometry, OD demand, and traffic control system. These input data are necessary to develop realistic simulation model. Normally, available travel demand can be observed by field observation such as roadside survey and vehicle license plate matching, or reference OD matrix from transport demand model (as a starting point of time-dependent traffic demand), although these data are not practical for time-dependent traffic consideration. However, based on lack of those described data, the OD demand used in this study was estimated from point traffic data by distributing downstream volume to upstream volume. This method is originally from FREQ model which is based on the intuitive proportional scheme as shown in Equation (3-1).

$$OD_{ij} = D_j \cdot \frac{O_i}{\sum_{i \in A} O_i} \qquad (3\text{-}1)$$

where OD_{ij} is the OD demand from zone i to j. D_j is total amount of volume at destination zone j. O_i is total amount of volume at origin zone i. The demand profile needs to be defined to release traffic demand as time-dependent function. The OD demand profile is aggregated to time intervals of five minutes.

3.2.2.2 Fitness Function

The fitness function used in this study was a combination of traffic volume and speed between observed data as shown in Equation (3-2) and simulation outputs which were the traffic volume and speed measured on the location of traffic detector station. The optimization process aimed to minimize the value of fitness function within predefined control definitions. Fitness function value of zero was an ideally expected.

$$F = \sum_{\text{detector}} \sum_{\text{interval}} \sum_{\text{run}} \frac{|vol_{obs} - vol_{sim}|}{vol_{obs}} + \frac{|speed_{obs} - speed_{sim}|}{speed_{obs}} \qquad (3\text{-}2)$$

where vol_{obs} and vol_{sim} are traffic volumes from field observation and simulation output respectively. $speed_{obs}$ and $speed_{sim}$ are traffic speeds from field observation and simulation output respectively.

3.2.2.3 Control Definitions

During genetic algorithm procedure, population size for each generation, number of generations for simulation, representative coding, selection method, crossover rate, and mutation rate, were implemented in this study. Definitions and recommended values for these parameters as shown in Table 3-1 were specified or recommended by previous studies which the control definitions could further conducted for on-line model calibration (Lee and Yang, 2001, Ma and Abdulhai, 2002). Due to this control definition, 400 times totally of simulation run were processed in this study.

Table 3-1 Control Definitions

Control	Definition
Population size	20
No. of generations	20
Representative coding	Binary with 5 bits for each parameter
Selection method	Roulette wheel with elitism
Crossover rate	0.80
Mutation rate	0.01

3.2.2.4 Parameters Selection

Each microscopic traffic simulation suite has its own set of parameters that affect on simulating of vehicle movements. It is a responsibility of a modeler in order to verify their traffic simulation model. A final simulation needs to be well calibrated and reflects traffic characteristics similar to the actual traffic as observed. Generally, driver behaviors and route choice models are important elements affecting core module of microscopic traffic modeling and are advisably adjusted for getting simulation output corresponding with field observation data. Driver behavior models have two core modules, car following and lane changing models. The model parameters can be divided by type of traffic network namely freeway facilities and signalized intersections (surface streets). For freeway facilities, four key model parameters are introduced:

- Mean following headway
- Driver reaction time
- Critical gap for lane changing
- Minimum separation under stop-and-go conditions

For signalized intersections, three key model parameters are introduced:

- Startup lost time
- Queue discharge headway
- Gap acceptance for unprotected left turns

Those model parameters may have different names in different microscopic traffic simulation suites and normally mean headway is a good global model parameter for calibration process. Route choice models have two model parameters that are perturbation and familiarity (Dowling et al., 2004).

In this study, PARAMICS microscopic traffic simulation suite was selected as it allows users to adjust these two core models; car following and lane changing models. Car following model determines the acceleration and deceleration. Lane changing model determines suitable gap when a lane change is made. The core parameters are queue gap distance, queuing speed, heavy vehicles weight, mean target headway, mean driver reaction time, speed memory, and minimum gap. However, two important key parameters were considered in this study because these two parameters obviously affect to the simulation results in the past studies (Lee and Yang, 2001). Two key parameters and their value ranges were defined as follows:

- Mean target headway ranged from 0.6 – 2.4 seconds
- Mean driver reaction time ranged from 0.4 – 1.6 seconds

For these two parameters, the program developer initiated a default value of one second for both parameters based on the validation under United Kingdom’s traffic characteristics where program was originated. However, these model parameters need to be calibrate subject to the traffic characteristics of site study that apply microscopic traffic simulation model in implementation. However, the default values for both model parameters were also considered in order to understand the importance of the calibration on traffic characteristics in the simulation modeling.

3.2.3 Development of Traffic State and Travel Time Estimation using On-line Microsimulation Model

The concept of on-line microsimulation was proposed to be an alternate method for estimating traffic state and travel time information on road segment as shown in Figure 3-4. From the figure, the on-line microsimulation is used as an estimator instead of conventional methods or macroscopic traffic model.

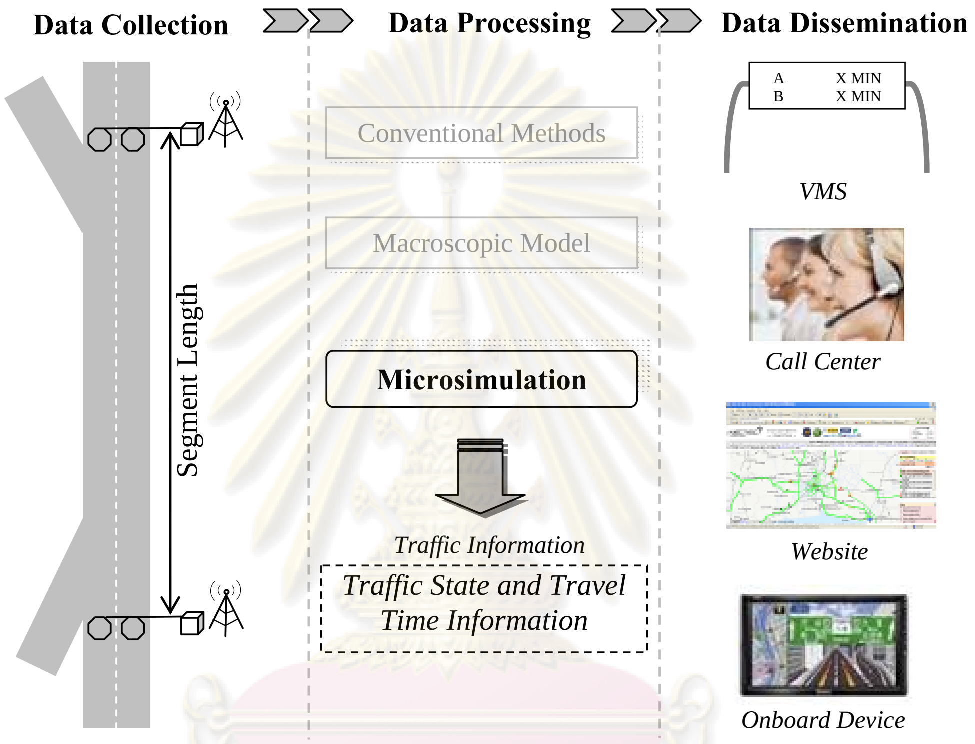


Figure 3-4 On-line Microsimulation in ATIS Framework

The components of microscopic traffic simulation model generally include physical component of road network, traffic control system, and driver-vehicle units which driver behavior models and route choice models are associated. The complex data and numerous model parameters are required by these components which need to be calibrated for a particular study area (Mcnally and Oh, 2002).

On-line microsimulation model can be used instead of conventional traffic state and travel time estimation methods as well as macroscopic traffic model for estimating travel time. Traffic data measured on point detection devices need to be transmitted to the traffic control center using communication system using cable optic or several wireless communications such as Asymmetric Digital Subscriber Line (ADSL), General Packet Radio Services (GPRS), and Worldwide Interoperability for Microwave Access (WIMAX). Traffic data are checked for outliers and correctness and then input to the on-line microsimulation model in order to estimate traffic state and travel time which occurs on each road segment. The use of microsimulation model should result in more accurate traffic state and travel time information than conventional methods in case of using on expressway with low density of point detectors or long segment length.

In order to develop on-line microsimulation model for estimating traffic state and travel time information, the process of on-line microsimulation was designed as shown in Figure 3-5.

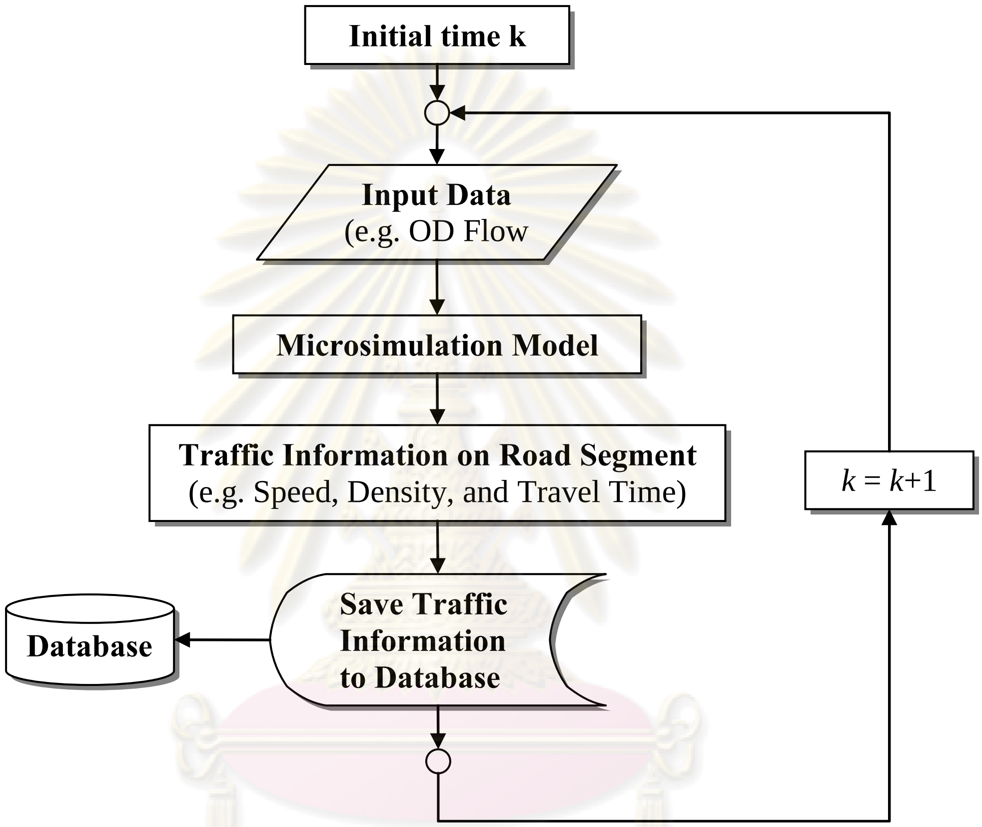


Figure 3-5 Flow chart of on-line microsimulation model

From Figure 3-5, the process starts for at k^{th} time interval, in which the corresponding OD flow demand is called as the input of the simulation model. Microsimulation model provides traffic state on segment for example speed, flow, density, stop time, and travel time information which are not directly measured from the field in real-time basis. Estimated traffic state and travel time information can be used to describe traffic state or traffic condition on each road segment. After that traffic information is saved on traffic database and then continues the input data at k+1 time interval. It is an advantage of using microsimulation for estimating travel time information in case of low density of detectors on roadway.

3.3 DEVELOPMENT OF FEEDBACK ESTIMATION FOR IMPROVING MICROSIMULATIN MODEL ACCURACY

In this study, microscopic traffic simulation was proposed to be a traffic state and travel time estimator instead of macroscopic traffic flow model which mostly proposed in previous studies. The numerical process of traffic state and travel time estimator was developed based on space-time discrete. At every time step, traffic state and travel time were estimated and further updated by feedback estimation procedure as illustrated in Figure 3-6.

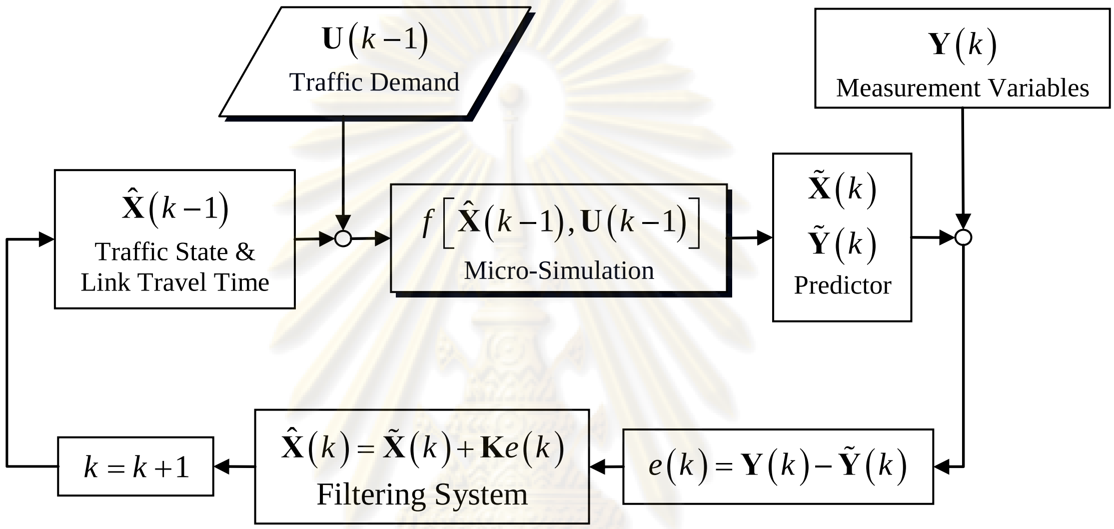


Figure 3-6 Feedback Estimation of Traffic State and Travel Time Framework

Following the flow in Figure 3 6, at every time step (i.e. 5 minutes time interval), traffic demand was estimated based on traffic volume measured by point detectors equipped on road section similar to the procedure of microsimulation model as shown in Figure 3 5. Consequently, traffic states including link flow, link density, link speed, and travel time were estimated provided by microsimulation model. Virtual traffic detector stations were developed on the same location as actual traffic detector equipped on road section. Actual traffic data on point detector was treated as measurement variables including flow and speed which was used to adjust prior estimated traffic state variables. Feedback estimation using Unscented Kalman Filter was developed in order to improve the accuracy of traffic state and travel time estimation which was estimated only by microsimulation model.

An efficient feedback estimation using Unscented Kalman Filter was defined the state variable x and measurement variables **y** as shown in Equation (3-3) and Equation (3-4) where where v_s^j and ρ_s^j are average speed and density on segment *j* (where *j* = 1,...,*N*) and w_s^i and q_s^i are speed and flow measured on virtual traffic detector *i* (where *i* = 1,...,*N*). State variable and measurement variable were estimated by only microsimulation model. The detail of Unscented Kalman Filter was described in Chapter 2.

$$\mathbf{x} = \left[v_s^j, \rho_s^j, \ldots, v_s^N, \rho_s^N \right] \tag{3-3}$$

$$\mathbf{y} = \left[w_s^i, q_s^i, \ldots, w_s^N, q_s^N \right] \tag{3-4}$$

3.4 STUDY ON SHORT-TERM TRAVEL TIME PREDICTION

One of the important components supporting ATIS and ATMS is a prediction which can help traffic operator in order to make decision in advance for managing the traffic with appropriate plan based on the future trend. The proper strategy for traffic management can be provided, for example informs the message to the traveler for rerouting on the in-vehicle route guidance or inform the traffic congested location on DMS.

Simple and easy to implement in practice was considered. Moreover, only estimated travel time in past time steps are available which receives from the microsimulation and microsimulation with UKF as shown in Figure 3-7.

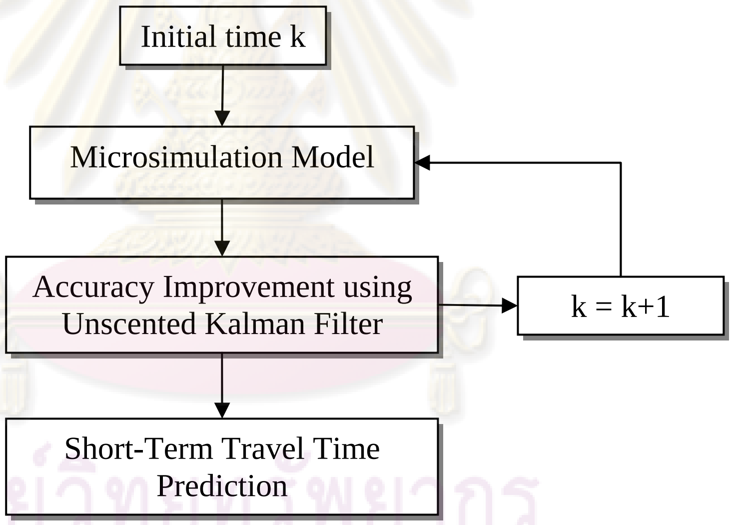


Figure 3-7 Flow Chart of Short-Term Travel Time Prediction as Connected with Microsimulation and Microsimulation+UKF

Two statistic methods for short-term prediction were studies which included simple moving average and exponential moving average. It is not complicated to apply with the proposed framework for short-term travel time prediction. Two methods were described as follow.

- **Simple Moving Average (SMA)**

The simple moving average is commonly used in finance applications with time series data to smooth out short-term fluctuation and show data trend (Harvey, 1990).

Simple moving average is a mean of previous N data points. The simple moving average was shown in Equation (3-5).

$$SMA_t(N) = \frac{\left(T_t^* + T_{t-1}^* + \ldots + T_{t-N+1}^*\right)}{N} \qquad (3\text{-}5)$$

The value of N affects the estimation quality of the time series which the largest value of N will provide good estimation when mean of time series are constant. In the other hand, the smallest value of N will provide good estimation when mean of time series data are fluctuated change. The prediction for any number of periods in the future is the same as the latest estimate under the assumption of constant underlying mean. The prediction equation was shown in Equation (3-6).

$$\hat{T}_{T+\tau} = SMA_t \quad \text{for } \tau = 1, 2, \ldots \qquad (3\text{-}6)$$

The variability of the noise has the largest effect for smaller of N value. The conflicting desires to increase N value to reduce the effect of variability due to the noise and to decrease N value to take the prediction more responsive to change in mean of time series data. However, the intermediate value of N is required in practical prediction.

- **Exponential Moving Average (EMA)**

The exponential moving average is also known as an exponentially weighted moving average which is a type of infinite impulse response filter. It applies weighting factors to exponentially decrease. The weighting for each older data point decreases exponentially, never reaching zero (Harvey, 1990). The exponential moving average is adopted in this study to predict short-term travel time as shown in Equation (3-7).

$$EMA_t = \alpha T_{t-1}^* + \left(1-\alpha\right) EMA_{t-1} \qquad (3\text{-}7)$$

where α is weighting factor, $0 < \alpha \leq 1$. T_{t-1}^* is the estimated travel time at time *t-1*. For any number of periods prediction in the future, the future value of travel time is the same as the latest estimate travel time in previous time step as shown in Equation (3-8).

$$\hat{T}_{T+\tau} = EMA_t \quad \text{for } \tau = 1, 2, \ldots \qquad (3\text{-}8)$$

The variance of the estimation error increases when the value of α increases. In order to minimize the effect of noise, it would like to make α as small as possible but this makes the prediction unresponsive to a change in the underlying of time series data. In order to make the prediction responsive to changes, the value of α as large as possible is required. However, the intermediate value of α is required in practical prediction.

In this study, four scenarios were designed to understand the benefit of Unscented Kalman Filter and the performance of travel time prediction separately by each segment. The four scenarios were defined as follows.

- Scenario 1: Travel time prediction using the route travel time which estimated by microsimulation.
- Scenario 2: Travel time prediction using the route travel time which estimated by micosimulation with UKF improvement.
- Scenario 3: Sum of the travel time prediction of estimated travel time using microsimulation by each segment
- Scenario 4: Sum of the travel time prediction of estimated travel time using microsimulation with UKF improvement by each segment.

3.5 MODEL EVALUATION

In order to evaluate estimated traffic state and travel time information, estimated and observed were plotted as diagonal plot link by link in order to investigate the under or over estimation of each method. Consequently, absolute percentage error (APE) and mean absolute percentage error (MAPE) were determined in this study to measure how large of estimation error by comparing observed and estimated traffic state and travel time information. Moreover, percentage error and mean square error were determined to understand positive and negative percentage error by period of time and amount of error. There were presented as shown in Equation (3-9), Equation (3-10), Equation (3-11), and Equation (3-12).

$$APE = \left| \frac{x_{obs}(k) - x_{est}(k)}{x_{obs}(k)} \right| \times 100 \tag{3-9}$$

$$MAPE = \frac{1}{n} \sum_{k=1}^{n} \left| \frac{x_{obs}(k) - x_{est}(k)}{x_{obs}(k)} \right| \times 100 \tag{3-10}$$

$$\%Error(k) = \frac{x_{est}(k) - x_{obs}(k)}{x_{obs}(k)} \times 100 \tag{3-11}$$

$$MSE = \frac{1}{n} \sum_{k=1}^{n} \left(x_{est}(k) - x_{obs}(k) \right)^2 \tag{3-12}$$

where $x_{obs}(k)$ and $x_{est}(k)$ is observed and estimated traffic state respectively (e.g. speed and travel time) at time *k*. MAPE of speed and travel time estimation are separately calculated.

CHAPTER IV

TRAFFIC DATA

In this chapter, the field data and study area in which two selected expressway sections of Hanshin Expressway and Bangkok Expressway are located in Japan and Thailand respectively are described. Moreover, the result of model parameters calibration is reported which it is further conducted in the development of microsimulation model for traffic state and travel time estimation.

4.1 FIELD DATA AND STUDY AREA

In order to develop microsimulation for estimating traffic state and travel time and also predicting travel time for expressway traffic, the actual site study was conducted which the factor of physical alignment and detector location were ignored. The site selection was considered the expressway corridor composed by main line, on-ramp, and off-ramp. There were two selected expressway sections conducted in this study which used in difference study.

The first site study was Matsubara line on Hanshin Expressway in Osaka, Japan. This site study was initiated to use in the study of model parameters calibration using genetic algorithm and further investigated the accuracy of link speed estimation using conventional methods in order to understand the performance of link speed estimation which affect the accuracy of travel time estimation.

The second site study was Chalerm Mahanakhon line on Bangkok Expressway in Bangkok, Thailand. This site study was conducted to use in the study of on-line microsimulation for traffic state and travel time estimation and also travel time prediction. The proposed method was evaluated against the observed travel time which conducted in this site study. In this site study, the performance of proposed on-line microsimualtion model was analyzed.

The two selected site studies were described in details as follows.

4.1.1 Hanshin Expressway Site

A 11.22 km. road section of the Matsubara line of the Hanshin expressway in Osaka, Japan in an outbound direction between Nanba and Matsubara junction was selected as the first study area that traffic data were collected 24 hours using overhead ultrasonic detectors on November 1, 1994. This data was used to calibrate traffic simulation model. Figure 4-1 and Figure 4-2 illustrate the location of study area and schematic diagram of study section on Hanshin expressway.

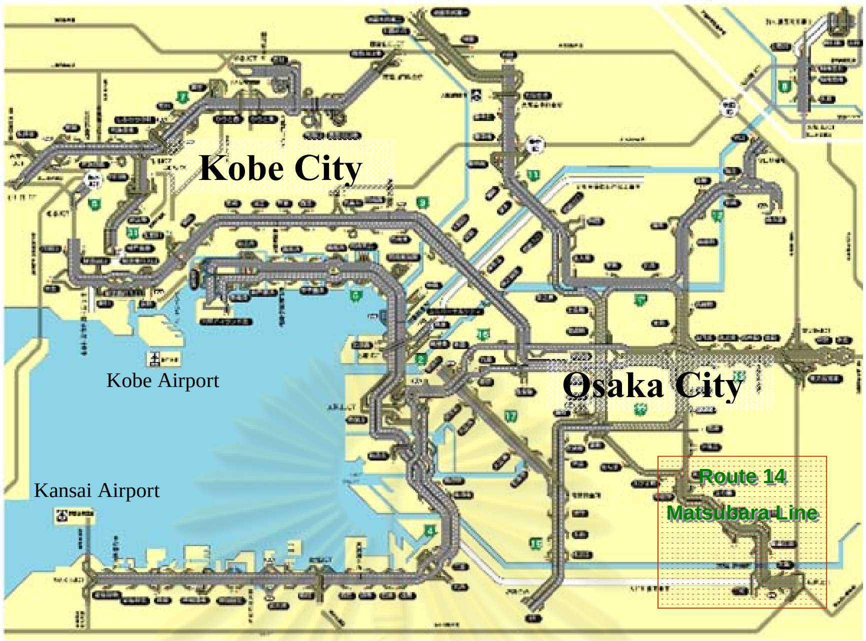


Figure 4-1 Location of Matsubara Line of Hanshin Expressway Network

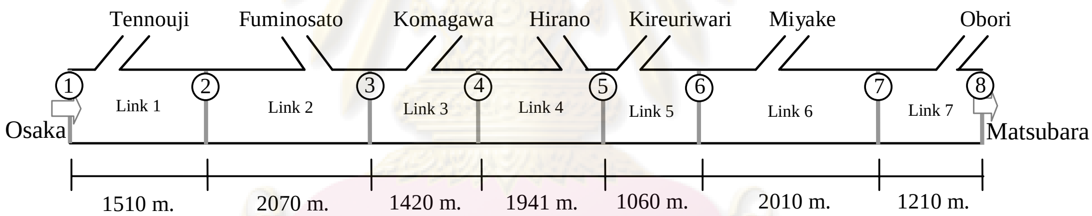


Figure 4-2 Schematic Diagram of Matsubara Line

From Figure 4-2, the selected expressway section was divided into seven links which have equipped with eight traffic detector stations. The distances of the links range between 1210 and 2070 meters. There were two lanes for the whole length of the study section with two on-ramps, and five off-ramps. Overhead ultrasonic detectors have been installed to measure traffic data on this expressway section as shown in Figure 4-3. Traffic data, volume, time mean speed, and occupancy, were collected by the detectors at 5-minute aggregation. For this Japan expressway study, these data were used to evaluate the performance of link speed estimation based on point traffic speed on the border of link and the difference of link speed estimation using conventional methods and microsimulation model was discussed.

Figure 4-3 Ultrasonic Detector on Hanshin Expressway, Osaka, Japan

4.1.2 Bangkok Expressway Site

About 11-km expressway section of the Chalerm Mahanakhon line on Bangkok Expressway Network in Bangkok, Thailand directional from Daokanong to Port junction as shown in Figure 4-4 is selected to be second study area in this study and schematic diagram of this site is shown in Figure 4-5.

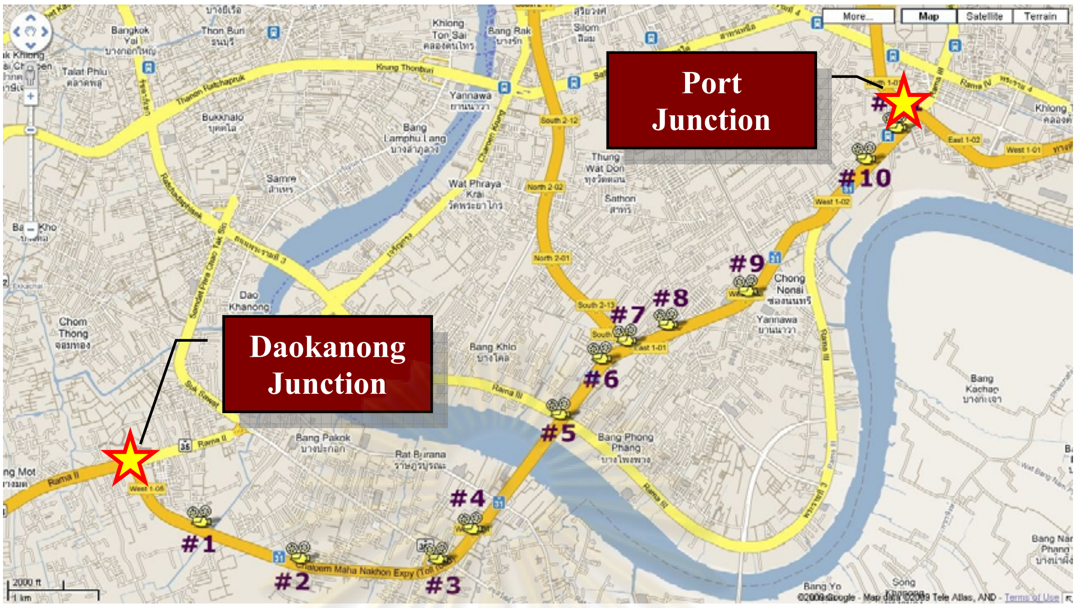


Figure 4-4 Daokanong – Port Junction on Bangkok Expressway Network

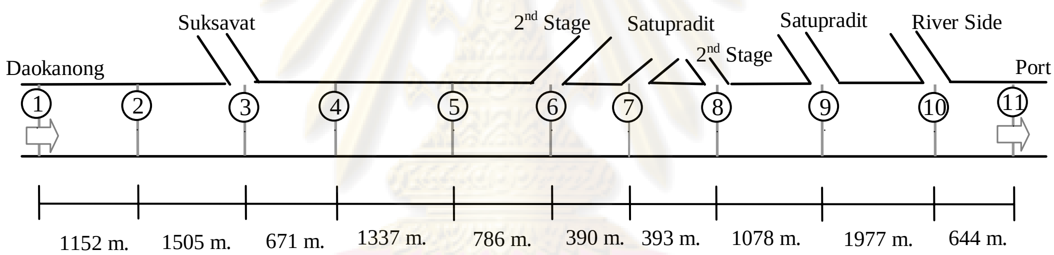


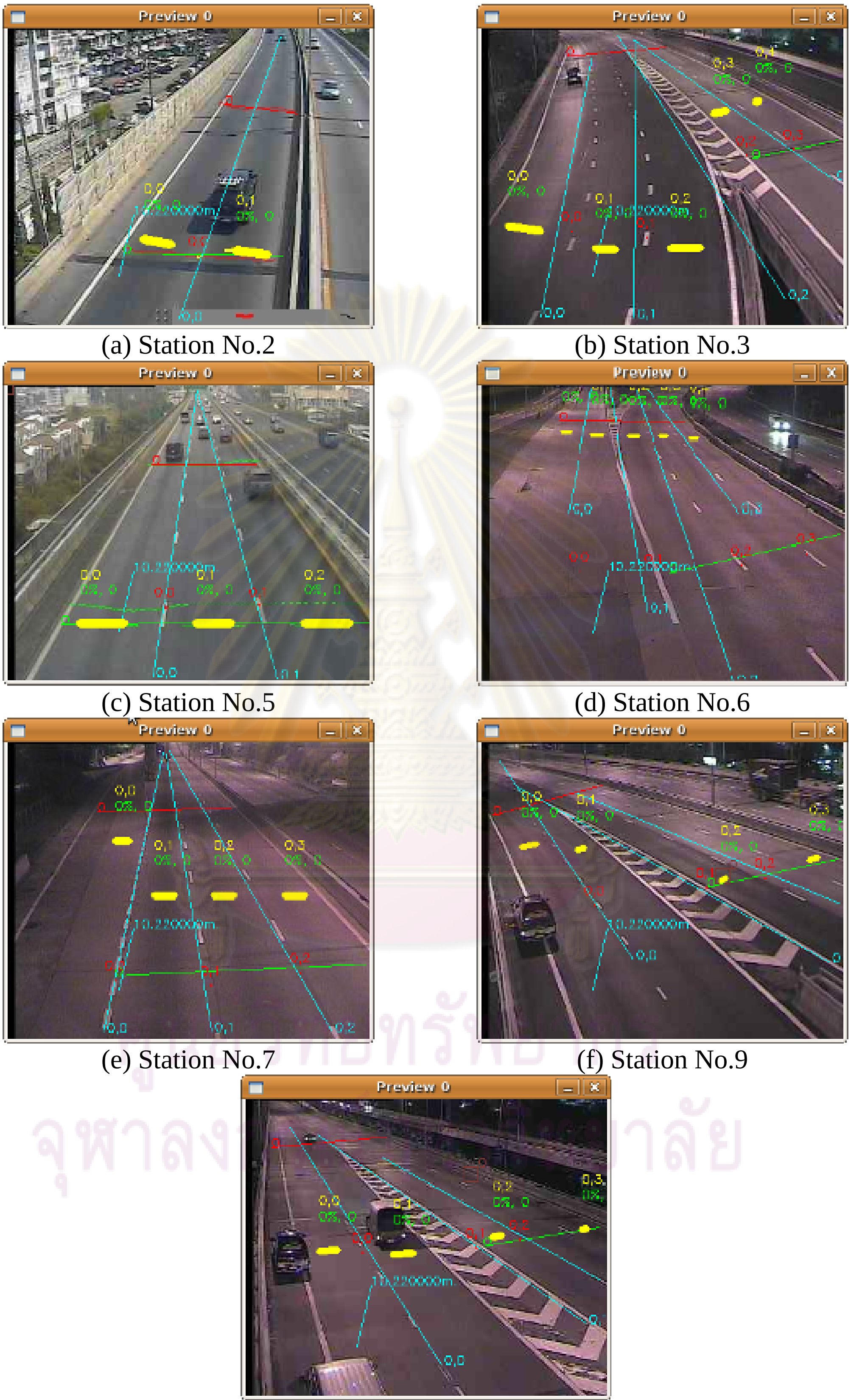
Figure 4-5 Schematic Diagram of Chalerm Mahanakhon Line

For the numerical analysis, the road section was divided into ten segments ranging from 390 meters to 1977 meters with four on-ramps and two off-ramps. The number of lanes varies from two to three lanes in some sections.

Based on the data collection plan, eleven stations of video image processing camera were planned and installed as shown in Figure 4 5. However, equipment at few data collection stations were broken, seven stations which were station no. 2, 3, 5, 6, 7, 9, and 10 were completed and the traffic data on June 9, 2010 from these stations were used in the study. Available detector stations measured traffic data on the predefined area which have field of view as shown in Figure 4 6. At the same time, digital video recorders were installed and recorded video from video image cameras on station no.2 and 10. The video data were further post processed in laboratory using vehicle matching manually in order to measure travel time data. The manual travel time (ground truth) data were used as a benchmark for accuracy evaluation which the sample size of observed travel time was followed the suggestion of travel time data collection manual (1998) which suggest the average coefficient of variation of 25% for congested traffic (15 – 30 minute per period). It was calculated the sample size according to Equation (4-1).

$$Sample\ size = \left(\frac{z \times c.v.}{e}\right)^2 \tag{4-1}$$

where *z* is z-statistic which the value of 1.96 (95% confidence) was used. c.v. is the average coefficient of variation which the suggested value of 25% was used (congested traffic, 15 – 30 minute time period). *e* is the relative error of 5%. From the calculation based on Equation (4-1), the calculated sample size that required for observing travel time was 96 vehicles in one hour, then 8 vehicles were observed for travel time per time interval of 5 minute. The observed vehicles from 06:00 until 21:00 of 1440 vehicles were totally observed in this study. Collected field traffic data were used to develop real-time traffic state and travel time estimation using microsimulation model.



(a) Station No.2
(b) Station No.3
(c) Station No.5
(d) Station No.6
(e) Station No.7
(f) Station No.9
(g) Station No.10

Figure 4-6 Field of View of Seven Point Detectors using Video Image Processing Camera

4.2 CALIBRATION RESULT OF SIMULATION MODEL

4.2.1 Calibration Result of Hanshin Expressway Site

In order to calibrate microsimulation model of Hanshin Expressway site on Matsubara line, traffic data from 08:00 until 10:00 were obtained to determine the proper model parameters. Based on Genetic Algorithm (GA) process, a total of 1200 (20 population, 3 replicated runs, and 20 generations) simulation runs were carried out. Each simulation run took approximately one minute to replicate 4 hours of traffic operation in the site study using a personal computer with CPU of 1.6 GHz. After complete 20 GA generations, genetic algorithm process showed the performance toward fitness function minimization by searching the optimal combinatorial model parameters within desired constraints as shown in Figure 4 7.

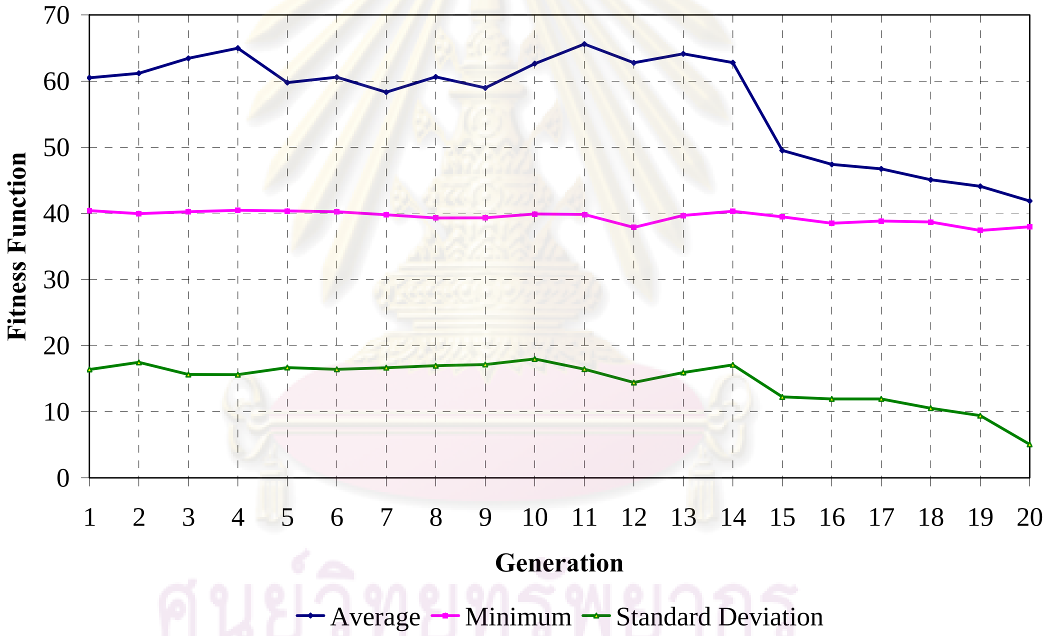


Figure 4-7 The Value of Fitness Function of Hanshin Expressway Site.

Figure 4-7 illustrates the plot of average, minimum, and standard deviation of fitness function for each generation. The figure shows that average value of fitness function decreases and is close to minimum value, with the number of generation increases. Moreover, the standard deviation value also decreases. It could be implied that the optimal combinatorial model parameters can be found for a defined generation number. The calibrated model parameters, after completion of the defined calibration criteria, yielded the values as shown in Table 4-1.

Table 4-1 Calibrated Value of Model Parameters for Hanshin Expressway Site

Model Parameters	Calibrated Value
Mean Target Headway	0.500 seconds
Mean Driver Reaction Time	1.135 seconds

Using the Expressway data in Japan, the calibrated parameters had the mean target headway of 0.500 second, which was much smaller than the default value of one second, calibrated under UK traffic condition suggested by program developer. According to the finding value, it could be implied that the drivers on Matsubara line of Hanshin expressway tend to accept smaller headway. The mean driver reaction time was 1.135 seconds, higher than default value of one second. It could be implied that drivers under UK traffic condition are more sensitive to the change of traffic condition than drivers on Matsubara line in Japan. Larger mean driver reaction time will lead to more occurrences of shock wave due to car following theory.

The effectiveness of the calibrated model parameters was verified by common comparison between variations of PARAMICS point processing data against observed traffic data on both traffic volume and speed. The mean absolute percentage errors (MAPE) were reported as shown in Figure 4-8 and Figure 4-9 as compared to MAPE of simulation output using default model parameters.

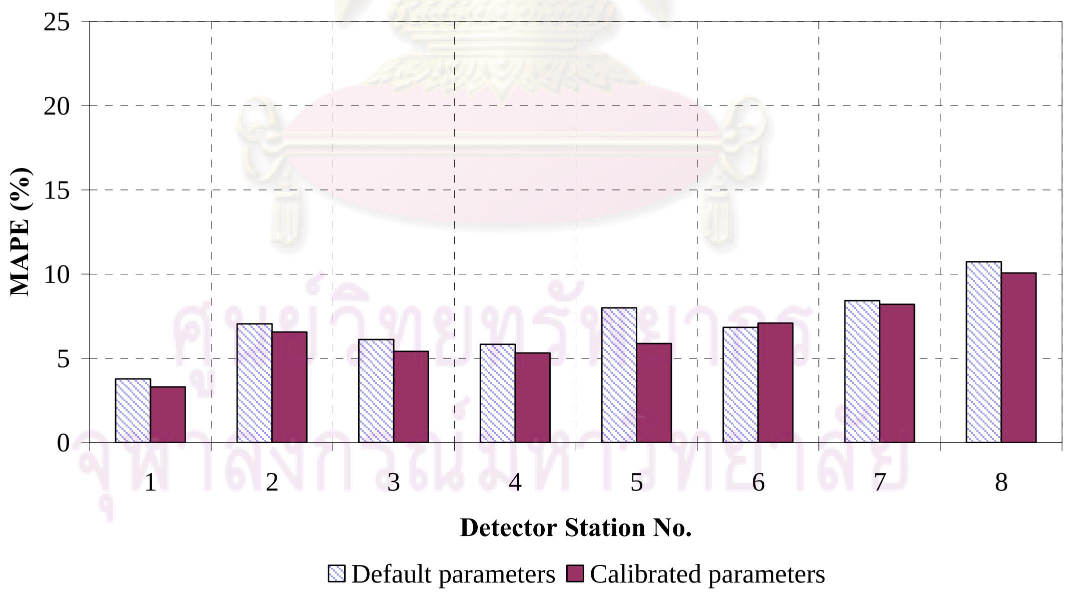


Figure 4-8 MAPE of Traffic Volume at Hanshin Expressway Site

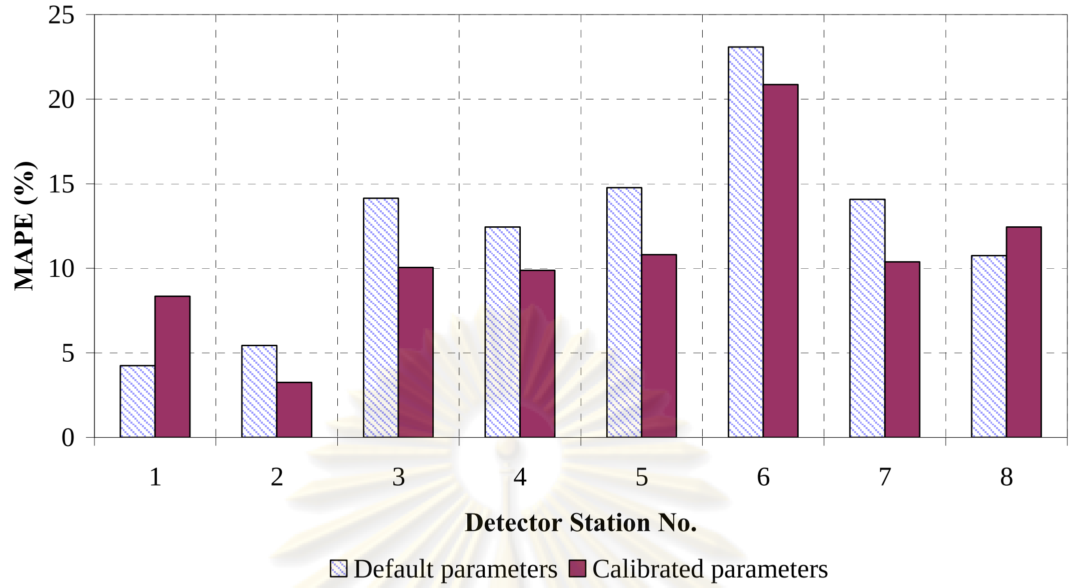


Figure 4-9 MAPE of Traffic Speed at Hanshin Expressway Site

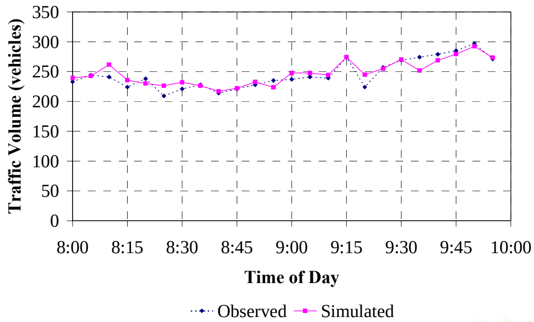
Using the calibrated parameters, it is shown that volume for 5-minute time interval at each point detector by PARAMICS microsimulation is quite close to the observed traffic volume. MAPE ranges from 3.30% to 10.08% with the average of 6.48% and the minimum and maximum MAPE are at the first and eighth detector station respectively. For traffic speed comparison, MAPE ranges from 3.25% to 20.86% with the average of 10.75% and the minimum and maximum MAPE are at the second and sixth detector station.

However, the average MAPE from microsimulation using default model parameters is higher than those using calibrated model parameters as shown in Table 4-2.

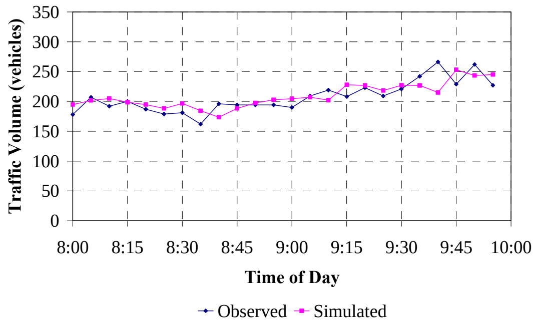
Table 4-2 Average Mean Absolute Percentage Error

Parameters	Volume	Speed
Default	7.10	12.37
Calibrated	6.48	10.75

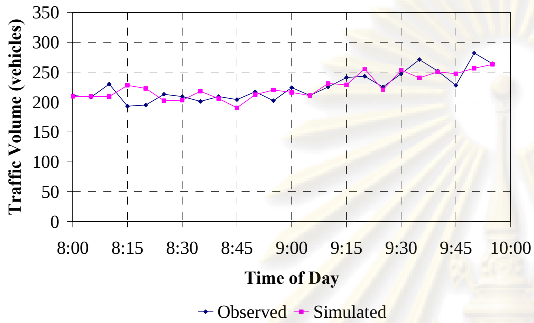
Simulation outputs using calibrated model parameters are close to observed traffic data although a bit improvement was observed, compared with simulation output using default model parameters. Although the only 20 generations of genetic algorithm process were designed in this study. However, the results have shown the level of MAPE better than the results using defaults model parameters. The MAPE could be reduced if more generations of genetic algorithm process were performed and the simulation output would be closer to observed traffic data. The comparison of traffic volume and speed between observed and simulated data are shown in Figure 4-11 and Figure 4-10.



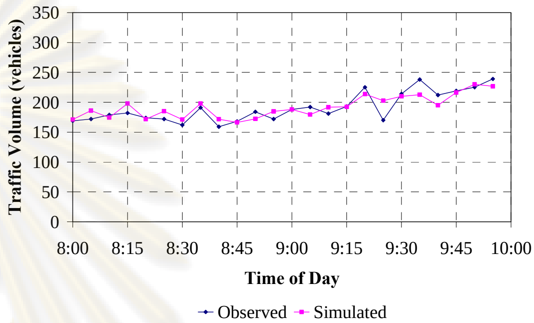
(a) Detector No.1



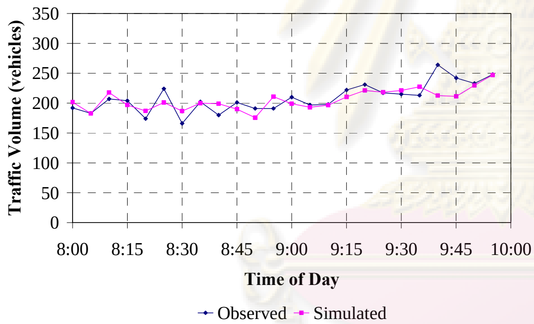
(b) Detector No.2



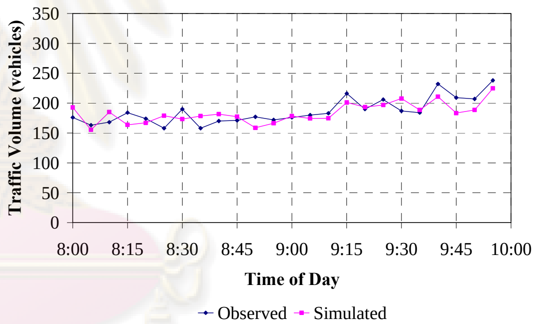
(c) Detector No.3



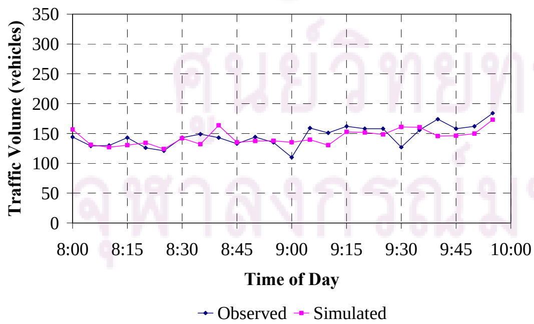
(d) Detector No.4



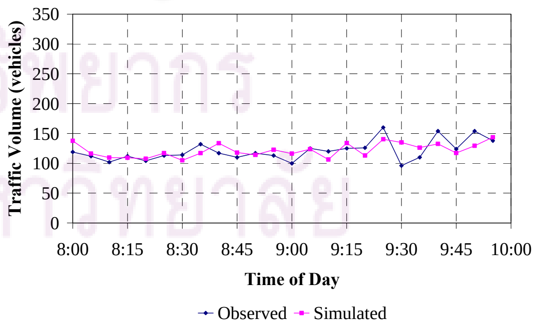
(e) Detector No.5



(f) Detector No.6

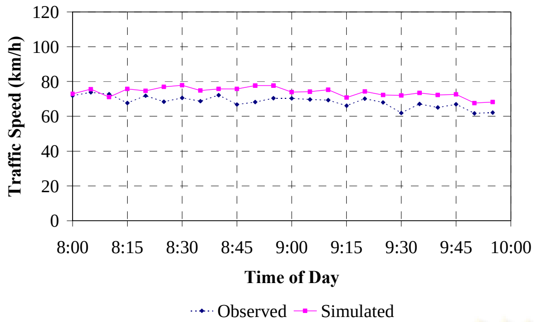


(g) Detector No.7

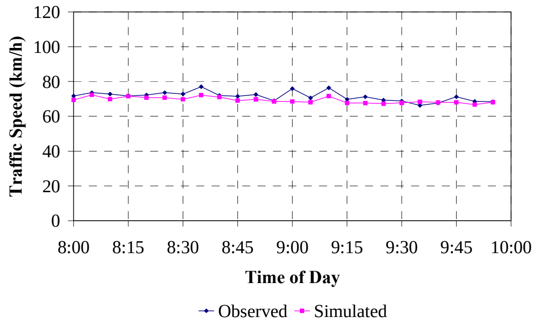


(h) Detector No.8

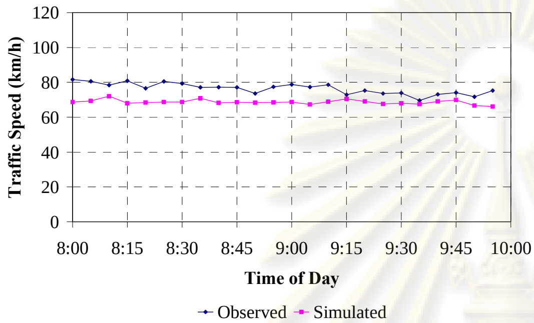
Figure 4-10 Observed and Simulated Traffic Volume on Matsubara Line at Hanshin Expressway Site



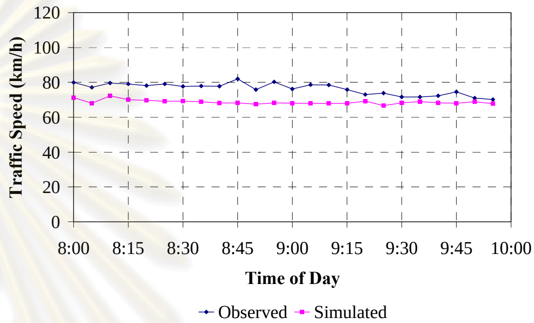
(a) Detector No.1



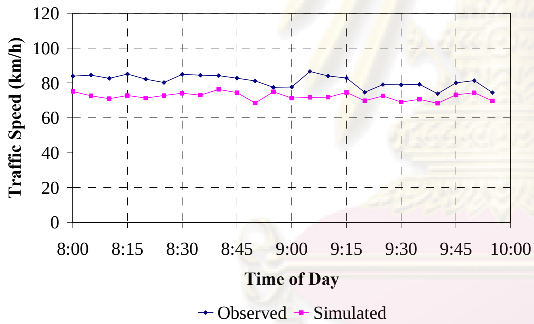
(b) Detector No.2



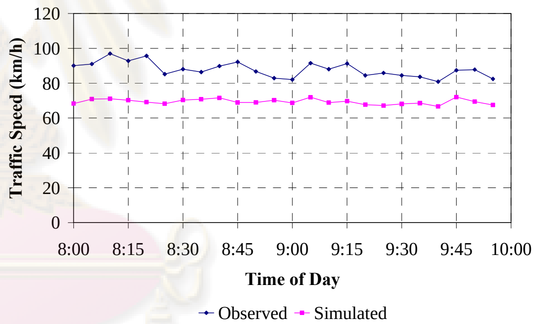
(c) Detector No.3



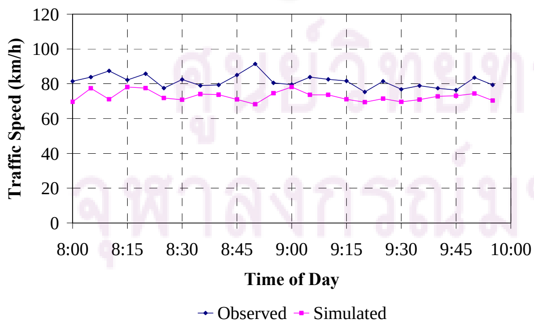
(d) Detector No.4



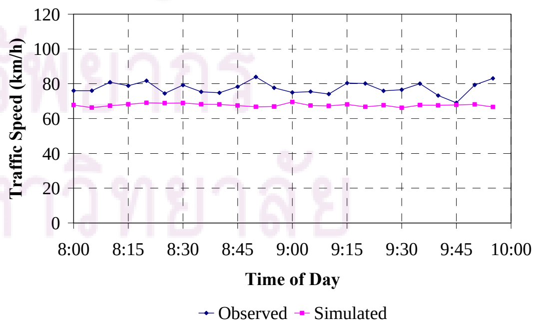
(e) Detector No.5



(f) Detector No.6



(g) Detector No.7



(h) Detector No.8

Figure 4-11 Observed and Simulated Traffic Speed on Matsubara Line at Hanshin Expressway Site

From Figure 4-11 and Figure 4-10, it shows that even the optimal model parameters were received using genetic algorithm. There are shown the difference between observed and estimated on both volume and speed which measured on point detector on the site study. However, estimated traffic volume is similar trend with observed traffic volume but estimated traffic speed is less than observed traffic speed about 10 kilometers but it is in the same trend.

4.2.2 Calibration Result of Bangkok Expressway Site

Traffic data from 06:00 until 10:00 were used in calibrating model parameters for Bangkok Expressway site. The calibration process was conducted in similar manner as the calibration of Hanshin Expressway site. From the result of model parameters calibration using GA, the value of fitness function is shown in Figure 4-12.

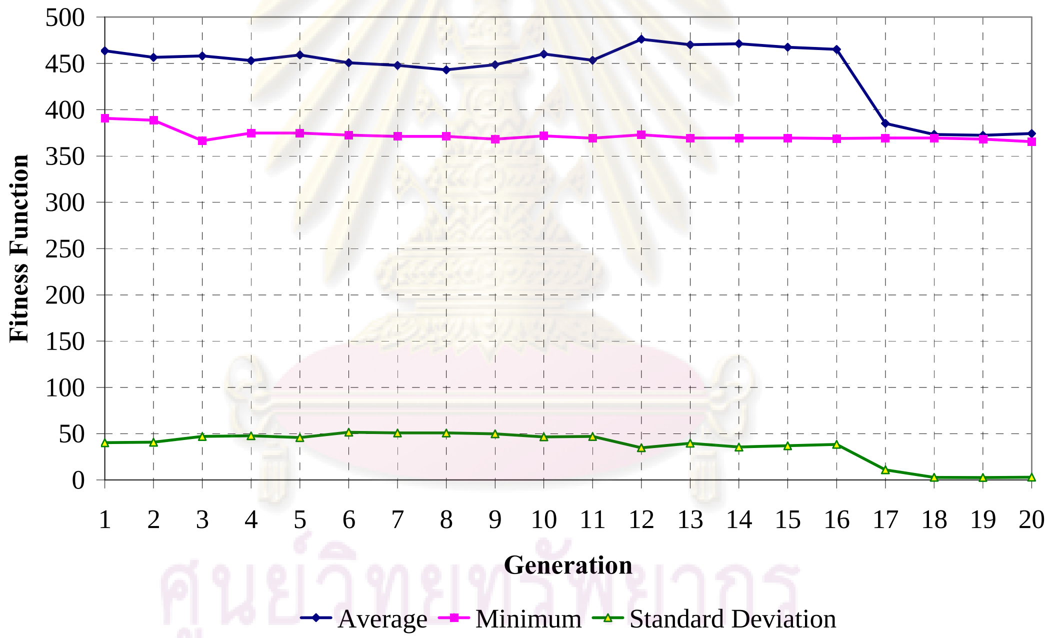


Figure 4-12 The Value of Fitness Function of Bangkok Expressway Site.

Figure 4-12 illustrates the plot of average, minimum, and standard deviation of fitness function for each generation. The figure shows that average value of fitness function decreases and is close to minimum value. Moreover, the standard deviation value also decreases in a similar manner as the value of fitness function of Hanshin Expressway site. It could be implied that a better combinatorial model parameters could be found for a defined generation number. The model parameter calibration with predefined criteria gives the model parameters as shown in Table 4-3.

Table 4-3 Calibrated Value of Model Parameters for Bangkok Expressway Site

Model Parameters	Calibrated Value
Mean Target Headway	0.550 seconds
Mean Driver Reaction Time	1.560 seconds

From Table 4-3, it is shown that the calibrated value of mean target headway and mean driver reaction time which are 0.550 second and 1.560 second respectively. Two model parameters for traffic characteristics of Bangkok Expressway site are a bit higher than the calibrated values of traffic characteristics on Hanshin Expressway site.

The impact of the calibrated model parameters was verified by common comparison between variations of PARAMICS point processing data against observed traffic data on both traffic volume and speed. The mean absolute percentage errors (MAPE) were reported as shown in Figure 4-13 and Figure 4-14.

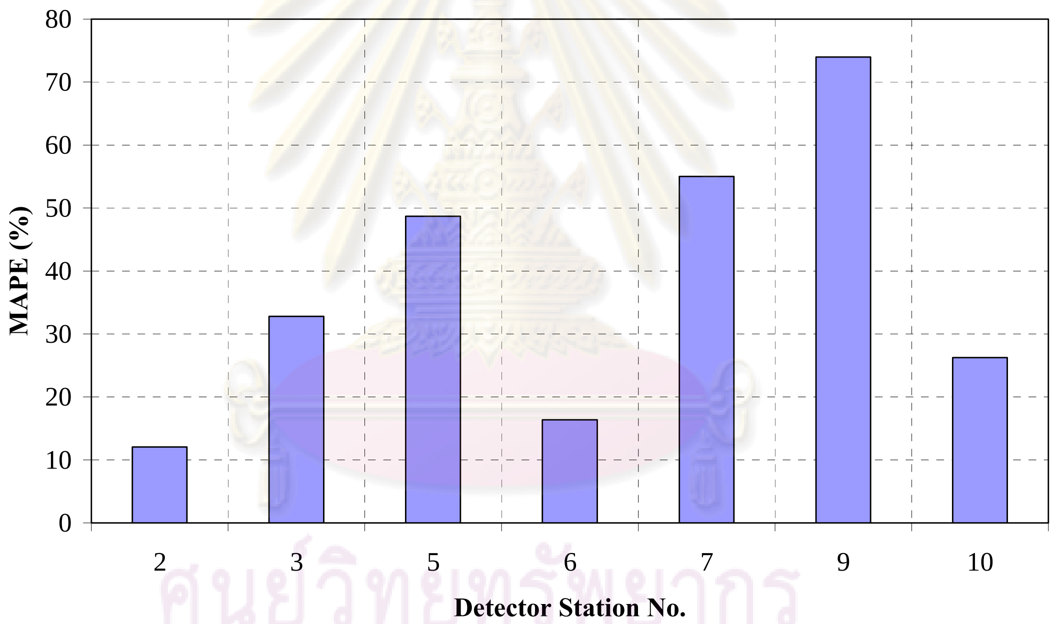


Figure 4-13 MAPE of Traffic Volume at Bangkok Expressway Site

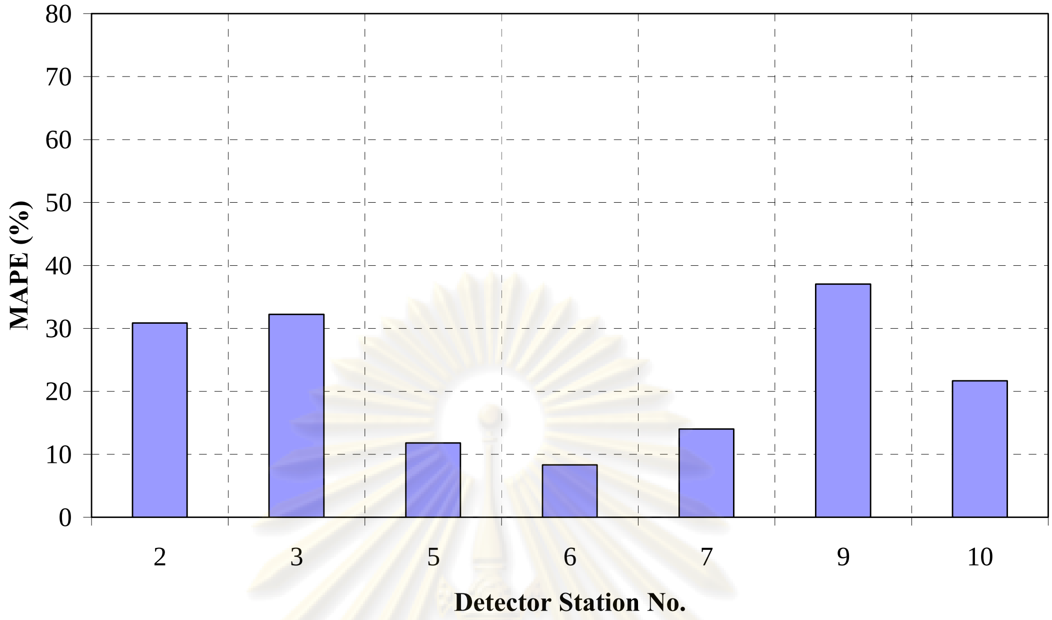


Figure 4-14 MAPE of Traffic Speed at Bangkok Expressway Site

From Figure 4-13, it is shown that MAPE of traffic volume between observed and estimated at seven traffic detector stations are ranged from 12.05 % (detector station no.2) to 73.98 % (detector station no.9) with the average MAPE value of 37.87 %. The calibrated model could emulate traffic volume at Bangkok Expressway site with an error under 20 % at traffic detector station no.2 and 6. For detector station no.3, 5, 7, 9, and10, it could emulate traffic volume with an error more than 20 %.

Figure 4-14 shows that MAPE of traffic speed at seven traffic detector stations range from 8.33 % (detector station no.) to 37.04 % (detector station no.9) with the average MAPE value of 22.28 %. The calibrated model could emulate traffic speed at Bangkok Expressway site with an error under 20 % on traffic detector station no.5, 6, and 7. For detector station no.2, 3, 9, and10, it could emulate traffic speed with an error more than 20 %.

The comparison of traffic volume and speed between observed and simulated data are shown in Figure 4-15 and Figure 4-16.

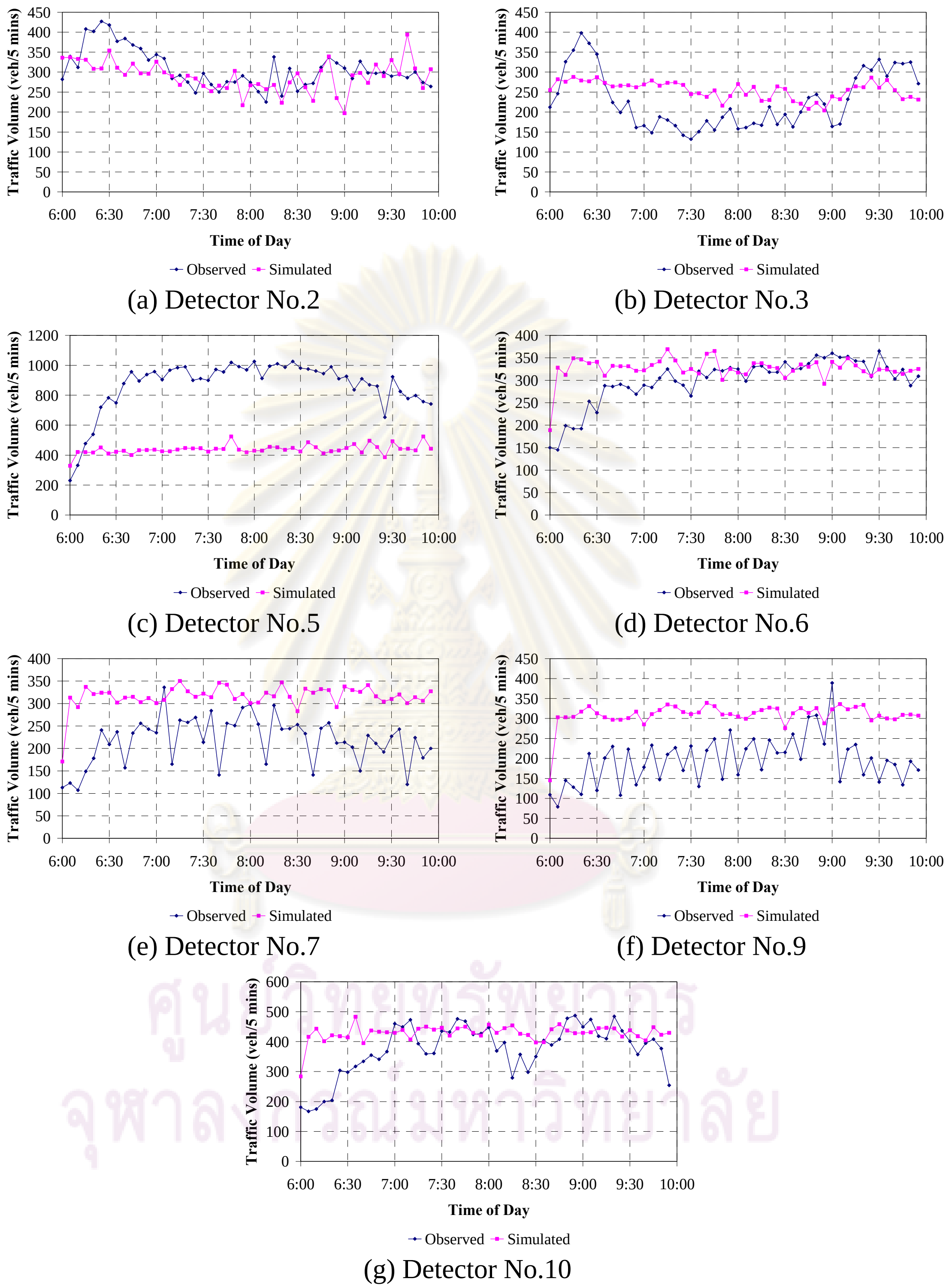
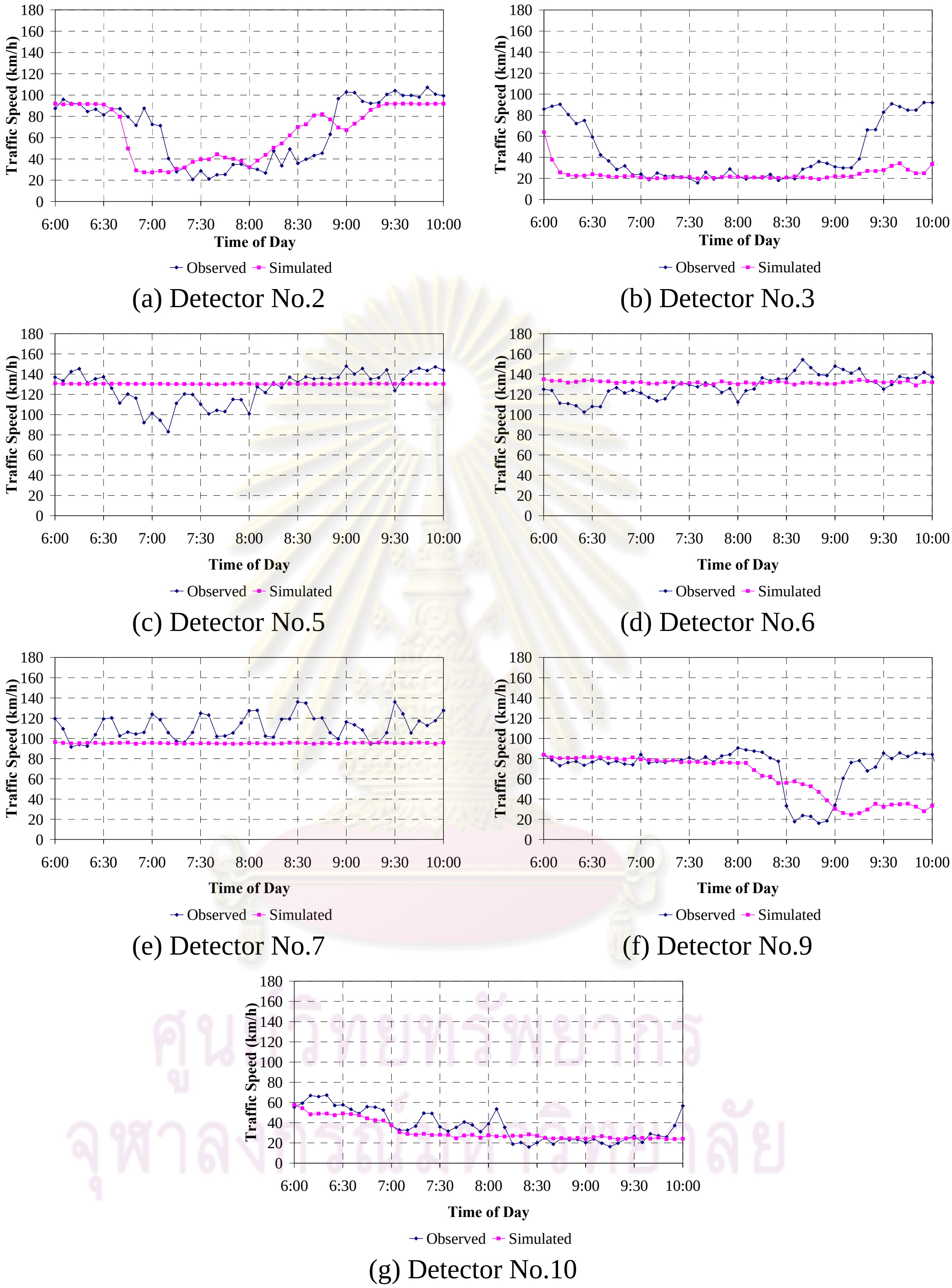


Figure 4-15 Observed and Simulated Traffic Volume at Detector Station at Bangkok Expressway Site



(a) Detector No.2

(b) Detector No.3

(c) Detector No.5

(d) Detector No.6

(e) Detector No.7

(f) Detector No.9

(g) Detector No.10

Figure 4-16 Observed and Simulated Traffic Speed at Detector Station at Bangkok Expressway Site

From Figure 4-15, most of detector stations show that estimated traffic volume is higher than observed traffic volume except detector station no.5 which the estimated traffic volume is less than observed traffic volume. A big difference in traffic volume comparison was occurred even the optimal model parameters received by genetic algorithm. It is note that the traffic condition under calibration period is congested.

From Figure 4-16, it shows that speed drop produced by microsimulation model occur faster than observation and it recover to normal speed slower than the observation. It can implied that even receiving the optimal model parameters by genetic algorithm, the estimated traffic speed still have difference when compared with observed traffic speed by discrete time step.

The microsimulation model attempted to replicate traffic based on calibrated model parameters which mean characteristics are defined but individual characteristic of driver occur in the actual traffic which microsimulation can not perfectly replicated. However, two study sites were calibrated and received optimal model parameters within predefine control criteria which the model parameters calibration using genetic algorithm can operate and also it can developed to be an on-line model parameters calibration for on-line microsimulation in order to repeat calibration by demand or integrate with the consistency checking module to monitor the error of on-line microsimulation model along the operation period.

4.3 CONCLUSION REMARKS

In this study, two expressway corridors in difference country were conducted as study sites consist of Matsubara line on Hanshin expressway in Japan and Chalerm Mahanakhon line on Bangkok expressway in Thailand. Two sites were used in difference parts which are summarized as follows.

For the study at the first site, the process of the development of combinatorial model parameters calibration using genetic algorithm was investigated. Matsubara line of Hanshin Expressway in Japan was selected in this study. Moreover, segment speed approximation based on point based detector station using conventional methods were evaluated to understand the performance for segment speed estimation which the conventional methods were further conducted to estimate segment travel time information.

For the study at the second site, the performance of microsimulation model was carried out on Chalerm Mahanakhon line of Bangkok Expressway Network in Bangkok in Thailand. . Moreover, this study site would also be used to evaluate the performance of microsimulation model with UKF improvement. Furthermore, it was also used to evaluate the performance of travel time prediction model.

Even the optimal model parameters were received by genetic algorithm within the predefined control criteria which the application of on-line calibration was concerned, but it was shown that a big difference are shown on both traffic volume and traffic speed when compared observation and estimation especially Bangkok expressway site in Thailand which the traffic data used in the calibration process is on the congestion period. In contrast, traffic data used in the calibration of Japan site study is uncongested. The microsimulation model show the estimation similar to the observation on both traffic volume and traffic speed. It can implied that replication error of microsimulation model has a big difference with actual traffic which it might have other model parameters which should study in the future study in order to improve the calibration process using genetic algorithm. However, mean target headway and mean driver reaction time were enough for this study in order to develop microsimulation model for estimating traffic state and travel time for travel time prediction.

CHAPTER V

NUMERICAL ANALYSIS

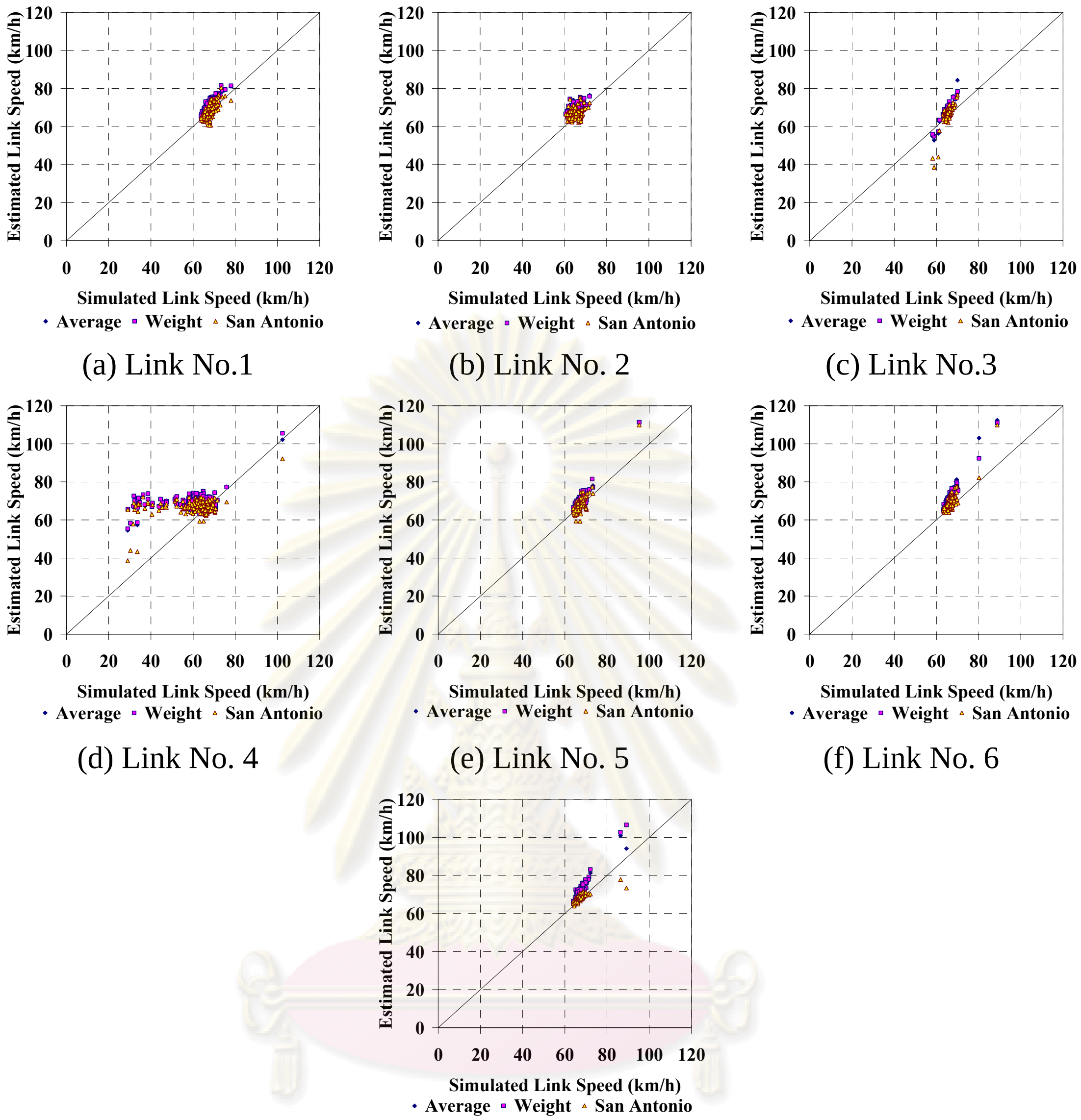
In order to assess the performance of the proposed approaches in order to reach the research objectives, the numerical analysis were performed in this chapter which included four parts. First, the evaluation of link speed estimation based on point detection system on expressway. Second, the dynamic traffic state and travel time estimation using microsimulation model. Third, the improvement of microsimulation model with feedback estimation using Unscented Kalman Filter. Final, the development of travel time prediction was presented.

5.1 EVALUATION OF LINK SPEED ESTIMATION BASED ON POINT DETECTION SYSTEM ON EXPRESSWAY

In this part, the link speed was estimated based on point detection system and the effectiveness of link speed estimation was evaluated. Traffic data on Matsubara line of Hansin expressway in Japan was used in this part. Seven links were defined by 8 traffic detection stations equipped with ultrasonic detectors on Matsubara line of Hanshin expressway. Three selected simple methods including average speed, weighted speed, and San Antonio were employed to calculate link speed based on traffic speed measured on upstream and downstream detector.

Figure 5-1 shows the range of observed speed and the result of link speed estimation. The observed speeds on the 1^{st}, 2^{nd}, and 3^{rd} link ranged between 60 and 80 km/h in which three simple methods performed quite well to estimate the link speed using speed data from upstream and downstream detectors. However, large error can be noticed on the 4^{th} link, almost all of estimated link speed is higher than the observed link speed. For the 5^{th}, 6^{th}, and 7^{th} link the observed and estimated speeds range between 60 and 80 km/h, similar to those the first three links. Estimated link speed values higher 80 km/h are observed on the 4^{th}, 5^{th}, 6^{th}, and 7^{th} link during 7:00 and 7:10. Since this was the initial period of simulation running, the speed may be ignored.

Estimated and observed link speed of each link was plotted as shown in Figure 5-1 to realize the over and under estimation using three simple methods.



(a) Link No.1 (b) Link No. 2 (c) Link No.3

(d) Link No. 4 (e) Link No. 5 (f) Link No. 6

(g) Link No. 7

Figure 5-1 Diagonal Plot between Estimated and Simulated Link Speed on Hanshin Expressway Site

The absolute percentage error (APE) was calculated every 5 minutes and then minimum, maximum, average, and standard deviation of APE are summarized in Table 5-1. If MAPE of 20% is the maximum MAPE that could be accepted, three simple methods have shown the MAPE below 20% except on the 4th link where MAPE is higher than 20%. The exception is the speed estimated by San Antonio method on the 4th link in which all MAPE is below 20%. However, the other three simple methods show the highest APE and standard deviation is also quite high on the 4th link. The 4th link was investigated in more details to understand why the estimated speed on this link had the high value of APE.

Table 5-1 MAPE and APE of Speed as Minimum, Maximum, and Standard Deviation (%) on Hanshin Expressway Site

Method		Link No.						
		1	2	3	4	5	6	7
Average	MAPE	4.38	5.14	4.16	20.28	3.78	7.16	5.03
	Min.	0.00	0.03	0.05	0.04	0.06	1.69	0.27
	Max.	11.30	19.00	20.52	127.27	16.61	28.53	16.77
	S.D.	2.38	3.39	2.30	29.08	2.50	3.49	2.44
Weighted average	MAPE	4.56	5.10	3.97	20.37	3.80	6.72	5.42
	Min.	0.09	0.06	0.05	0.01	0.03	1.48	0.08
	Max.	11.39	19.00	12.07	127.70	16.88	25.09	19.51
	S.D.	2.43	3.33	2.00	29.19	2.55	2.99	2.91
San Antonio	MAPE	2.50	3.91	3.10	17.40	2.72	4.01	1.70
	Min.	0.04	0.08	0.00	0.02	0.00	0.08	0.00
	Max.	11.27	18.80	34.55	124.54	15.32	23.76	17.76
	S.D.	2.23	3.00	3.83	25.99	2.15	2.92	1.70

As mentioned in Figure 5-1 and Table 5-1, a large disparity between the observed and estimated speed can be seen on the 4th link where three simple methods show an over estimation in representing link speed. Furthermore, the maximum value of APE is quite high although the MAPE is close to 20% when using average and weighted average method or below 20% when using San Antonio method. In order to investigate in details, time dependent of link speed and APE on the 4th link are plotted as shown in Figure 5-2 and Figure 5-3.

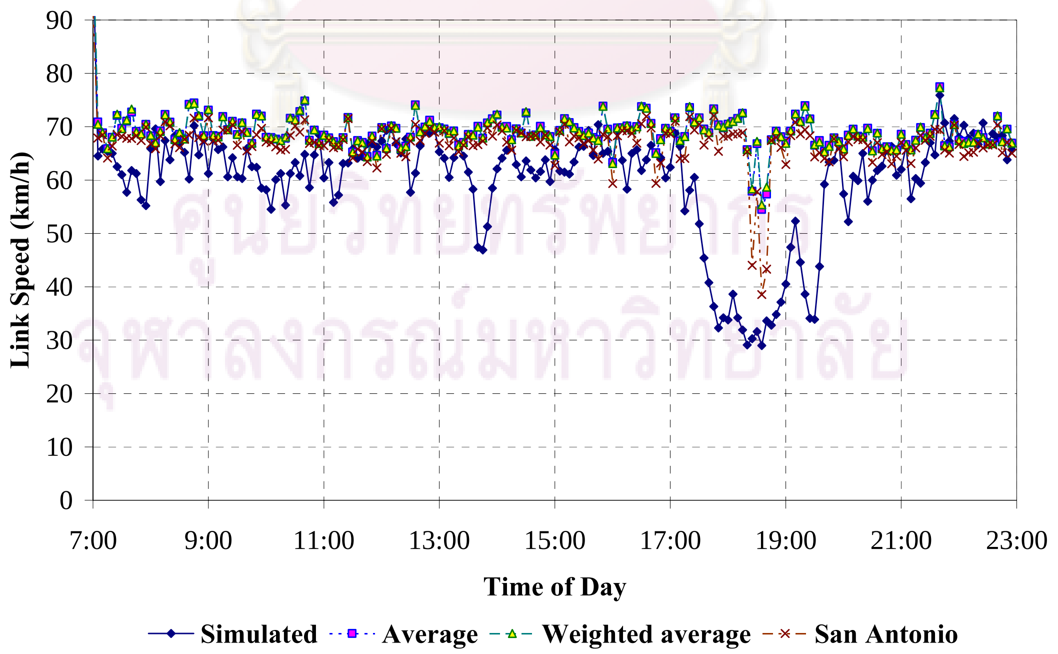


Figure 5-2 Time-Dependent Link Speed on the 4th Link on Hanshin Expressway Site

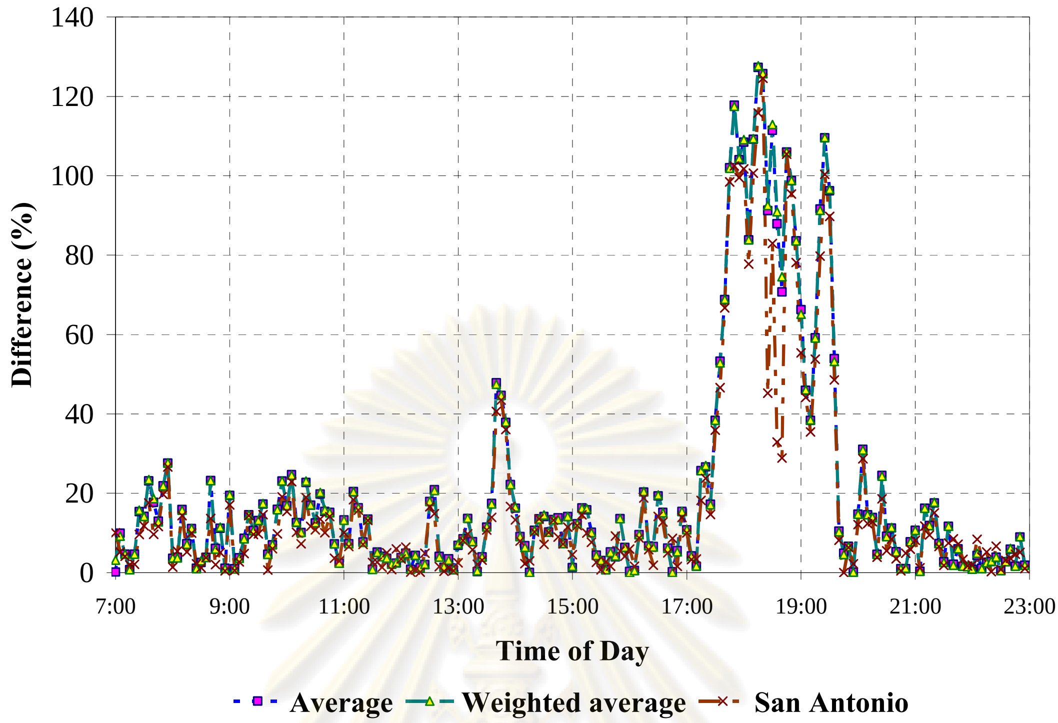


Figure 5-3 Time-Dependent Absolute Percentage Error of Link Speed on the 4th Link on Hanshin Expressway Site

Figure 5-3 shows that the link speed on the 4th link drops during 17:15 until 19:55 when three methods are badly performed during this period with high value of APE as illustrated in Figure 5-3. Therefore, the value of MAPE during uncongested and congested traffic condition was separately calculated and is shown in Table 5-2. The authors define period with speed drop as the congested condition and otherwise as the uncongested condition. It is found that three simple methods are quite well performed during uncongested condition but are badly performed during congested condition.

Table 5-2 Mean Absolute Percentage Error (%)

Method	Uncongested Traffic	Congested Traffic
Average	9.77	70.94
Weighted average	9.93	70.88
San Antonio	8.32	61.17

In this study, even if the effects of detector spacing and placement are neglected, we can not deny that these two effects seriously impact the reliability of link speed represented by the estimation of upstream and downstream speed of the link. Length of the 4th link is 1941 m, which is considered a long link so that traffic data from upstream and downstream detectors may not well represent link speed. Traffic speed measured at detector number 4 (upstream) and 5 (downstream) were plotted and compared with the observed link speed as shown in Figure 5-4.

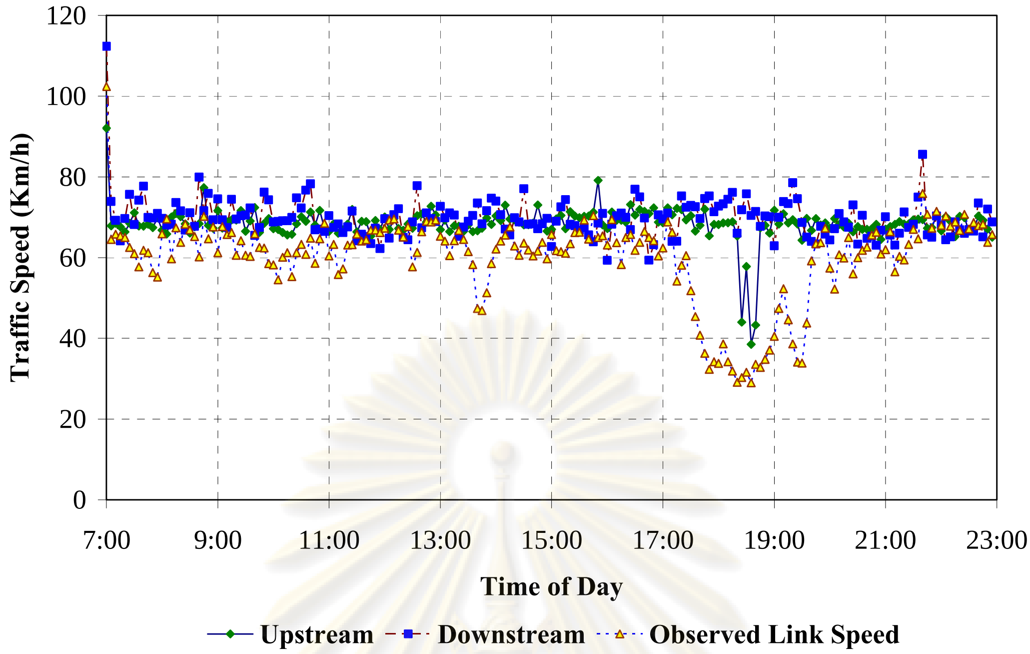


Figure 5-4 Observed Traffic Speed on Upstream and Downstream Detector Station and Observed Link Speed on the 4th Link on Hanshin Expressway Site

Figure 5-4 shows that observed link speed initially drops at 17:15 while detector station can capture speed drop at 18:20. It is too much lag that either upstream or downstream detector can capture this speed drop. The link length is too long to use spot speed from upstream and downstream detector station for representing link speed especially during congested condition. Traffic analyzer should realize this fact when they have to estimate link speed on expressway corridor with low density of detector stations similar to this case study. However, the effect of detector station numbers (reducing spacing) on the reliability of link speed estimation using simple methods can not be reported within this study.

The findings in this part illustrate that the weakness of using the three simple methods to estimate link speed on expressway are mainly due to large error under a congested traffic condition but it is quite well performed under an uncongested condition. Most of estimated link speeds during congestion period are overestimated. The effect of detector spacing and placement might be the serious factors that impact the reliability of estimated link speed using these simple methods. According to the case study, the length of the 4th link is too long to conduct the spot speed measured from upstream and downstream detector stations for representing link speed.

Moreover, it can notice that capability of conventional speed estimation methods are limited by their own algorithm. Estimated link speed using average, weighted average, and San Antonio methods provide only the value of link traffic speed between upstream and down stream traffic speed while simulated link speed use as benchmark are slower than the estimated speed which conventional can approximated based on upstream and downstream traffic speed measured by detectors.

5.2 REAL-TIME TRAFFIC STATE AND TRAVEL TIME ESTIMATION USING MICROSIMULATION

Traffic state and travel time were estimated by means of microsimulation. For this part, the study site on Chalerm Mahanakhon Line, Bangkok was used. Seven road segments were defined by 7 detection stations equipped with video image processing camera (camera at station no.1, 4 and 8 was unavailable), starting from station no.2 to station no.11. The three selected conventional methods of speed estimation as earlier presented included average, weighted average, and San Antonio speed estimation methods were employed for calculating segment travel time. However, the observed travel time information was available by matching vehicles started from detector station no.2 and finished at detector station no.10. So, seven segment travel times were aggregated into path travel time in which vehicle traversed from station no.2 and finish on station no.10. Real-time travel time estimated by on-line microsimulation and the three conventional methods were shown in Figure 5-5.

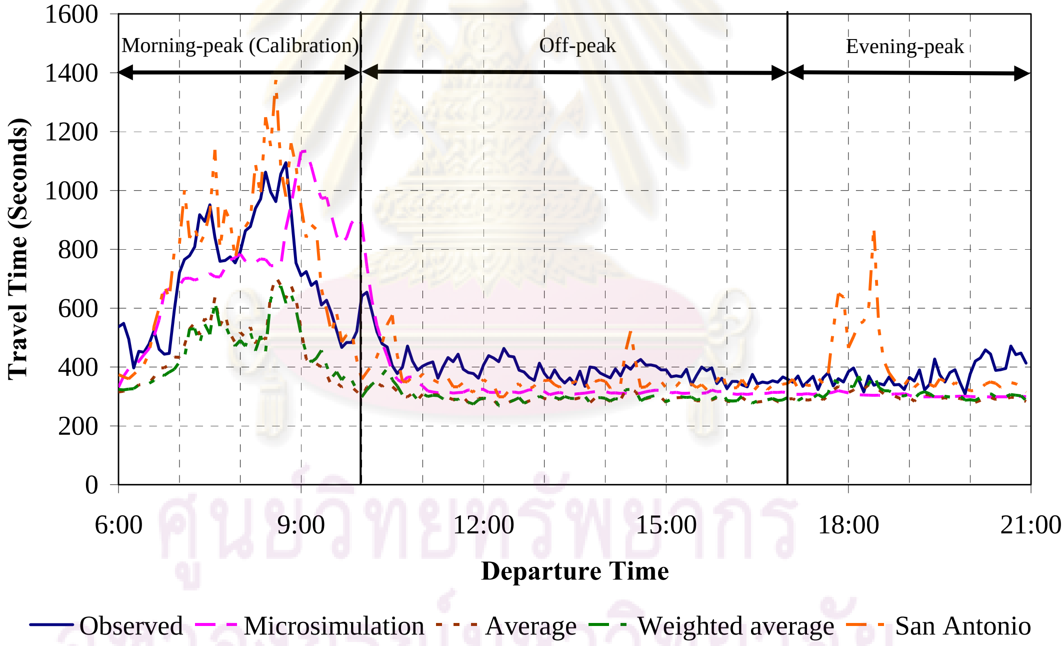
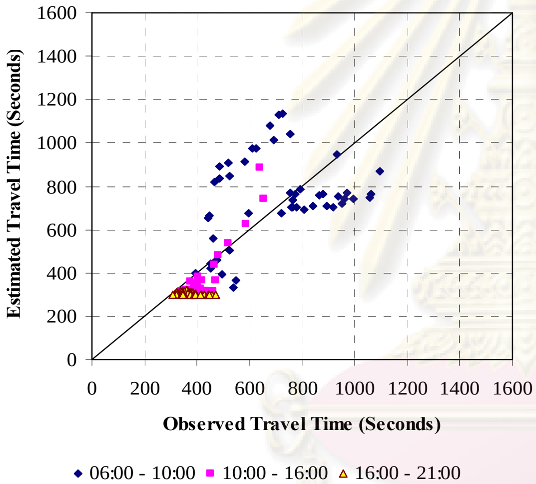


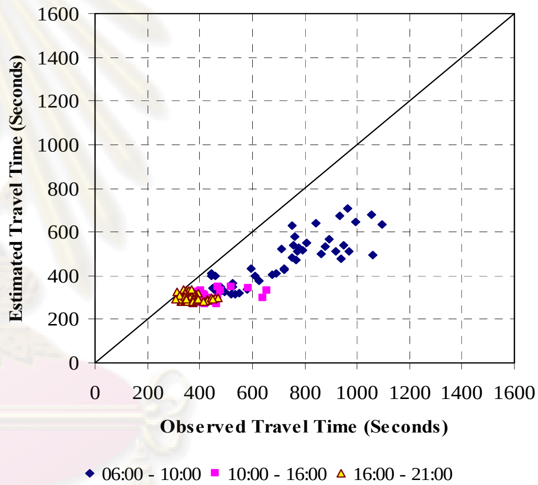
Figure 5-5 Comparison of Observed and Estimated Travel Time

From Figure 5-5, travel time estimated by on-line microsimulation is quite lower than the observed travel time from 07:00 until 09:00, higher than the observed travel time from 09:00 until 10:00, and lower than the observed travel time during off-peak and evening-peak period. Comparing the three conventional travel time estimation methods, San Antonio method is quite close to the observed travel time on three periods but it shows over estimation from 17:30 to 18:40 while on-line microsimulation method and average and weighted average method result in estimated travel time quite close to the observed travel time.

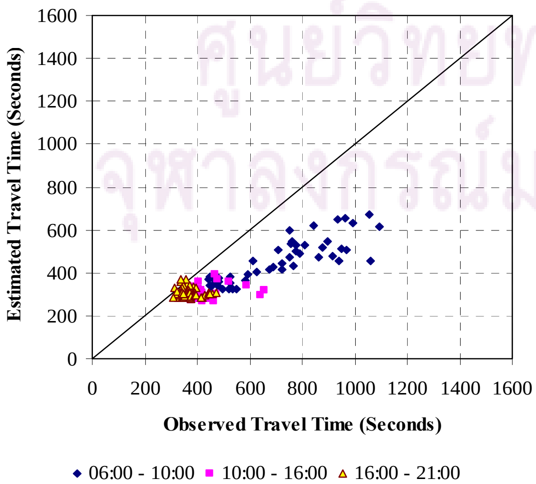
In order to illustrate over or under estimation on travel time of on-line microsimulation and the three conventional methods, estimated and observed travel time were plotted as shown in Figure 5-6. Figure 5-6(a) illustrates that travel time estimates by on-line microsimulation model are both under and over estimated during the morning-peak period (06:00-10:00). Note that this data set was also used for calibrating model parameters. During off-peak period and evening-peak period, travel time estimates are over and under estimation respectively. Figure 5-6(b) illustrates travel time estimation by average method in which the estimated travel time is under estimated in all three time periods. Figure 5-6(c) illustrates travel time estimation by weighted average method in which, similar to average method, the estimated travel time is under estimated in all three time periods. Figure 5-6(d) illustrates travel time estimation by San Antonio method, in which the estimated travel time is both under and over estimation in three time periods. The general trend of the estimation from the three methods is as follows: in the morning-peak period is most of methods give over estimation, during off-peak period they give both under and over estimation, and they give quite over estimation in the evening peak period.



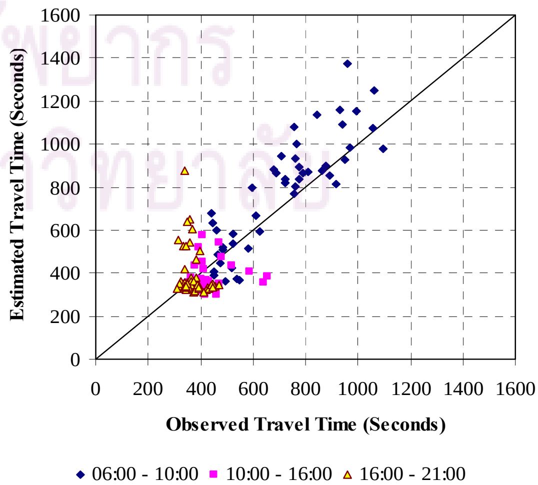
(a) Microsimulation



(b) Average



(c) Weighted Average



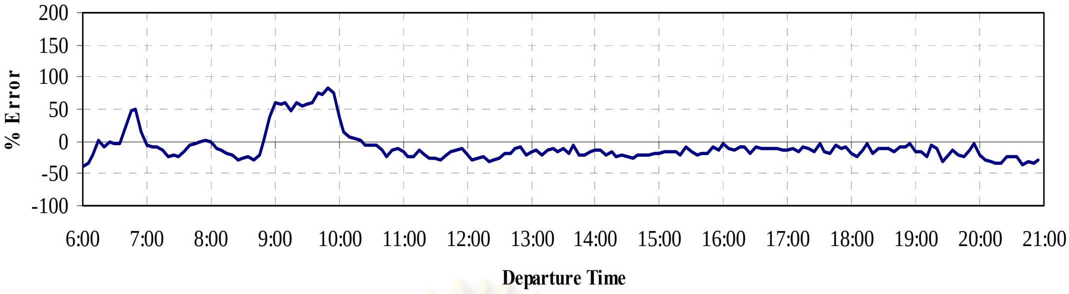
(d) San Antonio

Figure 5-6 Diagonal Plots between the Observed and Estimated Travel Time

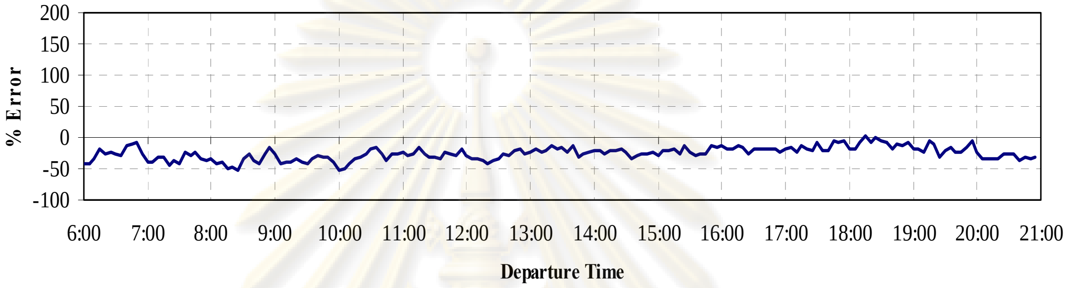
From Figure 5-6, it shows that average and weighted average method always provide estimated travel time less than the observed travel time or under estimation because it is the limitation of method as mention in previous part. Microsimulation model and San Antonio provide estimated travel time on both under and over estimation especially the estimation under congested condition.

As previously described on how under and over estimation of each travel time estimation methods, the levels of percentage error were calculated and plotted by departure time as shown in Figure 5-7. The figure could show how much the percentage error on each travel time estimation methods every 5 minutes.

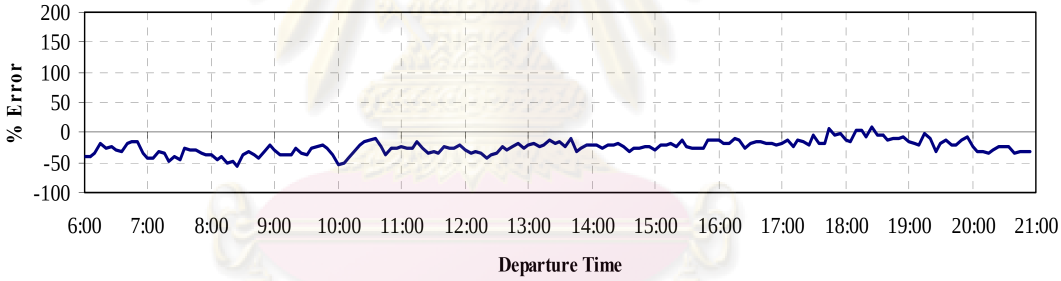
Figure 5-7(a) illustrates that the travel time estimated by on-line microsimulation deviates approximately within lower and upper bound of 50%, except from 09:00 to 10:00 which the estimated travel time is higher than the observed travel time more than 50%. Figure 5-7(b) and Figure 5-7(c) show that the estimated travel times by average and weighted average method are under estimated with most of estimation are lower than the observed travel time about 50% with smallest error at 18:30. Figure 5-7(d) shows that the travel time estimated by San Antonio has a huge percentage error of travel time estimation, about 150% higher than the observed travel time at 18:30 while other methods yield more accurate travel time estimates.



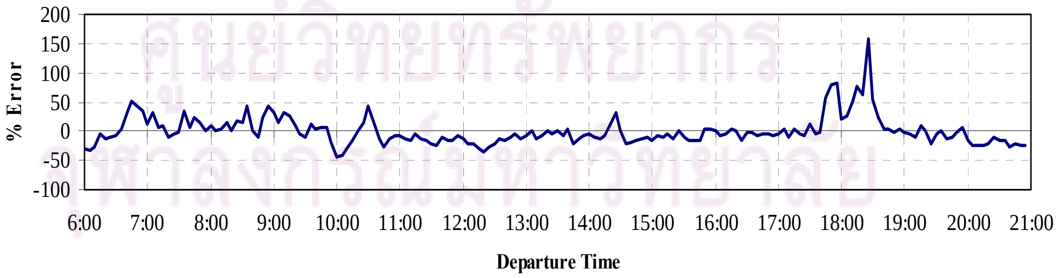
(a) Microsimulation



(b) Average



(c) Weighted Average



(d) San Antonio

Figure 5-7 Percentage error of travel time estimated by microsimulation and three conventional methods

According to the deviation of percentage error of travel time estimates as shown in Figure 5-7, minimum, maximum, mean absolute percentage error, and MAPE standard deviation of travel time estimates by on-line microsimulation model and three conventional methods were analyzed and shown by three time periods in Table 5-3.

Table 5-3 Minimum, Maximum, Mean Absolute Percentage Error, and Standard Deviation of Travel Time Estimates by On-Line Microsimulation and Three Conventional Methods

Methods	(a) Morning-peak period (06:00-10:00)			
	Min	Max	MAPE	Std.
Microsimulation	-38.29	84.12	28.66	23.99
Average	-53.65	-8.71	33.22	9.71
Weighted average	-57.34	-14.26	33.92	9.53
San Antonio	-33.26	52.66	16.90	13.50
Methods	(b) Off-peak period (10:00-16:00)			
	Min	Max	MAPE	Std.
Microsimulation	-32.42	38.17	17.65	7.21
Average	-53.25	-12.83	25.92	7.75
Weighted average	-53.68	-10.28	25.21	8.31
San Antonio	-44.23	42.20	14.17	9.88
Methods	(c) Evening-peak period (16:00-21:00)			
	Min	Max	MAPE	Std.
Microsimulation	-36.56	-2.42	16.13	8.61
Average	-36.92	3.15	18.48	9.14
Weighted average	-35.02	9.90	16.82	8.82
San Antonio	-26.37	158.68	19.31	27.35

Table 5-3(a) shows that the estimated travel time during morning-peak period estimated by the on-line microsimulation model has the minimum error of -38.29%, the maximum error of 84.12%, a mean absolute percentage error of 28.66%, and a MAPE standard deviation of 23.99%. The estimated travel time by San Antonio is the most accurate which has the minimum error of -33.26%, the maximum error of 52.66%, a mean absolute percentage error of 16.90%, and a MAPE standard deviation of 13.50%. Travel time estimated between 06:00 and 10:00 using San Antonio is more reliable than using microsimulation but the maximum errors of San Antonio is quite high and fluctuates in all time periods.

Table 5-3(b) shows that estimated travel time during off-peak period estimated by on-line microsimulation model has the minimum error of -32.42%, the maximum error of 38.17%, a mean absolute percentage error of 17.65%, and a MAPE standard deviation of 7.21%. The estimated travel time by San Antonio is still the most accurate which has the minimum error of -44.23%, the maximum error of 42.20%, a mean absolute percentage error of 14.17%, and a MAPE standard deviation of 9.88%. However, the minimum and maximum error of travel times by San Antonio deviates greater than those by microsimulation. Furthermore, the MAPE standard deviation of San Antonio is higher than that of microsimulation as the error of travel time by San Antonio fluctuates more than the error of travel time by microsimulation during off-peak period.

Table 5-3(c) shows that estimated travel time during evening-peak period estimated by on-line microsimulation model has the minimum error of -36.56%, the maximum error of -2.42%, a mean absolute percentage error of 16.13%, and a MAPE standard deviation of 8.61%. San Antonio has the minimum error of -26.37%, the maximum error of 158.68%, a mean absolute percentage error of 19.31%, and a MAPE standard deviation of 27.35%. It is obviously shown that the estimated travel time using microsimulation model is more reliable than San Antonio during evening-peak period.

Furthermore, the absolute percentage error was plotted as shown in Figure 5-8 in order to clearly illustrate the fluctuation of absolute error. The errors of travel time by microsimulation were compared against the three convention methods. Figure 5-8 shows that the absolute percentage error of estimated travel time using microsimulation model is higher than those by the conventional methods between 09:00 and 10:00 and then the absolute percentage error of estimated travel time information by San Antonio is higher than microsimulation model and other conventional methods between17:30 and 18:30. MAPE is illustrated by compared microsimulation with three conventional methods as shown in Figure 5-9.

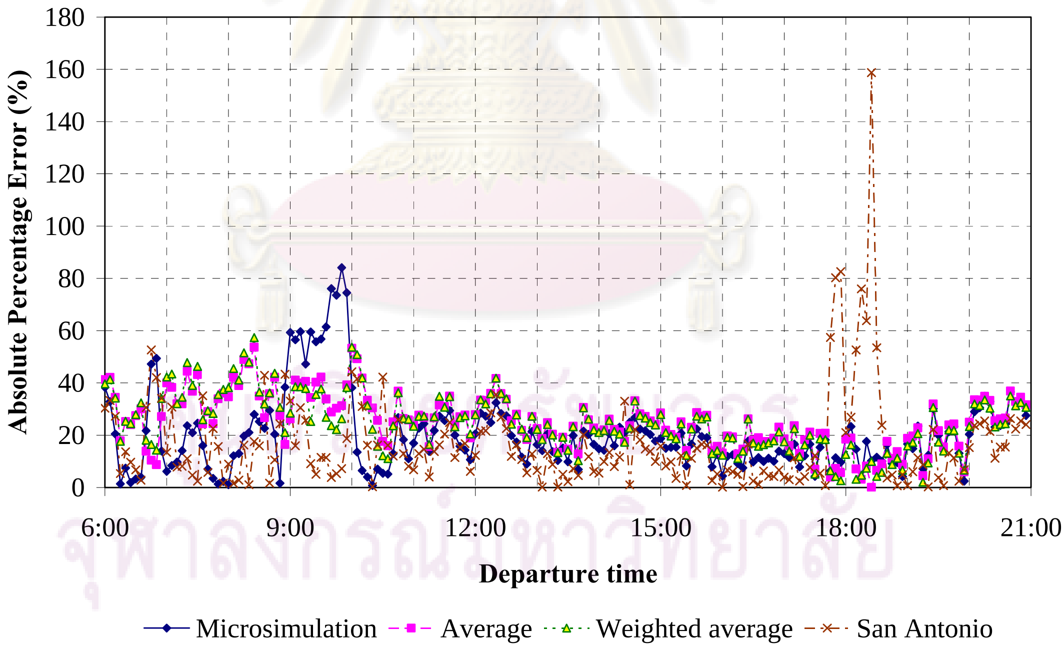


Figure 5-8 Absolute Percentage Errors of On-line Microsimulation and Three Conventional Methods by Departure time.

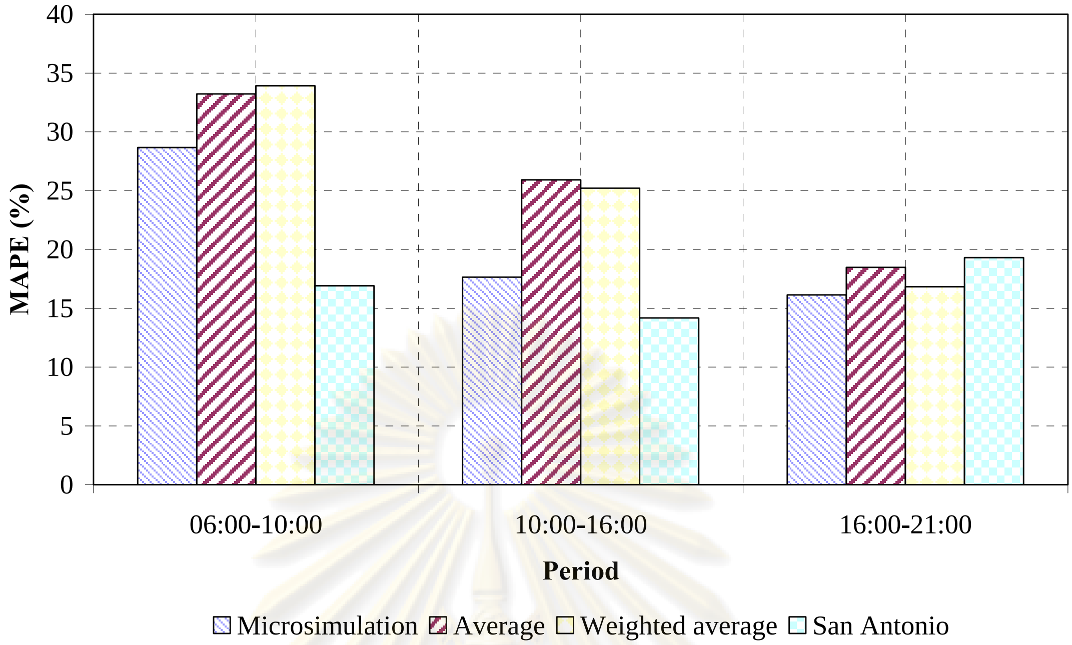


Figure 5-9 Mean Absolute Percentage Errors of Travel Time Estimated by On-line Microsimulattion and Three Conventional Travel Time Estimation Methods

Referring to Figure 5-9, from 06:00 to 10:00 (morning-peak period), on-line microsimulation for travel time estimation is quite well performed. It is more accurate than conventional methods average and weighted average but less accurate than C3 which has MAPE value less than 20%. MAPE of average and weighted average during morning-peak period has MAPE value more than 30%. From 10:00 to 16:00 (off-peak period), travel time estimation by average and weighted average deviate by approximately 25% while travel time estimation by on-line microsimulation is less than 20% and that of San Antonio is less than 15%. From 16:00 to 21:00 (evening-peak period), on-line microsimulation model shows the best performance for estimating travel time with less MAPE value than the conventional methods.

From this part, it was found that microsimulation model provides more accurate and reliable travel time than average, weighted average, and San Antonio. The average and weighted average methods have their own limitation in order to capture link speed which carries to the estimation error on travel time estimation. During congestion periods which is the challenge of estimation model, microsimulation model was still shown the best method to estimate travel time even the San Antonio method is more accurate but it is unreliable as obviously shown huge error in the evening while traffic is uncongested. The traffic speed on detector was drop in the evening but it was affected to the link speed during evening period.

5.3 IMPROVEMENT OF MICROSIMULATION BY FEEDBACK ESTIMATION USING UNSCENTED KALMAN FILTER

In this part, Unscented Kalman Filter was employed to improve the accuracy of traffic state and travel time estimate over the method of only straightforward microsimulation modeling being previous used. Prior estimated traffic states included traffic speed and traffic density on the seven links on Bangkok Expressway site. Real-time traffic speed and traffic flow measured on seven detector stations on site study were collected as measurement update based on feedback estimation using Unscented Kalman Filter procedure. Traffic states on seven links were posterior estimated as shown in Figure 5-10 and Figure 5-11. Moreover, the comparisons of traffic speed and traffic flow on both observed and simulated are shown in Figure 5-12 and Figure 5-13.

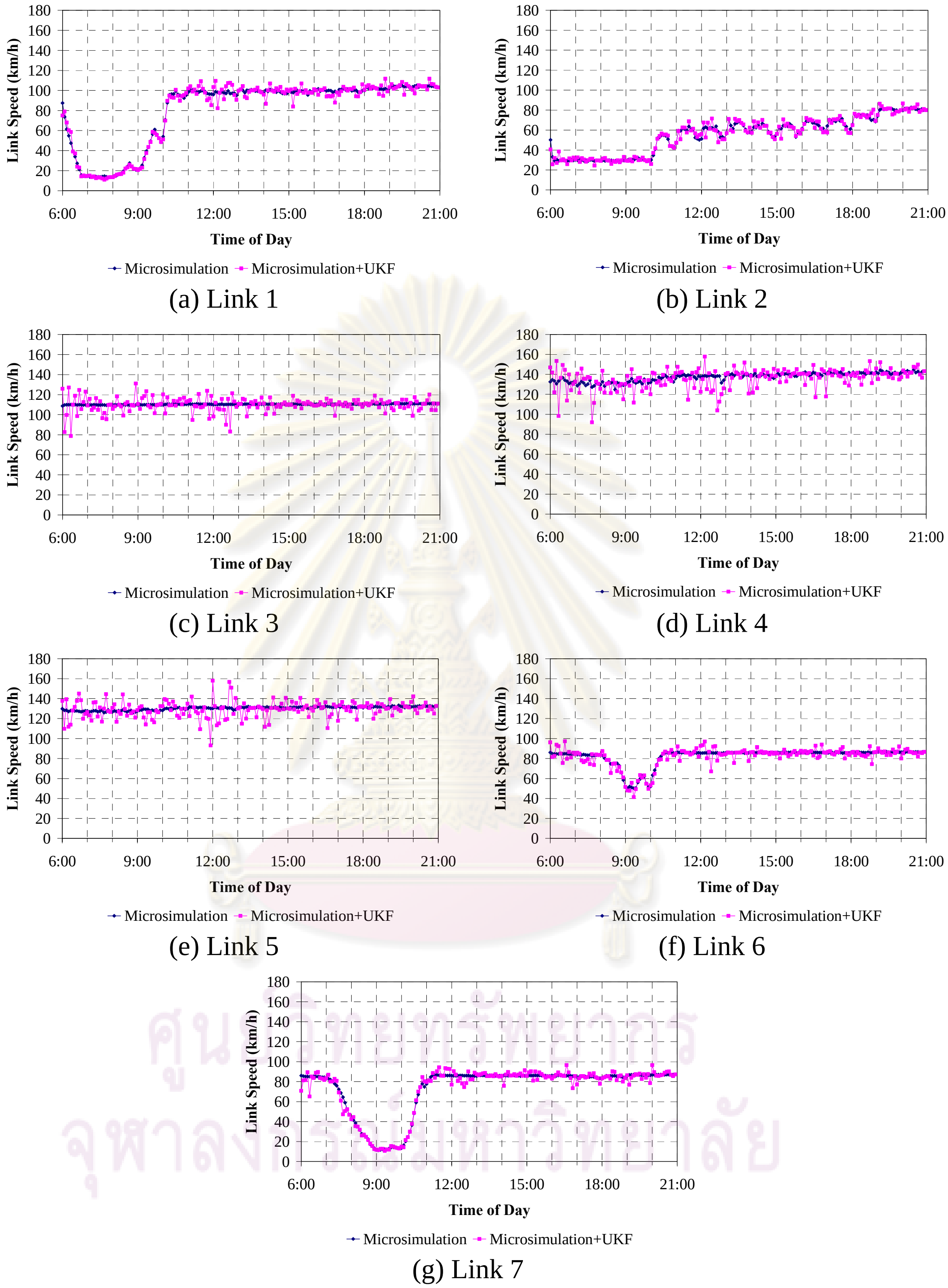
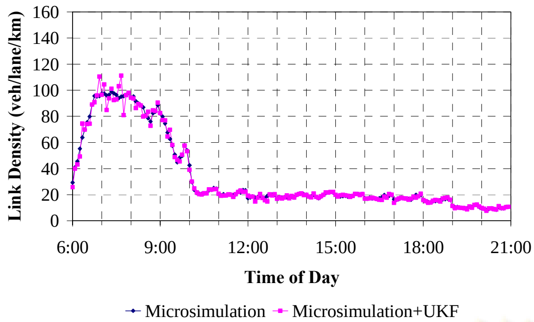
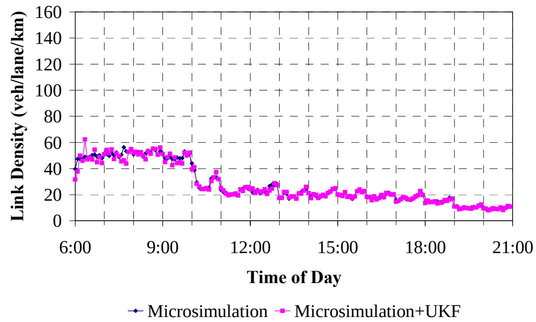


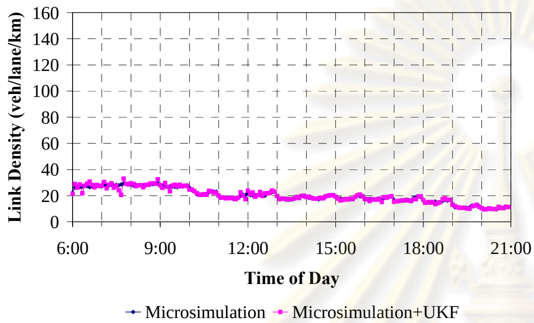
Figure 5-10 Prior Estimated Link Speed using Microsimulation and Posterior Estimated Link Speed using Microsimulation+UKF



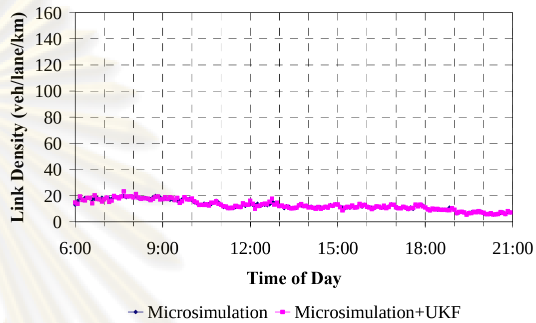
(a) Link 1



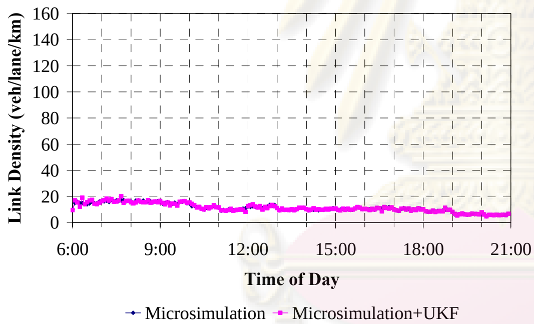
(b) Link 2



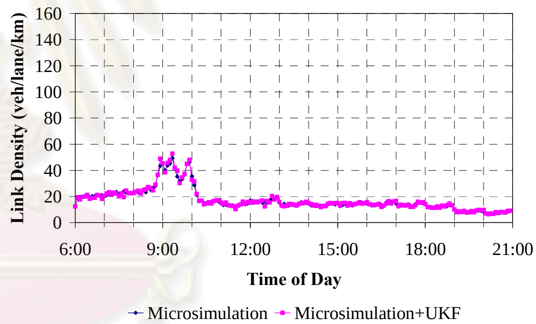
(c) Link 3



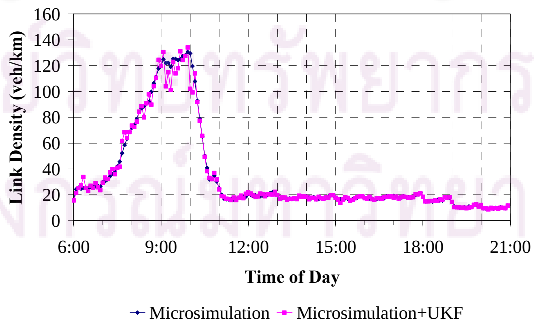
(d) Link 4



(e) Link 5

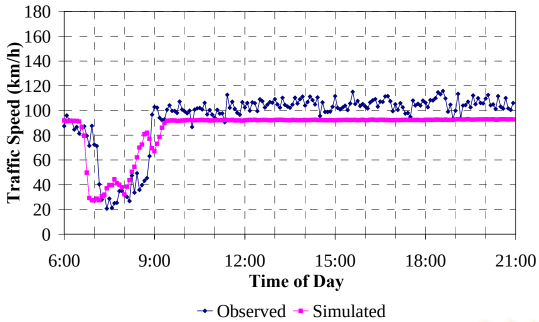


(f) Link 6

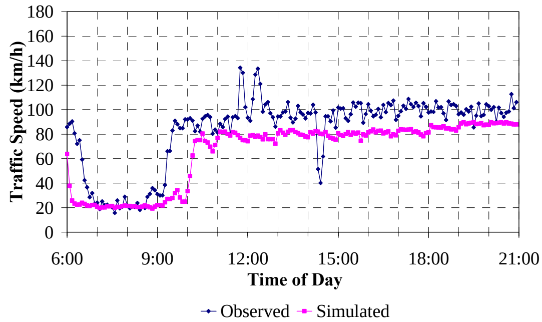


(g) Link 7

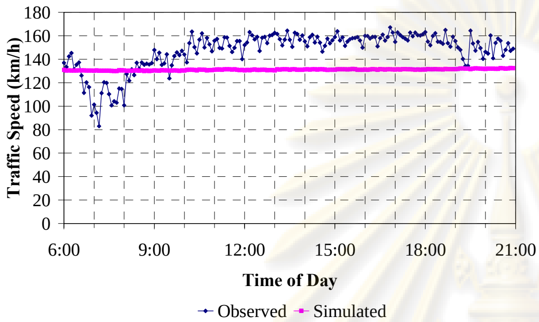
Figure 5-11 Prior Estimated Link Density using Microsimulation and Posterior Estimated Link Density using Microsimulation+UKF



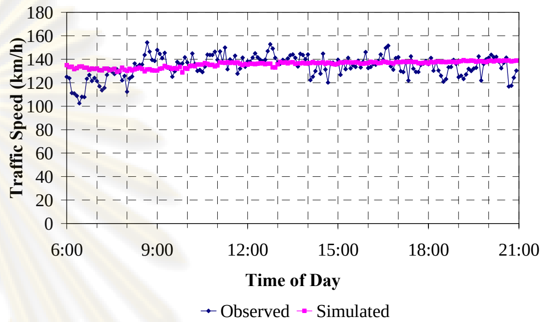
(a) Detector No.2



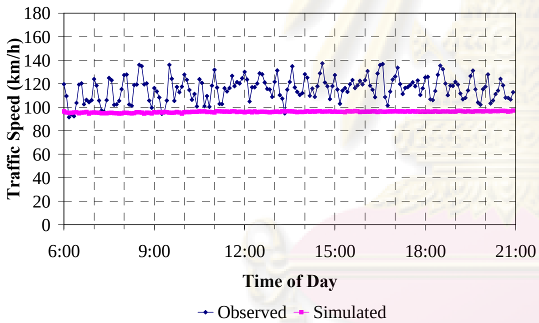
(b) Detector No.3



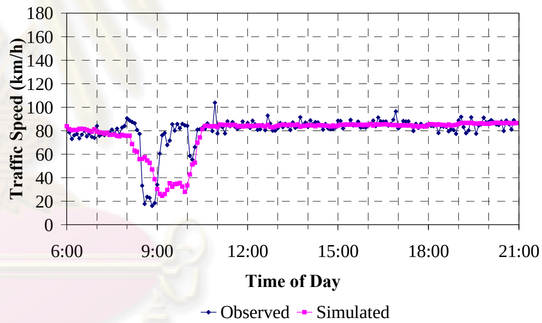
(c) Detector No.5



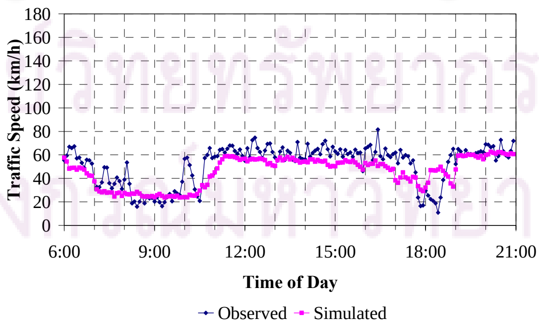
(d) Detector No.6



(e) Detector No.7

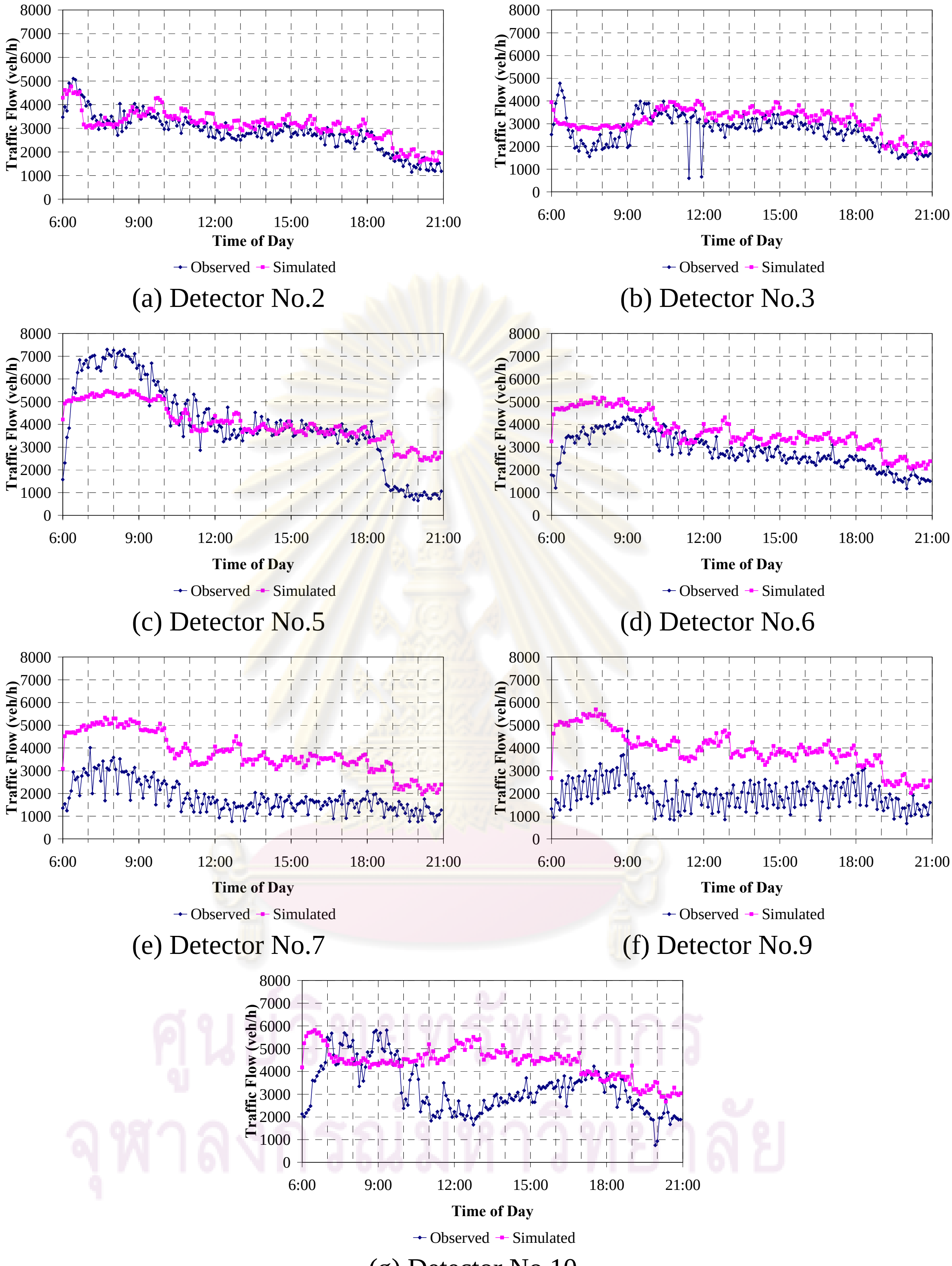


(f) Detector No.9



(g) Detector No.10

Figure 5-12 Observed and Simulated Traffic Speed at Detector Station on Bangkok Expressway



(a) Detector No.2
(b) Detector No.3
(c) Detector No.5
(d) Detector No.6
(e) Detector No.7
(f) Detector No.9
(g) Detector No.10

Figure 5-13 Observed and Simulated Traffic Flow at Detector Station on Bangkok Expressway

From Figure 5-10 and Figure 5-11, the seven expressway's links were divided based on detector stations which are described as shown in Table 5-4. The figures present link speed and link density respectively which compare prior estimated value using microsimulation model and posterior estimated value using microsimulation model with UKF improvement. It is shown that posterior estimated traffic states on expressway segments are fluctuated along discrete time based on prior estimated traffic states using microsimulation model only.

Table 5-4 Definition of Divided Link on Bangkok Expressway

Link No.	From	End
1	Detector No.2	Detector No.3
2	Detector No.3	Detector No.4
3	Detector No.4	Detector No.5
4	Detector No.5	Detector No.6
5	Detector No.6	Detector No.7
6	Detector No.7	Detector No.9
7	Detector No.9	Detector No.10

From Figure 5-12 and Figure 5-13, the comparison between observed and estimated traffic speed and traffic flow are displayed respectively. The data came from actual traffic detector station on Bangkok Expressway site study and virtual traffic detector station on microsimulation model.

In order to evaluate the proposed methods, similar to the data analysis of the previous section, the observed travel time was considered starting from detector station no.2 and then finishing at detector station no.10. It is noted that the route travel time (from station no.2 to station no.10) would be compared rather than individual link travel time comparison. The comparison of travel time information between observed and posterior estimated travel time information is illustrated in Figure 5-14.

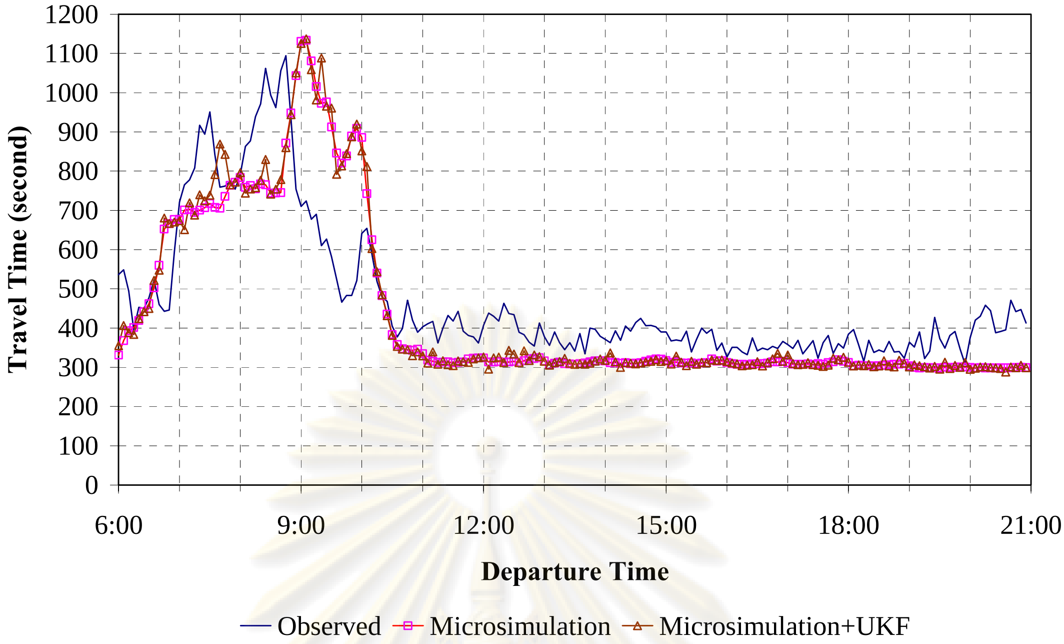
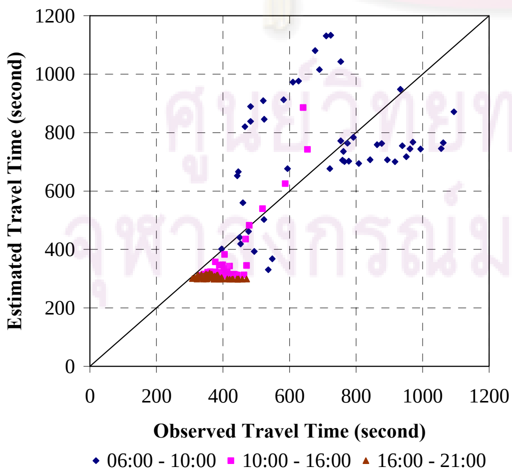
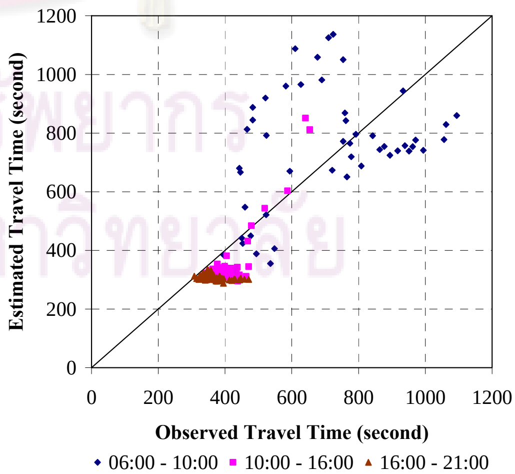


Figure 5-14 Comparison of Travel Time Information estimated by Microsimulation and Microsimulation+UKF

From Figure 5-14, Figure 5-14(a) shows the comparison between observed and prior estimated of travel time information using microsimulation model. Figure 5-14(b) shows the comparison between observed and posterior estimated of travel time information using microsimulation with UKF improvement. The diagonal plot between observed and posterior estimated travel time information is illustrated in Figure 5-15 which is classified by three time periods.



(a) Microsimulation



(b) Microsimulation+UKF

Figure 5-15 Diagonal Plot of Observed and Estimated Travel Time using Microsimulation+UKF

From Figure 5-15, the diagonal plot between observed and estimated travel time is illustrated in order to understand over and under estimation of estimation models. Figure 5-15(a) shows a diagonal plot of microsimulation model only and Figure 5-15(b) show the diagonal plot of microsimulation with UKF improvement. It is shown that Figure 5-15(a) and Figure 5-15(b) are quite similar which it is both over and under estimation of travel time during the first time period (06:00 – 10:00). For the second period (10:00 – 16:00) and third period (16:00 – 21:00), most of travel times are under estimated.

For further evaluation analysis, a percentage error was calculated and illustrated by discrete time as shown in Figure 5-16 in order to understand the magnitude of error. Furthermore, an absolute percentage error is illustrated in Figure 5-17.

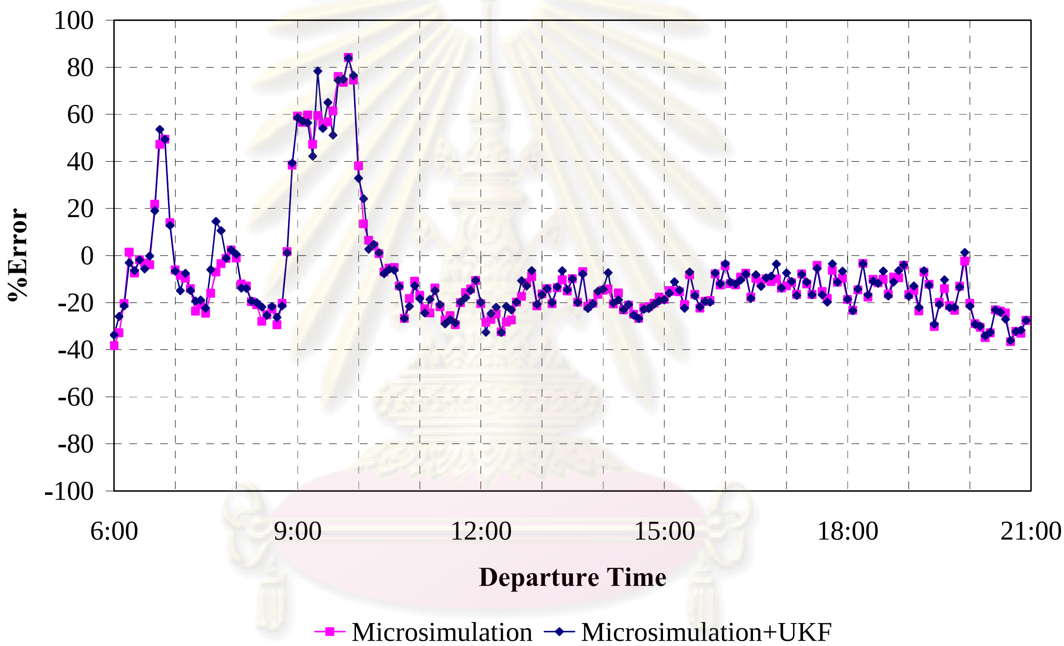


Figure 5-16 Percentage Error of Travel Time Information Estimated by Microsimulation and Microsimulation+UKF

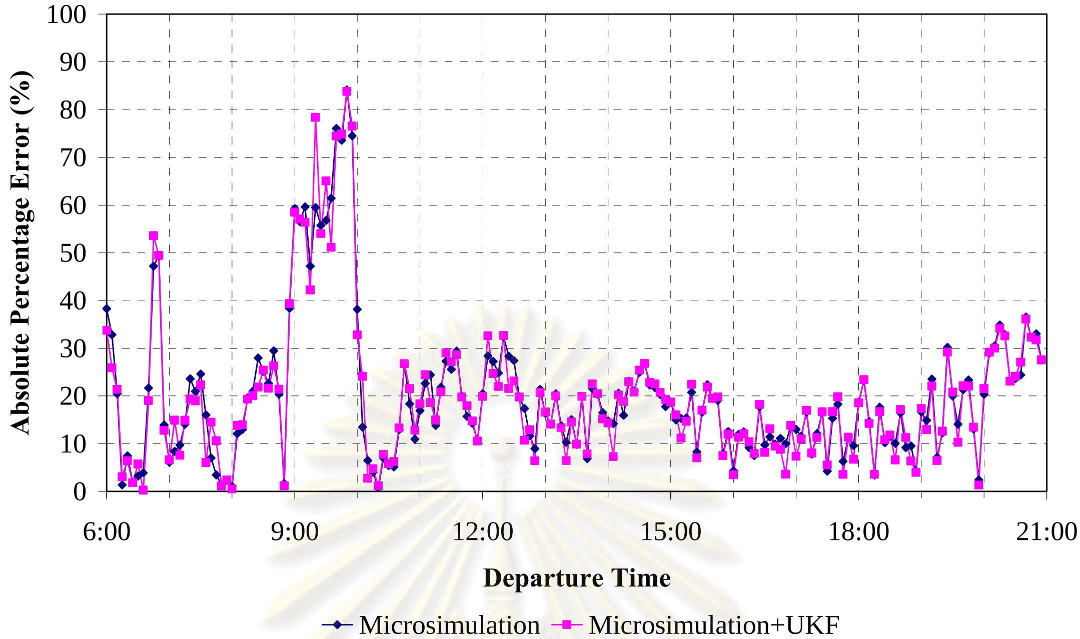


Figure 5-17 Absolute Percentage Error of Travel Time Estimated by Microsimulation and Microsimulation+UKF

From Figure 5-17 shows that the absolute percentage errors of travel time estimated by microsimulation and microsimulation with UKF improvement are quite similar. However, posterior estimated travel time information is more accurate than prior estimated. In order to summarize the accuracy of estimated travel time information, the mean absolute percentage error were determined as shown in Figure 5-18 by three periods. Two models were compared and the values of MAPE were listed in Table 5-5.

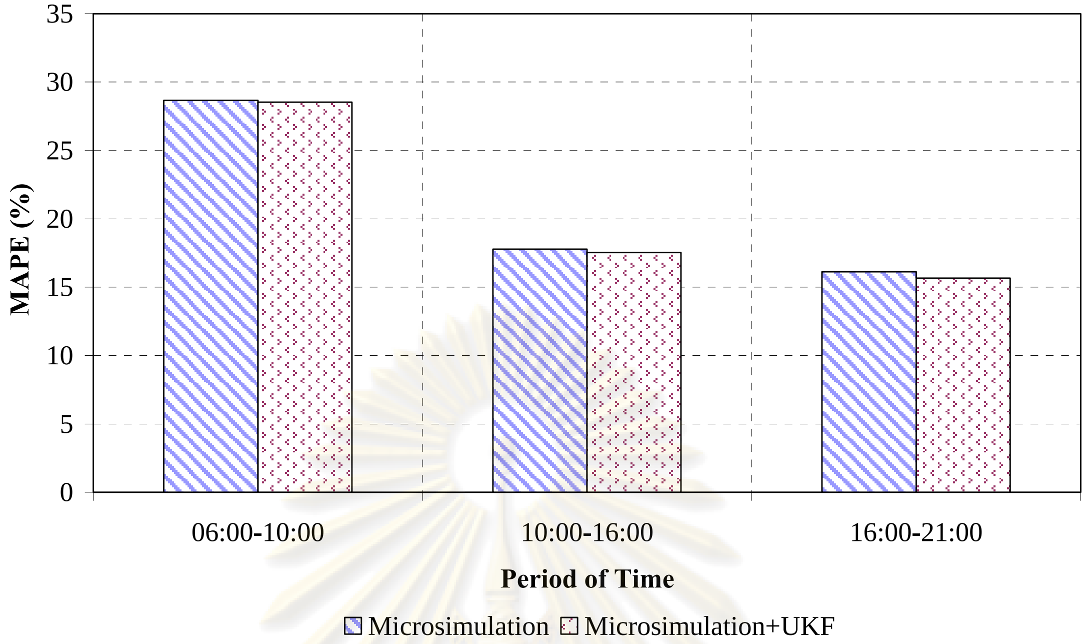


Figure 5-18 Comparison of MAPE of Travel Time between Microsimulation and Microsimulation+UKF

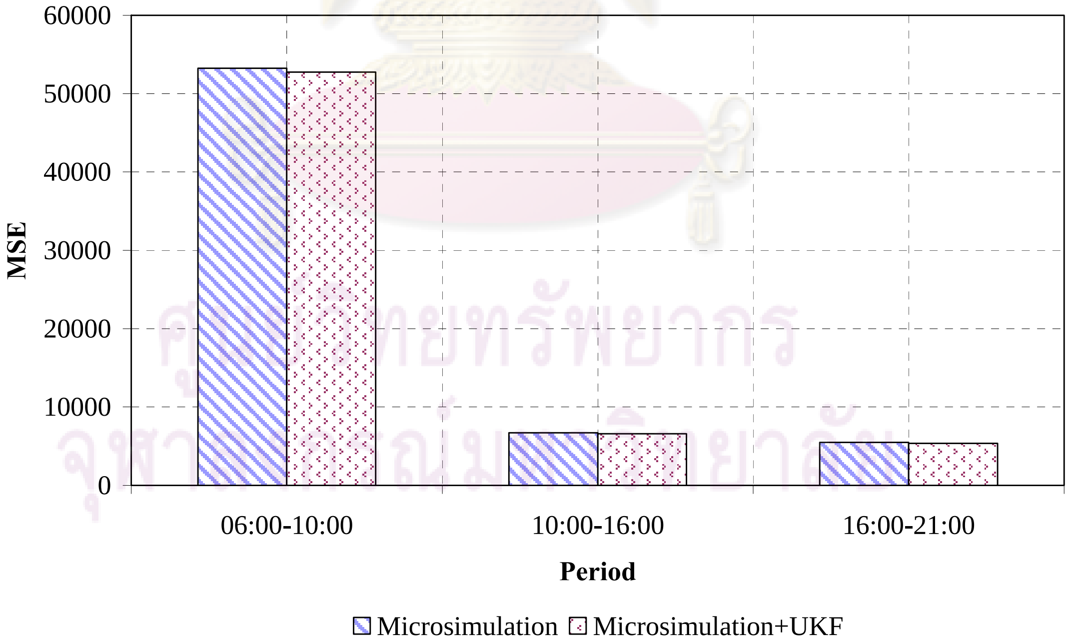


Figure 5-19 Comparison of MSE of Travel Time between Microsimulation and Microsimulation+UKF

Table 5-5 MAPEs Values by Time period from Microsimulation and Microsimulation+UKF (%)

Model	Period		
	06:00 – 10:00	**10:00 – 16:00**	**16:00 – 21:00**
Microsimulation only	28.66	17.78	16.13
Microsimulation+UKF	28.53	17.54	15.67

Table 5-6 MSE Values by Time period from Microsimulation and Microsimulation+UKF

Model	Period		
	06:00 – 10:00	**10:00 – 16:00**	**16:00 – 21:00**
Microsimulation only	53223.43	6713.28	5478.63
Microsimulation+UKF	52739.80	6592.70	5356.91

From Table 5-5, microsimulation model can provided travel time information during period of 06:00 – 10:00, 10:00 – 16:00, and 16:00 – 21:00 with MAPE of 28.66%, 17.78%, and 16.13% respectively. Furthermore, microsimulation with UKF can improve the accuracy of prior estimated travel time information with microsimulation model only. The values of MAPE are 28.53 %, 17.54%, and 15.67% for the three period of time respectively. The feedback estimation using UKF can improve travel time information which prior estimated by microsimulation model with 0.13%, 0.25%, and 0.46% for three periods of time respectively.

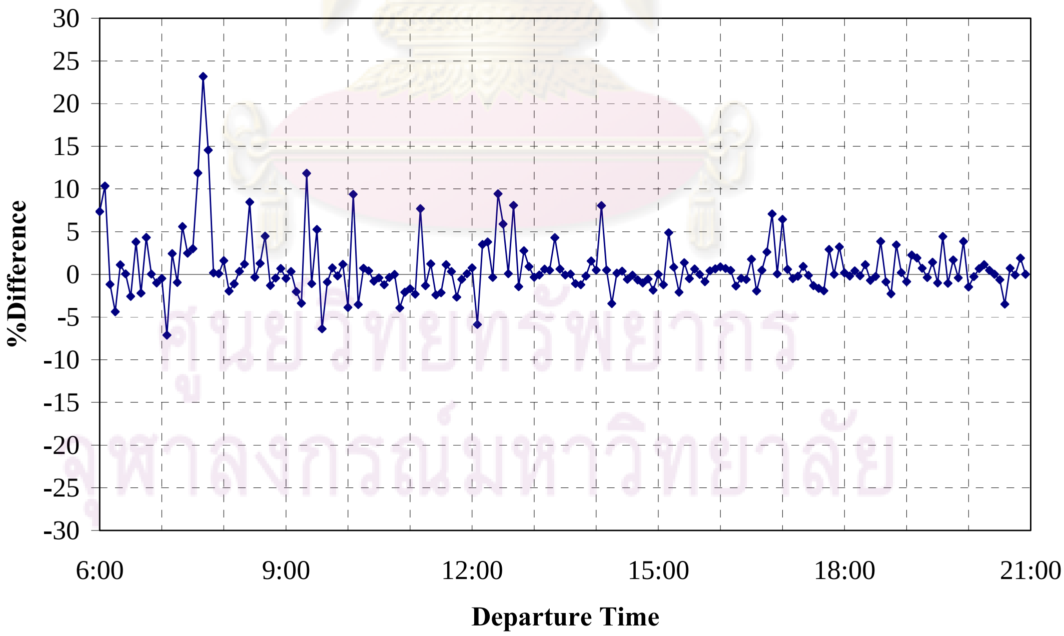


Figure 5-20 Difference of Estimated Travel Time between Microsimulation and Microsimulation+UKF

From Figure 5-20, it shows the difference of estimated travel time between microsimulation and microsimulation with UKF improvement. It is shown that difference of 23% occurs between 07:00 and 08:00. Other differences are in the range of 10%. It can imply that Unscented Kalman Filter was large improved prior estimated travel time by microsimulation model during congested periods which the difference between observed and estimated speed on detector station are large. In contrast, a small improvement during uncongested periods because of the difference between observed and estimated speed on detector station are small.

However, Unscented Kalman Filter can help a bit improvement of the accuracy on travel time provided by microsimulation model. The Unscented Kalman Filter could help a big improvement if the measurement equation is changed to be a travel time instead of point flow and speed. Therefore, probe vehicle data is required in this case in order to receive the observed real-time travel time which it is interest to improve the proposed method in the future study when probe vehicle is available in practice.

5.4 TRAVEL TIME PREDICTION

In this part, short-term travel time prediction was studied relied on estimated travel time provided by microsimulation model and microsimulation with accuracy improvement by Unscented Kalman Filter. The predefined four scenarios were repeated as follows.

- Scenario 1: Travel time prediction using the route travel time which estimated by microsimulation.
- Scenario 2: Travel time prediction using the route travel time which estimated by micosimulation with UKF improvement.
- Scenario 3: Sum of the travel time prediction of estimated travel time using microsimulation by each segment
- Scenario 4: Sum of the travel time prediction of estimated travel time using microsimulation with UKF improvement by each segment.

Due to four scenarios, two simple statistic methods including simple moving average and exponential moving average were applied in order to predict travel time by considered the time series pattern of estimated travel time. The results were shown by each method according to four scenarios.

- ***Simple Moving Average***

Due to the study of applying simple moving average of *N* time steps for predicting travel time, it was found that four scenarios are not show significant difference in the accuracy when compare with observed travel time. The time series data patterns of estimated travel time on Bangkok expressway site was fluctuated along the evaluation period especially during congestion period which time series data pattern is rapidly changed. From 06:00 until 09:00, the estimated travel time on test section was showed positive slope or the travel time was increased due to traffic congestion. From 09:00 until 10:00, the estimated travel time on test section was show negative slope or the travel time was decreased according to the recovery of traffic condition after congestion period. After 10:00 until 21:00, estimated travel time was showed neither positive nor negative slope which can implied that estimated travel time in this period are constant mean with varying noise by discrete time.

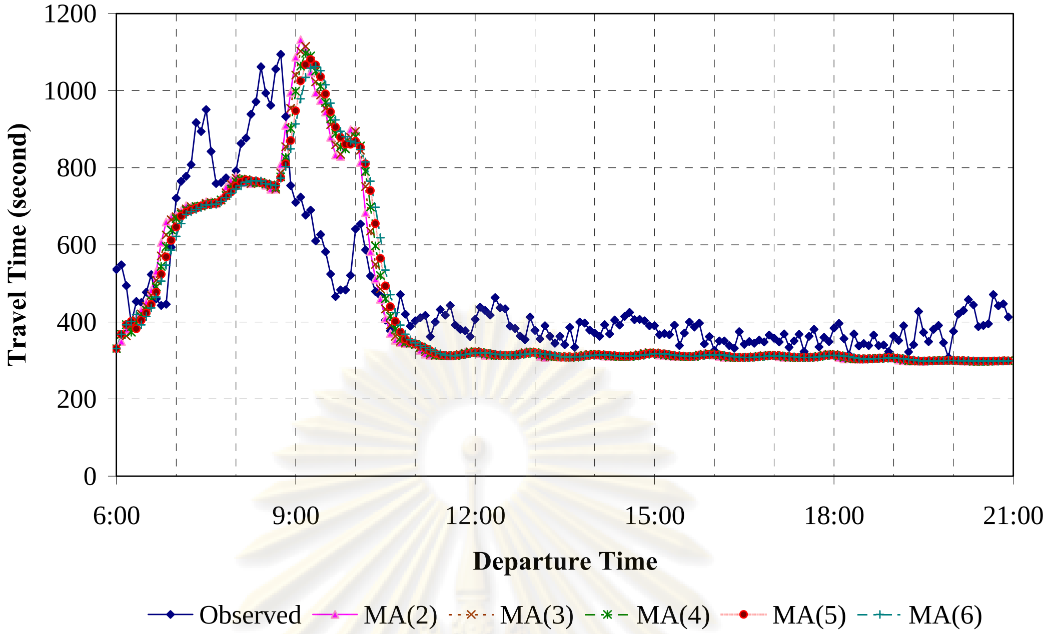
Based on the changing of time series pattern of estimated travel time as earlier mention, the *N* value was highly concerned in order to capture the changing of time series pattern of estimated travel time. The *N* values of 2 until 6 were conducted to determine the proper N value and understand the effect of N value and responsive change of time series pattern of estimated travel time.

Observed travel time was used to compare with four scenarios to show the magnitude of accuracy which mean square error and mean absolute percentage error were calculated and summarize into three period of time which are 06:30 until 10:00, 10:00 until 16:00, and 16:00 until 21:00 as shown in Table 5-7.

Table 5-7 Mean Absolute Percentage Error and Mean Absolute Percentage Error of Four Scenarios

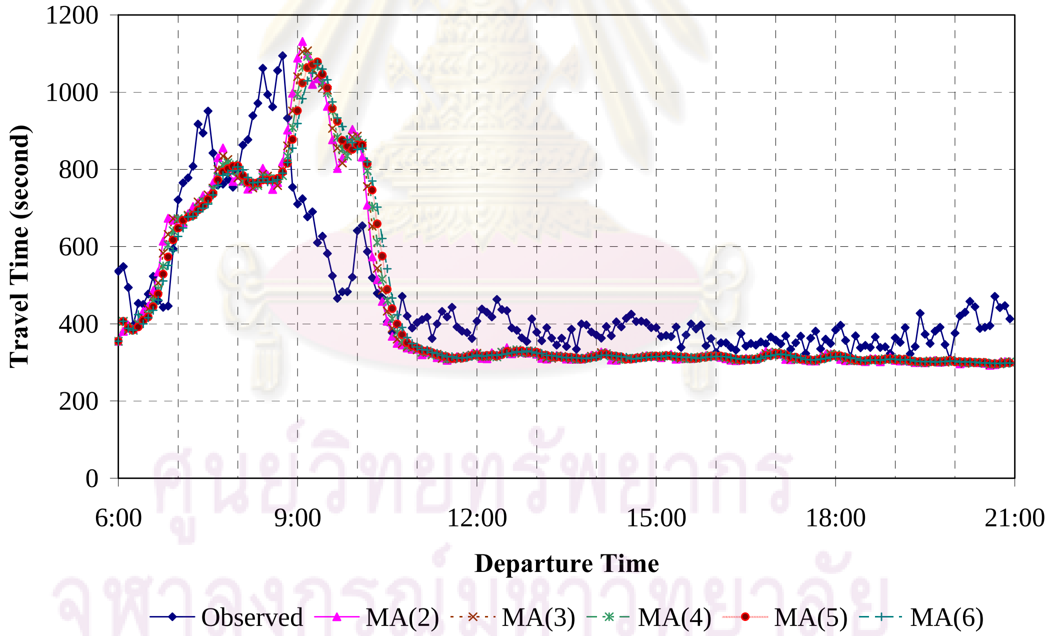
Scenario 1: Microsimulation						
	Mean Square Error			Mean Absolute Percentage Error		
	06:30-10:00	10:00-16:00	16:00-21:00	06:30-10:00	10:00-16:00	16:00-21:00
MA(2)	59386.47	7154.65	5454.21	30.37	18.04	16.09
MA(3)	59628.54	7670.85	5429.37	30.31	18.56	16.06
MA(4)	59823.98	8221.23	5413.27	30.17	19.09	16.01
MA(5)	60211.33	8804.16	5400.25	30.12	19.53	15.97
MA(6)	60801.68	9444.29	5387.75	30.22	20.03	15.93
Scenario 2: Microsimulation+UKF						
	Mean Square Error			Mean Absolute Percentage Error		
	06:30-10:00	10:00-16:00	16:00-21:00	06:30-10:00	10:00-16:00	16:00-21:00
MA(2)	58821.34	7061.98	5305.14	30.52	17.79	15.59
MA(3)	59042.60	7622.96	5275.08	30.44	18.30	15.56
MA(4)	59359.74	8204.69	5259.64	30.12	18.84	15.52
MA(5)	59801.10	8792.36	5241.07	29.95	19.28	15.49
MA(6)	60483.10	9382.65	5220.66	29.70	19.76	15.44
Scenario 3: Microsimulation (by segment)						
	Mean Square Error			Mean Absolute Percentage Error		
	06:30-10:00	10:00-16:00	16:00-21:00	06:30-10:00	10:00-16:00	16:00-21:00
MA(2)	59386.39	7154.79	5454.12	30.37	18.04	16.09
MA(3)	59628.63	7671.01	5429.27	30.31	18.56	16.06
MA(4)	59824.12	8221.43	5413.19	30.17	19.09	16.01
MA(5)	60211.54	8804.39	5400.16	30.12	19.53	15.97
MA(6)	60801.90	9444.54	5387.67	30.22	20.03	15.93
Scenario 4: Microsimulation+UKF (by segment)						
	Mean Square Error			Mean Absolute Percentage Error		
	06:30-10:00	10:00-16:00	16:00-21:00	06:30-10:00	10:00-16:00	16:00-21:00
MA(2)	58820.30	7061.90	5304.90	30.52	17.79	15.59
MA(3)	59041.51	7622.94	5274.85	30.44	18.30	15.56
MA(4)	59358.75	8204.70	5259.39	30.12	18.84	15.52
MA(5)	59800.23	8792.36	5240.79	29.95	19.28	15.48
MA(6)	60482.28	9382.66	5220.38	29.70	19.76	15.44

From Table 5-7, it shows that mean square error and mean absolute percentage error of four scenarios are not significant different. From 06:30 until 10:00, mean square error is increased when the *N* value is increased which the *N* value of two is shown the smallest value of mean square error in every scenarios. From 10:00 until 16:00, mean square error is also increased when the *N* value is increased which the *N* value of two is also shown the smallest value of mean square error in every scenarios. The last period from 16:00 until 21:00 is shown that the mean square error is decreased when the *N* value is increased which the *N* value of six is shown the smallest mean square error based on this analysis. Observed and predicted travel time of four scenarios was illustrated as shown in Figure 5-21 and Figure 5-22.



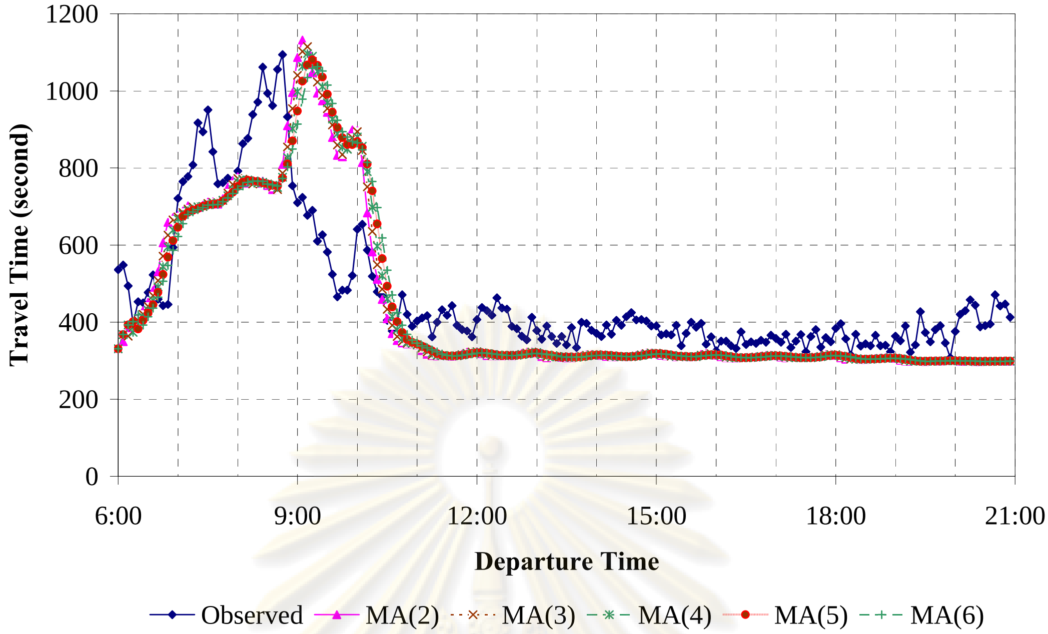
o

(a) Scenario 1

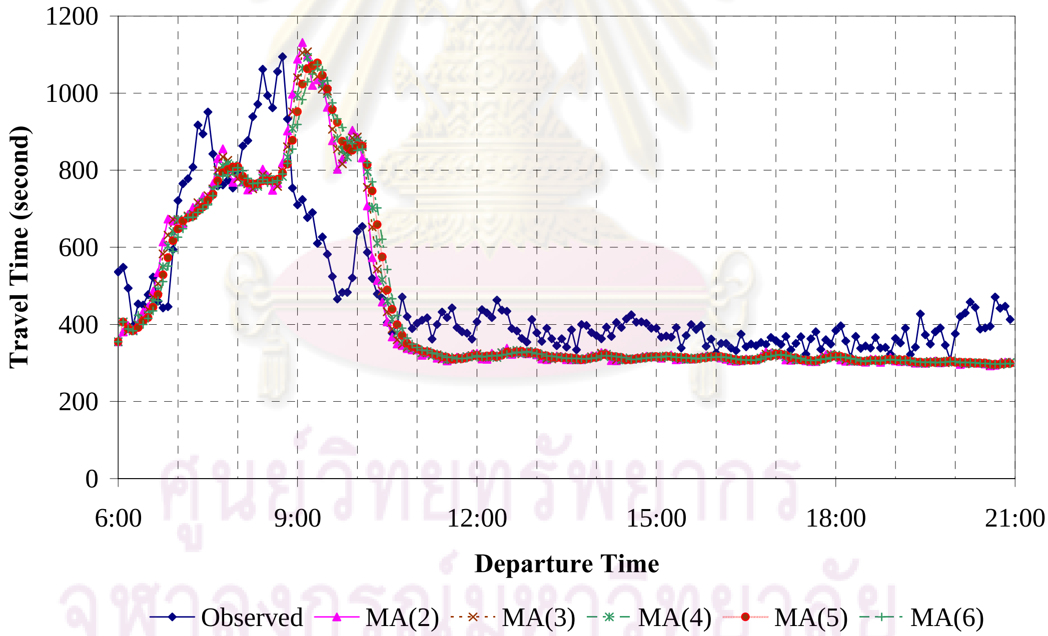


(b) Scenario 2

Figure 5-21 Observed and Predicted Travel Time by Scenario 1 and Scenario 2 using Simple Moving Average



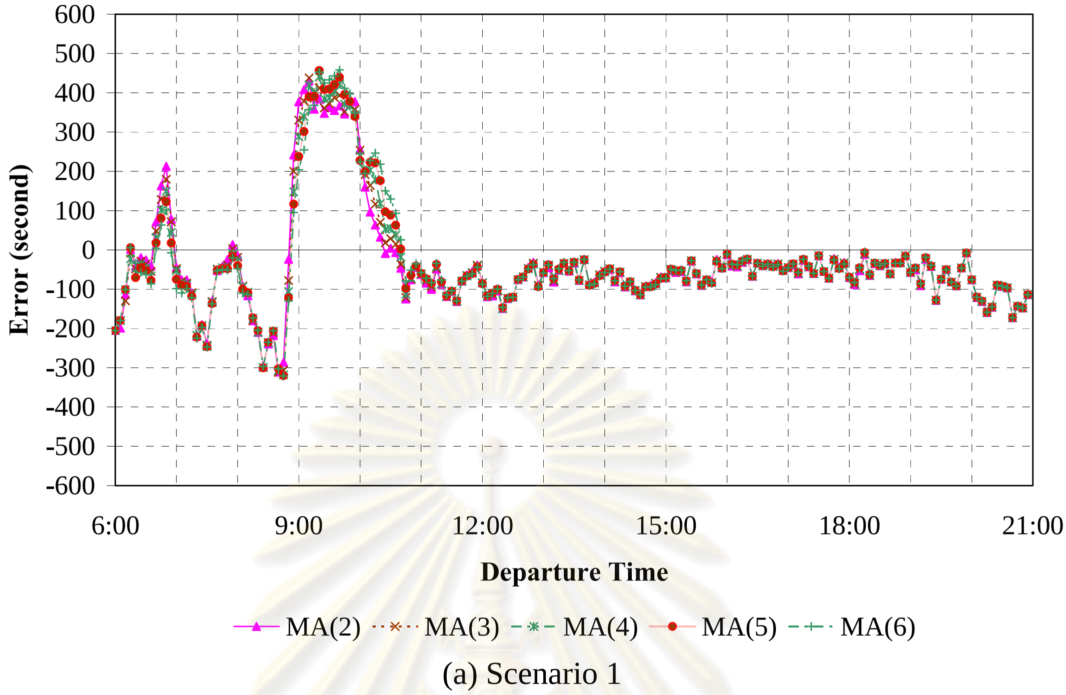
(a) Scenario 3



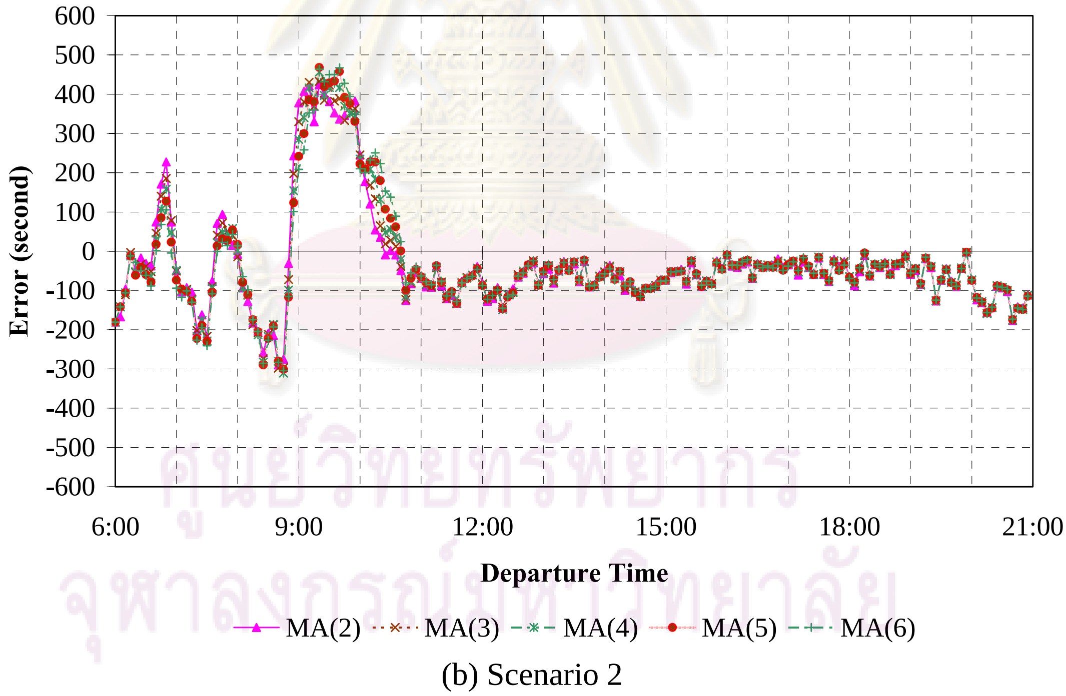
(b) Scenario 4

Figure 5-22 Observed and Predicted Travel Time of Scenario 3 and Scenario 4 using Simple Moving Average

Due to the predicted travel time of four scenarios, the magnitude of prediction error in second were calculated and illustrated in Figure 5-23 and Figure 5-24 to present the variation of prediction error by discrete time series.

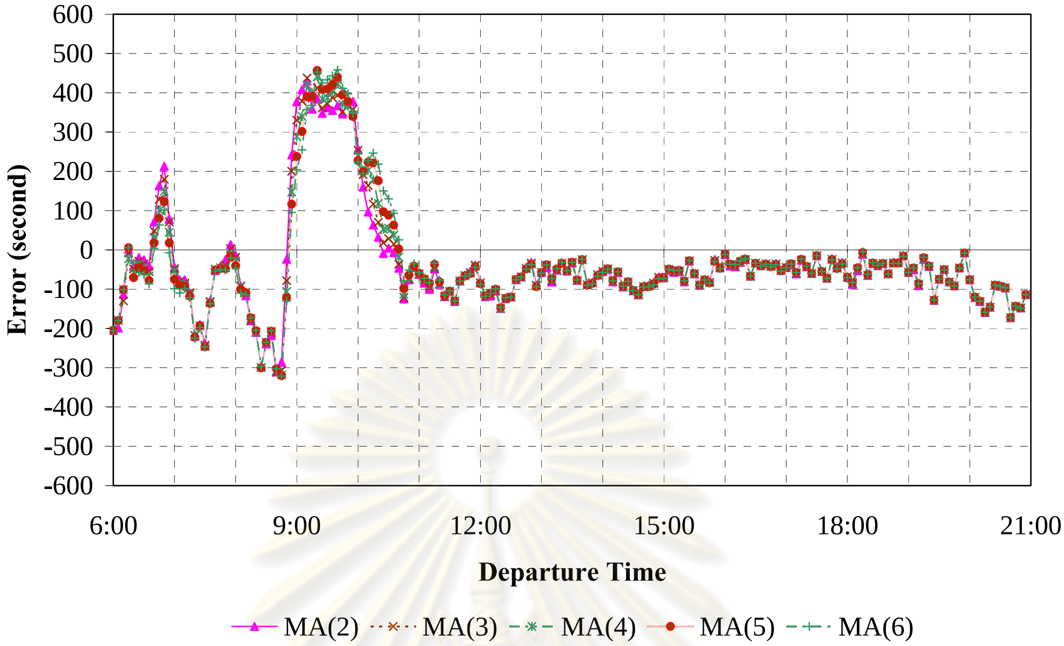


(a) Scenario 1

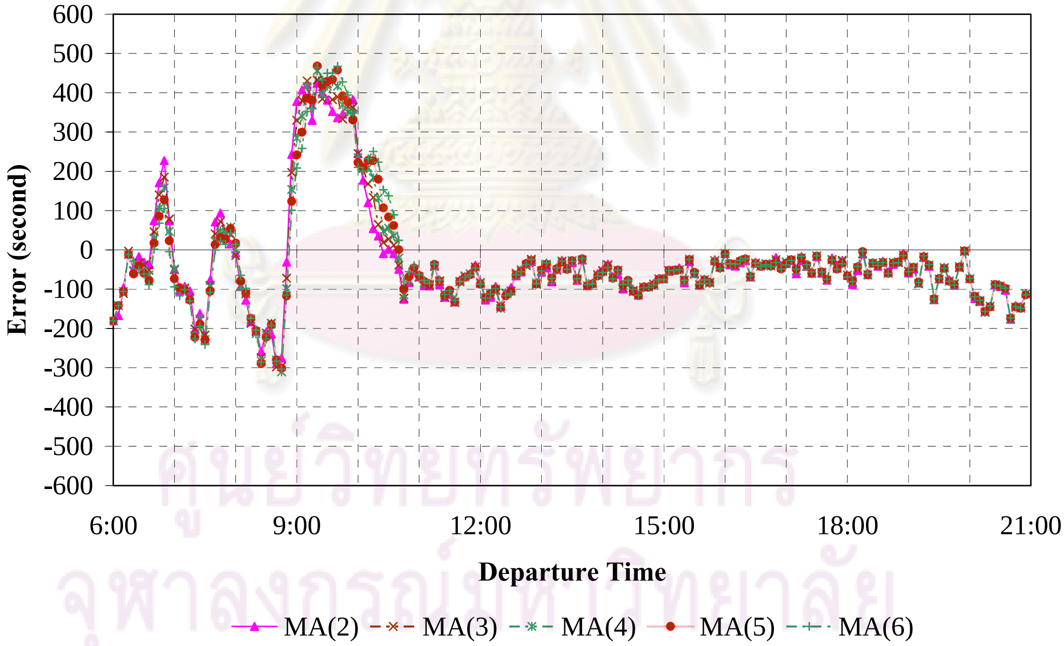


(b) Scenario 2

Figure 5-23 The Travel Time Prediction Error of Scenario 1 and 2



(a) Scenario 3



(b) Scenario 4

Figure 5-24 The Travel Time Prediction Error of Scenario 3 and 4

From Figure 5-23 and Figure 5-24, it shows the variation of prediction error for four scenarios which during the first congested period from 06:00 until 09:00, it is shown that prediction errors are fluctuated from over estimated of 200 second and under estimated of 300 seconds. From 09:00 until 11:00, the traffic congestion is relieved which estimated travel time is decrease across time. The prediction error is over estimated about 400 seconds. After 11:00 until 21:00, the prediction error is under estimated which fluctuated from 0 to 100 seconds. However, prediction error of scenario 2 and 4 about 08:00 are different compared with scenario 1 and 3 which it can implied that individual prediction by each segment provide different prediction value. It can capture individual pattern of estimated travel time in each segment and then reflected the total route travel time differ from the prediction which relied on total of estimated travel time.

From the finding of applied simple moving average for predicting travel time, it can concluded that scenario 4 or the sum of the travel time prediction of estimated travel time using microsimulation with UKF improvement by each segment shows more accuracy than other scenarios by using N value of two is proper for the congested traffic period but N value of six is proper for the uncongested traffic period. The benefit of using scenario 4 could reflect estimated travel time if there are some incidents on any segment of travel route.

- ***Exponential Moving Average***

Due to the finding of applied exponential moving average for predicting travel time using time series data of estimated travel time provided by microsimulation model, the patterns of estimated travel time were as same as earlier described. The optimal α values were analyzed in order to get minimum value of mean square error relied on the first period estimated travel time using SPSS. The mean square error was calculated by compared with observed travel time as shown in Table 5-8.

Table 5-8 Mean Square Error of Predicted Travel Time of Four Scenarios

Period	Scenario 1	Scenario 2	Scenario 3	Scenario 4
06:10-10:00	56049.40	55838.17	56344.08	56482.49
10:00-16:00	7959.15	8071.44	4336.47	4523.74
16:00-21:00	5432.38	5290.63	1606.27	1594.91

From Table 5-8, it shows the mean square error of predicted travel time of four scenarios performed in the same direction that the first period 06:10 until 10:00 has highest value of mean square error, and then it has smallest value of mean square error at the last period 16:00 until 21:00. Due to the mean square error of four scenarios, it can imply that scenario 2 provides smallest value of mean square error compared with others scenario during 06:10 until 10:00. Scenario 3 has smallest value of mean square error compared with others scenario during 10:00 until 16:00. Scenario 4 has smallest value of mean square error compared with others scenarios during 16:00 until 16:00.

In order to illustrate observed and predicted travel time, it was plotted and illustrated as shown in Figure 5-25 and it was calculated to understand the magnitude of prediction error across discrete time as shown in Figure 5-26.

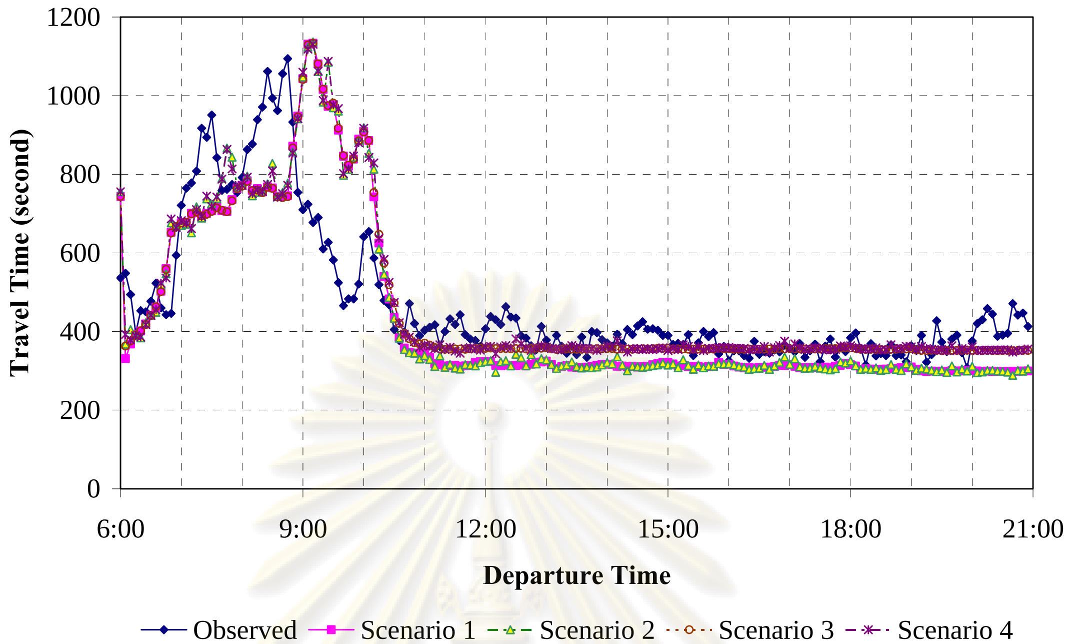


Figure 5-25 Observed and Predicted Travel Time of Four Scenarios using Exponential Moving Average

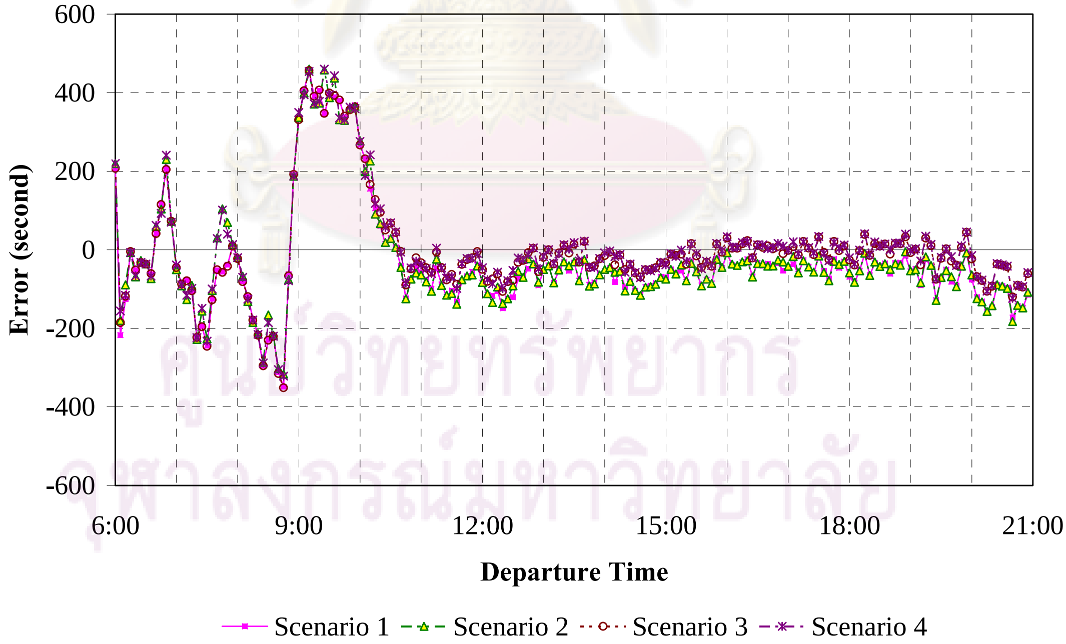


Figure 5-26 The Travel Time Prediction Error of Four Scenarios

From Figure 5-25 and Figure 5-26, it shows that a huge error occur between 09:00 and 10:00 which over estimation of 400 second on every scenarios. The travel time prediction using microsimulation model improved by Unscented Kalman Filter (scenario 4) show less error than others scenario especially after 12:00 which is uncongested period.

In this part, it was found that moving average with two time step or MA(2) provided by microsimulation with Unscented Kalman Filter improvement by segment is shown the lowest mean square error in all periods. The time series of travel time was fluctuated and changed quickly by time discrete.

In the case of travel time prediction using exponential moving average, the microsimulation with Unscented Kalman Filter improvement (scenario 2) show the smallest value of mean square error during 06:10 until 10:00. The travel time prediction using the microsimulation model by segment shows the smallest value of mean square error during 10:00 until 16:00. The microsimulation with Unscented Kalman Filter improvement by segment shows the smallest value of mean square error. Moreover, the exponential moving average shows the performance over the moving average.

CHAPTER 6

CONCLUSION AND RECOMMENDATION

Due to the drawback of using travel time calculation by speed base and flow base for approximating traffic state and travel time information on expressway section using traffic data measured by traffic detection system. The accuracy of estimation is depending on the number of equipped detectors on road section. The more detectors are equipped, the more accuracy can estimate. However, the accuracy improvement by increasing the number of detector is necessary but it requires much more budget. In order to overcome the drawback, this study was proposed an alternative method to estimate traffic state and travel time information for short-term prediction on expressway section. The microscopic traffic simulation software was proposed to be a real-time microsimulation model acting as a traffic state and travel time estimator instead of practical calculation methods or using macroscopic traffic flow model.

In order to develop microsimulation model for traffic state and travel time estimation, four objectives were defined in this study. First, to develop a combinatorial model parameter calibration for microscopic traffic simulation model using genetic algorithm. Second, to develop a framework of real-time traffic state and travel time estimation using microsimulation. Third, to apply Unscented Kalman Filter to improve the accuracy of traffic state and travel time information estimated by on-line microsimulation model. Fourth, to study short-term prediction for OD travel time information.

In order to accomplish the objectives, three modules were designed according to four objectives which three modules were as follows.

- Development of microsimulation model for real-time traffic state and travel time estimation.
- Development of real-time traffic state and travel time estimation using microsimulation model.
- Study short-term travel time prediction.

First module, the development of microsimulation model for real-time traffic state and travel time estimation consist of two sub module inside which were the microsimulation modeling and model parameters calibration. In this study, microsimulation modeling did not strict to any software package of microscopic traffic simulation. Any software can employ to use as an on-line microsimulation model if it has the capability to operate as on-line estimator. For the model parameters calibration, genetic algorithm was introduced in this study to calibrate model parameters which the further development for on-line calibration is considered.

Second module, the development of real-time traffic state and travel time estimation using microsimulation model has two sub modules. The first sub module was the using microsimulation only to estimate traffic state and travel time. Three conventional methods conducted in practices which are the methods using for approximating link speed based on traffic speed measured from upstream and downstream detectors. Three conventional methods were average, weighted average, and San Antonio which it was compared with the estimated travel time provided by microsimulation model. The comparison of conventional methods and microsimulation model were presented to understand the performance in order to estimate travel time on both uncongested and congested traffic condition on expressway corridor. In order to enhance the accuracy of traffic state and travel time information which prior estimated using microsimulation model, the accuracy improvement using feedback estimation with Unscented Kalman Filter was developed in order to give posterior estimate traffic state and travel time information. Traffic state and travel time information was posterior estimated using virtual and observed traffic speed and traffic flow that were measured from traffic detectors both simulation model and actual expressway. The estimated travel time using microsimulation only and microsimulation with Unscented Kalman Filter improvement were compared in order to present how much the Unscented Kalman Filter can improve the accuracy.

The final module, the study short-term travel time prediction was introduce simple methods which the main considerations were easy to implement and proper with the series data of estimated travel time provided by microsimulation model and microsimulation with Unscented Kalman Filter improvement. Two simple methods are simple moving average and exponential moving average. Four scenarios were designed for experimental analysis in order to determine the suitable approach and method to use for predicting short-term travel time. The predefined four scenarios were designed as follows.

- Scenario 1: Travel time prediction using the route travel time which estimated by microsimulation.
- Scenario 2 Travel time prediction using the route travel time which estimated by micosimulation with UKF improvement.
- Scenario 3 Sum of the travel time prediction of estimated travel time using microsimulation by each segment
- Scenario 4 Sum of the travel time prediction of estimated travel time using microsimulation with UKF improvement by each segment.

Due to the three main modules, five parts of experiment were analyzed in order to accomplish the objectives of this study were as follows

- Combinatorial model parameter calibration using genetic algorithm.
- Comparison of link speed estimation based on point detection system on expressway
- Real-time traffic state and travel time estimation using microsimulation.
- Improvement of microsimulation by feedback estimation using Unscented Kalman Filter
- Study short-term travel time prediction.

The conclusion and recommendation of five experiments were discussed as follows.

- **Combinatorial Model Parameters Calibration using Genetic Algorithm for Microscopic Traffic Simulation Model**

Two key model parameters including mean target headway and mean driver reaction time were optimized to yield the optimal parameter calibration. The calibration used genetic algorithm instead of conventional model parameters calibration procedure. Matsubara line on Hanshin expressway in Japan was selected as the site study and this section was modeled on PARAMICS microsimulation suite. The calibration process using genetic algorithm optimizer and PARAMICS microsimulation suite could produce simulated traffic outputs closely corresponding with the observed traffic data although only 20 generations of genetic algorithm process were conducted in this study. The MAPE could be more improved with additional generations of genetic algorithm process.

However, this study selected only two key parameters of several model parameters that PARAMICS microsimulation allow users to readjust to yield the best fit with local conditions. The better fit to the reality should be accrued when calibrating all these parameters. Therefore, it is not always true that simulated traffic model can provided goodness of fit when adjusted only two model parameters as shown in this study.

For the future study, additional model parameters should be considered in order to find the optimal combination of model parameters to get simulation model closest to the actual traffic. The fully automatic process of genetic algorithm optimizer would be developed with several genetic algorithm types, real value representative, others selection method, different crossover and mutation rate. The investigation on these optimization procedures could lead to higher computation performance. Moreover, different fitness function might be tested to get several sets of combinatorial model parameters. The validation with different sets of observed traffic data should be processed when available, especially travel time data. Moreover, automated parameters optimization concept could be used to dynamically readjust the simulation model when consistency checking module could check the excess error between observed and simulated data to make the simulation model consistently close to the real network throughout the operation. Moreover, the study of on-line model parameters calibration using genetic algorithm is challenge in the future study in order to calibrate on demand or predefined criteria on consistency checking module which application programming interface (API) is required.

- **Evaluation of Link Speed Estimation based on Point Detection System on Expressway**

Traffic speed on expressway especially link speed is an important traffic parameter that traffic operators are required. Traffic detectors such as loop detector, ultrasonic, infrared, and video image processing are conducted on expressway operation system in many countries. There are several limitations of this equipment such as detector station spacing, detector placement, and aggregation time interval. Traffic analyzers should realize these limitations when analyze traffic parameters using traffic data measured by these traffic detection system. Especially, simple methods that are normally used to estimate link speed using upstream and downstream speeds measured on both side of the links.

The findings in this study illustrate that the weakness of using the three simple methods to estimate link speed on expressway are mainly large error under congested condition but it is quite well performed under uncongested condition. Most of estimated link speeds during congestion period are overestimated. The effect of detector spacing and placement might be the serious factors that impact with the reliability of estimated link speed using simple methods. According to the case study, the length of the 4^{th} link is too long to conduct the spot speed measured from upstream and downstream detector stations for representing link speed. However, average, weighted average, and San Antonio method have their own limitation based on the calculation because it can not provided estimated link speed less than the value of traffic speed measured on upstream or downstream detector while simulated link speed is smaller. It means that conventional methods can not capture a good estimated link speed which also carries to the error on the travel time estimation.

For the future study, the improvement of speed estimation method could improve the reliability of estimated link speed based on upstream and downstream detector data which normally and presently equipped on expressways. Improved methods should be uncomplicated to implement. However, detector density improvement is the suitable solution but it is a huge cost to invest on infrastructure. The benefit of using these kinds of traffic data and investment cost that expressway operators have to be traded-off. Another solution to improve the reliability of estimated link speed is the application of intelligent transportation system such as automatic vehicle location (AVL) and automatic vehicle identification (AVI) which is vehicle equipped GPS unit and toll tag readers in case of expressway. There are several techniques to integrate these ITS data with the existing detector to improve the reliability of estimated link speed.

- **Microsimulation Model for Traffic State and Travel Estimation**

Travel time information on expressway is an important piece of traffic parameters that are required by operators and travelers. In practice, traffic detectors such as loop detector, ultrasonic, infrared, and video image processing are employed on expressways in many countries. There are several limitations of these kinds of equipment such as detector station spacing, detector placement, and aggregation time interval. Traffic analyzers should realize these limitations when analyzing traffic parameters using traffic data measured from these traffic detection arrangements. The travel time estimation can be inaccurate when it is estimated on a segment with low density of point detectors, or long segment length, using conventional methods that are normally used for estimating segment speed using upstream and downstream speeds measured at both ends of the segment.

On-line microsimulation is found to be a good method for estimating travel time. The findings in this study illustrate that the on-line microsimulation model is quite well performed. Nonetheless, a closer look at the estimation shows that this method gives under and over estimation during morning-peak period and under estimation in both off-peak and evening-peak period. MAPE values are calculated for three periods which are 28.66%, 17.65%, and 16.13% respectively. These values can be compared with those from three conventional methods; average, weighted average, and San Antonio. MAPE values on three time periods imply that San Antonio is the most accurate method during both evening-peak and off-peak-period with a MAPE value lower than 20%. Microsimulation is shown the best performance for estimating travel time during evening-peak period when San Antonio has a huge over estimation in this period while on-line microsimulation model, average, and weighted average are more accurate.

Moreover, it could be interpreted that the estimated travel time using microsimulation is the most reliable method, compared to the conventional methods in this study. MAPE value of travel time estimated by microsimulation is comparatively low in the first period and then the smallest in the third period while the values of MAPE by San Antonio vary by time periods and are more unpredictable. The algorithm of San Antonio is highly sensitive because it relies on the minimum value of measured traffic speeds between upstream and downstream detector station. Travel time estimation by San Antonio is easily over estimated when traffic speed decreases especially at the location where detector station is located close to merging area. Spot speeds at ends of the segment are not a good proxy of a link speed, and thus resulting in less accurate travel time. However, detector density improvement is another suitable solution but it is a huge cost to invest on infrastructure. The benefit of using these kinds of traffic data and investment cost that expressway operators have to be traded-off.

For the future study, the estimation of travel time by on-line microsimulation should be further improved by integrating dynamic feedback estimation using filtering techniques and by model refinement on model parameters for specific periods. The improved methods should be uncomplicated to implement in practice. Furthermore, the study to improve the reliability of estimated travel time by integrated intelligent traffic detector such as automatic vehicle location (AVL) and automatic vehicle identification (AVI). Traffic data gathering by these detectors could be combined with on-line microsimulation for increasing the accuracy of traffic state and also travel time information.

- **Feedback Estimation using Uncented Kalman Filter to Enhance Traffic Information provided by Microsimulation Model**

From the numerical result, it was shown that feedback estimation using Unscented Kalman Filter can improve the accuracy of travel time information which prior estimated by microsimulation. MAPE are 28.53 %, 17.54%, and 15.67% by three period of time respectively. It could be said that feedback estimation using UKF can improve travel time information which prior estimated by microsimulation model with 0.13%, 0.25%, and 0.46% at three period of time respectively on Bangkok Expressway site study which have low density of traffic detector stations.

For the direction of future study, the accuracy of travel time information could be improved if mobile traffic data such as GPS probe data or cellular probe data are available in real-time basis. It could be used as measurement variables in order to improve prior estimated travel time estimation provided by microsimulation model. It maybe increases the accuracy of travel time information on expressway section. However, this mobile traffic data is unavailable in practice on Bangkok Expressway in Thailand.

- **Travel Time Prediction**

In this study, travel time prediction based on the time series of travel time which provided by difference scenarios were analyzed using difference prediction methods. Two prediction methods were moving average and exponential moving average which are the simple and easy to implement on existing time series data that provided by microsimulation model. It was found that moving average with two time step or MA(2) provided by microsimulation with Unscented Kalman Filter improvement by segment is shown the lowest mean square error in all periods. The time series of travel time was fluctuated and changed quickly by time discrete.

In the case of travel time prediction using exponential moving average, the microsimulation with Unscented Kalman Filter improvement (scenario 2) show the smallest value of mean square error during 06:10 until 10:00. The travel time prediction using the microsimulation model by segment shows the smallest value of mean square error during 10:00 until 16:00. The microsimulation with Unscented Kalman Filter improvement by segment shows the smallest value of mean square error. Moreover, the exponential moving average shows the performance over the moving average.

For the future study, the historical travel time should be measured in order to under stand the seasonal or pattern of travel time which it could conduct to develop accurate travel time prediction model in both short-term and long-term basis. The long-term travel time prediction is very importance for advance traffic management system that traffic operator can make decision on the traffic management plan to operate the expected traffic state which will occur in the near future.

Even the microsimulation model with Unscented Kalman Filter is well performed but it was develop based on the traffic characteristic on expressway corridor. If the application of large network is required, the advance origin and destination flow estimation and also traffic assignment should be considered which is more complicated and challenge for the future study.

REFERENCES

Anderson, J. and Bell, M. (1998) Travel Time Estimation in Urban Road Networks. *Proceeding of IEEE Conference.*

Billi, M., Ambrosino, G. and Boero, M. (1994) *Artificial Intelligent Applications to Traffic Engineering*, VSP BV, AH Zeist.

Bob Rupert, et al. (2003) Traveler Information Systems in Europe. Federal Highway Administration (FHWA), U.S. Department of Transportation.

Bureau of Public Road (1964) Traffic Assignment Manual. U.S. Dept. of Commerce, Urban Planning Division, Washington D.C.

Chen, M. and Chien, S. I. J. (2000) Determining the Number of Probe Vehicles for Freeway Travel Time Estimation using Microscopic Simulation. *Transportation Research Board 79th annual meeting.* Washington D.C.

Cheu, R.-L., et al. (1998) Calibration of FRESIM for Singapore Expressway Using Genetic Algorithm. *Journal of Transportation Engineering*, 124, 526-535.

Chien, S. I.-J. and Kuch, C. M. (2003) Dynamic travel time prediction with real time and historical data. *Journal of Transportation Engineering*, 129, 608.

Chu, L., Liu, H. X., Oh, J.-S. and Recker, W. (2004) A Calibration Procedure for Microscopic Traffic Simulation. *The 83rd TRB Annual Meeting.* Washington, D.C., Transportation Research Board.

Chu, L. and Recker, W. (2004) Micro-simulation Modeling Approach to Applications of On-line Simulation and Data

Fusion. In California Path Atms Center, I. O. T. S., University of California at Irvine (Ed.).

Coifman, B. (2001) Improved velocity estimation using single loop detectors. *Transportation Research Part A: Policy and Practice*, 35, 863-880.

Coifman, B. (2003) Estimating density and lane inflow on a freeway segment. *Transportation Research Part A: Policy and Practice*, 37, 689-701.

Coifman, B., Dhoorjaty, S. and Lee, Z.-H. (2003) Estimating median velocity instead of mean velocity at single loop detectors. *Transportation Research Part C: Emerging Technologies*, 11, 211-222.

Cunningham, S. I.-J., Barton, T. and Austroads (1995) Design Vehicles and Turning Path Templates. IN AUSTROADS, A. (Ed.).

D'este, G. M., Zito, R. and Taylor, M. A. P. (1999) Using GPS to Measure Traffic System Performance. *Computer-Aided Civil and Infrastructure Engineering*, 14, 255-265.

Dailey, D. J. (1999) A statistical algorithm for estimating speed from single loop volume and occupancy measurements. *Transportation Research Part B: Methodological*, 33, 313-322.

Dion, F. and Rakha, H. (2006) Estimating dynamic roadway travel times using automatic vehicle identification data for low sampling rates. *Transportation Research Part B: Methodological*, 40, 745-766.

Dowling, R., Skabardonis, A. and Alexiadis, V. (2004) Traffic Analysis Toolbox Volume III: Guidelines for Applying Traffic Microsimulation Software. IN U.S. Department of Transportation, F. H. A. (Ed.). FHWA COTR: John Halkias, Office of Transportation Management.

Fries, R., Inamdar, I., Chowdhury, M., Taaffe, K. and Ozbay, K. (2007) Feasibility of Traffic Simulation for Decision Support in Real-Time Regional Traffic Management. *Transportation Research Record: Journal of the Transportation Research Board*, 2035, 169-176.

Grol, V., H.J.M., Danech-Pajouh, M., Manfredi, S. and Whittaker, J. (1999) DACCORD: On-line Travel Time Prediction. *World Conference on Transport Research Society.*

Guo, J., Williams, B. and Smith, B. (2008) Data Collection Time Intervals for Stochastic Short-Term Traffic Flow Forecasting. *Transportation Research Record: Journal of the Transportation Research Board*, 2024, 18-26.

Harvey, A. C. (1990) *Forecasting, structural time series models and the kalman filter*, Cambridge University Press.

Hawkins, R., and Stopher, P. R. (2004) *Collecting data with GPS : those who reject, and those who receive / by Renee Hawkins & Peter R Stopher*, [Sydney] :, Institute of Transport Studies, the University of Sydney and Monash University.

Hellinga, B. R. (2002) Improving Freeway Speed Estimates from Single-Loop Detectors. *Journal of Transportation Engineering*, 128, 58-67.

Ishak, S. & Al-deek, H. (2002) Performance Evaluation of Short-Term Time-Series Traffic Prediction Model. *Journal of Transportation Engineering*, 128, 490-498.

Ishizaka, T., Fukuda, A. and Narupiti, S. (2005) Evaluation of Probe Vehicle System by using Micro-Simulation Model and Cost Analysis. *Journal of Eastern Asia Society for Transportation Studies*, Volume 6, 2502-2514.

Julier, S. J. and Uhlmann, J. K. (2004) Unscented filtering and nonlinear estimation. *Proceedings of the IEEE*, 92, 401-422.

Juri, N. R., Unnikrishnan, A. and Waller, S. T. (2007) Integrated Traffic Simulation - Statistical Analysis Framework for Online Prediction of Freeway Travel Time. *Transportation Research Record*, 2039, 24 - 31.

Karl, C. A. and Trayford, R. S. (1999) Delivery of real-time and predictive travel time information : experiences from a Melbourne trial. *The 6th World Congress on Intelligent Transport System.* Totonto, Canada.

Kisgyorgy, L. and Rilett, L. R. (2002) Travel Time Prediction by Advanced Neural Network. *Periodica Polytechnica Civil Engineering.*

Klein, L. A., Mills, M. K. and Gibson, D. R. P. (2006) Traffic Detector Handbook: Third Edition. IN U.S. DEPARTMENT OF TRANSPORTATION, F. H. A. (Ed.).

Kothuri, S. M., Tufte, K., Hagedorn, H., Bertini, R. L. and Deeter, D. (2007) Survey of Best Practices in Real Time Travel Time Estimation and Prediction. *Compendium of Technical Papers, Institute of Transportation Engineers, District 6 Annual Meeting.* Portland, Oregon.

Kothuri, S. M., Tufte, K. A., Ahn, S. and Bertini, R. L. (2007) Using Archived ITS Data to Generate Improved Travel Time Estimates. *The 86th Annual Meeting of the Transportation Research Board.* Washington D.C.

Lee, D.-H. and Yang, X. (2001) Parameter Calibration for PARAMICS Using Genetic Algorithm. *The 80th TRB Annual Meeting.* Washington, D.C., Transportation Research Board.

Li, L., Liu, B. and Mizuta, H. (2009) Travel time prediction by combining real-time and statistical data according to congestion level. *16th World Congress and Exhibition on Intelligent Transport Systems and services.* Stockholm.

Liang, Z., Jian-Min, X. and Ling-Xiang, Z. (2005) Arterial speed studies with taxi equipped with global positioning receivers as probe vehicle. *Wireless Communications, Networking and Mobile Computing, 2005. Proceedings. 2005 International Conference on.*

Long Cheu, R. and Chi Wen Tay, G. (2004) Sampling Strategies for Probe-Vehicle-Based Freeway Incident Detection Algorithms. *Transportation Research Record: Journal of the Transportation Research Board*, 1867, 80-88.

Long Cheu, R., Xie, C. and Lee, D.-H. (2002) Probe Vehicle Population and Sample Size for Arterial Speed Estimation. *Computer–Aided Civil and Infrastructure Engineering*, 17, 53-60.

Lum, K. M., Fan, H. S. L., Lam, S. H. and Olszewski, P. (1998) Speed-Flow Modeling of Arterial Roads in Singapore. *Journal of Transportation Engineering*, 124, 213-222.

Ma, J., Dong, H. and Zhang, H. (2007) Calibration of Microsimulation with Heuristic Optimization Methods. *Transportation Research Record: Journal of the Transportation Research Board*, 1999, 208-217.

Ma, T. and Abdulhai, B. (2002) Genetic Algorithm-Based Optimization Approach and Generic Tool for Calibrating Traffic Microscopic Simulation Parameters. *Transportation Research Record: Journal of the Transportation Research Board*, 1800, 6-15.

Mcnally, M. G. and Oh, J.-S. (2002) Technical Memorandam on Calibration / Validation of Traffic Microsimulation Models. IN (OCTA), O. C. T. A. (Ed.).

Mihaylova, L., Boel, R. and Hegyi, A. (2007) Freeway traffic estimation within particle filtering framework. *Automatica*, 43, 290-300.

Nanthawichit, C. (2003) Dynamic Estimation of Traffic States on Expressway for Advanced Traffic Surveillance Systems. *Transportation and Traffic Systems Engineering, Graduate School of Engineering.* Hokkaido, Hokkaido University.

Nour-Eddin, E. F. (2005) Bayesian and Evidential Approaches for Traffic Data Fusion: Methodological Issues and Case Study. *Transportation Research Board 85th Annual Meeting* Washingtin D.C.

Oh, C., Ritchie, S. and Oh, J.-S. (2005) Exploring the Relationship Between Data Aggregation and Predictability to Provide Better Predictive Traffic Information. *Transportation Research Record: Journal of the Transportation Research Board*, 1935, 28-36.

Pan, C., Lu, J., Wang, D. and Ran, B. (2008) Data Collection Based on Global Positioning System for Travel Time and Delay for Arterial Roadway Network. *Transportation Research Record: Journal of the Transportation Research Board*, 2024, 35-43.

Park, B. and Qi, H. (2006) Microscopic Simulation Model Calibration and Validation for Freeway Work Zone Network – A Case Study of VISSIM. *Proceeding of the IEEE ITSC 2006, IEEE Intelligent Transportation Systems Conference.* Toronto, Canada.

Park, D. and Rilett, L. R. (1999) Forecasting Freeway Link Travel Times with a Multilayer Feedforward Neural Network. *Computer-Aided Civil and Infrastructure Engineering,* 14, 357-367.

Petty, K. F., et al. (1998) Accurate estimation of travel times from single-loop detectors. *Transportation Research Part A: Policy and Practice,* 32, 1-17.

Pushkar, A., Hall, F. L. and Acha-Daza, J. A. (1994) Estimation of Speeds from Single Loop Freeway Flow and Occupancy Data Using Cusp Catastrophe Model. *Transportation Research Record,* 1457.

Remy, J. G. (2001) Computing travel time estimates from GSM signalling messages: the STRIP project. *Intelligent Transportation Systems, 2001. Proceedings. 2001 IEEE.*

Schultz, G. G. and Rilett, L. R. (2004) Analysis of Distribution and Calibration of Car-Following Sensitivity Parameters in Microscopic Traffic Simulation Models. *Transportation Research Record, Journal of Transportation Research Board,* 1876, 41 - 51.

Sisiopiku, V. P., Rouphail, N. M. and Tarko, A. (1994) Estimating Travel Time on Freeway Segments. IN URBAN TRANSPORTATION CENTER, U. O. I. A. C. (Ed.).

Smith, B. L. and Ulmer, J. M. (2003) Freeway Traffic Flow Rate Measurement: Investigation into Impact of Measurement Time Interval. *Journal of Transportation Engineering,* 129, 223-229.

Taylor, M. A. P., Bonsall, P. W. and Young, W. (2000) Data on Travel Times. In Understanding Traffic Systems: Data, Analysis, and Presentation. Ashgate Publishing Ltd.

Taylor, M. A. P., Woolley, J. E. and Raicu, R. (2000) Review of RACV Travel Time Monitoring Program. Transportation Systems Centre, University of South Australia.

Taylor, M. A. P., Woolley, J. E. and Zito, R. (2000) Integration of the global positioning system and geographical information systems for traffic congestion studies. *Transportation Research Part C: Emerging Technologies,* 8, 257-285.

Toledo, T., Ben-Akiva, M., Darda, D., JHA, M. and Koutsopoulos, H. (2004) Calibration of Microscopic Traffic Simulation Models with Aggregate Data. *Transportation Research Record: Journal of the Transportation Research Board,* 1876, 10-19.

Toledo, T., et al. (2003) Calibration and Validation of Microscopic Traffic Simulation Tools: Stockholm Case Study. *Transportation Research Record: Journal of the Transportation Research Board,* 1831, 65-75.

Turner, S. M., Eisele, W. L., Benz, R. J. and Holdener, D. J. (1998) Travel Time Data Collection Handbook. IN U.S. DEPARTMENT OF TRANSPORTATION, F. H. A. (Ed.). Texas Transportation Institute.

Van Lint, J. W. C. (2008) Online Learning Solutions for Freeway Travel Time Prediction. *Intelligent Transportation Systems, IEEE Transactions on,* 9, 38-47.

Vanajakshi, L. D., Williams, B. M. and Rilett, L. R. (2009) Improved Flow-Based Travel Time Estimation Method from Point Detector Data for Freeways. *Journal of Transportation Engineering,* 135, 26-36.

VICS (1995) Vehicle Information and Communiation System (VICS).

Wang, Y. and Nihan, N. (2000) Freeway Traffic Speed Estimation with Single-Loop Outputs. *Transportation Research Record: Journal of the Transportation Research Board,* 1727, 120-126.

Wang, Y. and Nihan, N. L. (2003) Can Single-Loop Detectors Do the Work of Dual-Loop Detectors? *Journal of Transportation Engineering,* 129, 169-176.

Wang, Y., Papageorgiou, M. and Messmer, A. (2007) Real-Time Freeway Traffic State Estimation Based on Extended Kalman Filter: A Case Study. *TRANSPORTATION SCIENCE,* 41, 167-181.

Wei, C., Iroyo, T. and Asakura, Y. (2007) Short-Term Travel Time Prediction using Linear Model. *Journal of Eastern Asia Society for Transportation Studies,* Volume 7, 2219-2229.

Welch, G. and Bishop, G. (2006) An Introduction to the Kalman Filter. Department of Computer Science, University of North Carolina at Chapel Hill.

Wright, A. H. (1991) Genetic Algorithm for Real Parameter Optimization. *Foundations of Genetic Algorithms.* Morgan Kaufmann.

Wu, C. F. (2001) The Study of Vehicle Travel Time Estimation using GPS. *Department of Transportation Technology&Management.* National Chiao Tung University, Taipei.

Yanying, L. and Mcdonald, M. (2002) Link travel time estimation using single GPS equipped probe vehicle. *Intelligent Transportation Systems, 2002. Proceedings. The IEEE 5th International Conference on.*

Ye, Z., Zhang, Y. and Middleton, D. (2006) Unscented Kalman Filter Method for Speed Estimation Using Single Loop Detector Data. *Transportation Research Record: Journal of the Transportation Research Board,* 1968, 117-125.

Yu, S.-H. (2002) On the Study of Automatic Traffic Surveillance System. *Electrical Engineering.* Yuan-Ze University, Chungli.

Yuh-Horng, W., Tsu-Tian, L. and Hsun-Jung, C. (2005) Hybrid models toward traffic detector data treatment and data fusion. *Networking, Sensing and Control, 2005. Proceedings. 2005 IEEE.*

Zhang, X. and Rice, J. A. (2003) Short-term travel time prediction. *Transportation Research Part C: Emerging Technologies,* 11, 187-210.

Zhang, Y. and Xie, Y. (2008) Forecasting of Short-Term Freeway Volume with v-Support Vector Machines. *Transportation Research Record: Journal of the Transportation Research Board,* 2024, 92-99.

Zito, R. and Taylor, M. A. P. (1994) The Uses of GPS in Travel Time Surveys. *Traffic Engineering and Control.*

BIOGRAPHY

Piti Rotwannasin was born on January 5, 1978 in Bangkok, the capital city of Thailand. He finished his undergraduate study majoring in Transportation Engineering from Suranaree University of Technology, Nakornratchasrima, Thailand in 2000. After graduation, he worked at Bureau of Traffic Safety, Department of Highways, Ministry of Transportation, Thailand.

In 2003, he continued on graduated study at Civil Engineering Department, Chulalongkorn University and received Master's degree in Civil Engineering majoring in Transportation Engineering in 2006. His Master's thesis was titled as "Impact of Truck Lane Restriction on Highway Traffic" under supervision of Associate Professor Dr. Kasem Choocharukul.

In 2006, he received scholarship from the Office of the Higher Education Commission, Ministry of Education, Thailand to study degree of Doctor of Philosophy program in Civil Engineering, Department of Civil Engineering, Faculty of Engineering, Chulalongkorn University. After graduation, he went to compensate scholarship as a lecturer at Civil Engineering Department, Engineering Faculty, Burapha University, Thailand.