TRAVEL TIME ESTIMATION AND PREDICTION FOR URBAN ARTERIAL ROADS

Mr. Porntep Puangprakhon

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By	Mr. Porntep Puangprakhon
Field of Study	Civil Engineering
Thesis Advisor	Associate Professor Sorawit Narupiti, Ph.D.

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 Supot Teachavorasinskun, D.Eng.)

THESIS COMMITTEE

....Chairman
(Associate Professor Sompong Sirisoponsilp, Ph.D.)

....Thesis Advisor
(Associate Professor Sorawit Narupiti, Ph.D.)

....Examiner
(Associate Professor Chotirat Ratanamahatana, Ph.D.)

....Examiner
(Associate Professor Kasem Choocharukul, Ph.D.)

....External Examiner
(Pattara Kiatisevi, Ph.D.)

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เป็นที่ทราบกันดีว่าเวลาการเดินทางเป็นข้อมูลสำคัญในระบบสารสนเทศการจราจรและระบบบริหารจัดการจราจรอัจฉริยะ ข้อมูลเวลาการเดินทางที่ถูกต้องช่วยให้ผู้ควบคุมการจราจรและผู้ใช้ถนนสามารถตัดสินใจได้อย่างเหมาะสม อันก่อให้เกิดประโยชน์ทั้งแก่ผู้ใช้ถนนเองและระบบโดยรวม ผู้ให้บริการข้อมูลจราจรส่วนใหญ่มักให้ข้อมูลสภาพจราจรปัจจุบันแก่ผู้รับข้อมูลโดยมีสมมติฐานว่าสภาพจราจรยังคงไม่เปลี่ยนแปลงในอนาคตอันใกล้ หากพิจารณาในแง่ประสิทธิภาพการใช้ประโยชน์ข้อมูลแล้ว การให้ข้อมูลสภาพจราจรในอนาคตที่ได้จากการคาดการณ์อย่างเหมาะสมย่อมมีประโยชน์กับระบบสารสนเทศการจราจรและระบบบริหารจัดการจราจรอัจฉริยะกว่าการให้เพียงข้อมูลสภาพจราจรปัจจุบันแต่อย่างเดียว

วิทยานิพนธ์นี้นำเสนอวิธีการประมาณเวลาการเดินทางและวิธีการทำนายเวลาการเดินทางในอนาคตระยะสั้นโดยใช้ข้อมูล Probe โดยเลือกถนนในเขตเมืองในพื้นที่ศูนย์กลางธุรกิจของกรุงเทพมหานครซึ่งมีพฤติกรรมที่ซับซ้อนและไม่เป็นเชิงเส้นเป็นพื้นที่ศึกษาเพื่อตรวจสอบการใช้งานได้ของเทคนิคการประมาณและการพยากรณ์ที่เสนอ เริ่มจากการนำเสนอวิธี “Running Speed and Stopped Delay (RSSD) method” เพื่อประมาณเวลาการเดินทางและความเร็วในการเดินทางบนถนนในเขตเมืองโดยใช้ข้อมูลเชิงตำแหน่งจากยานพาหนะติดตั้ง GPS ที่มีการเก็บข้อมูลความถี่สูง วิธีการดังกล่าวได้รับการปรับปรุงจากวิธีการพื้นฐานโดยใช้ข้อดีของข้อมูล GPS ซึ่งมีการเก็บทั้งค่าพิกัดและความเร็วของยานพาหนะ นอกจากนี้ได้แสดงการวิเคราะห์เปรียบเทียบข้อจำกัดของอุปกรณ์ที่ใช้เก็บข้อมูลเพื่อให้ผลการประมาณของวิธีการที่นำเสนอมีระดับความถูกต้องเท่ากับวิธีการพื้นฐาน ถัดมาได้นำเสนอวิธีการแจกแจงเวลาการเดินทางลงบนถนนช่วงต่างๆ จากข้อมูลเชิงตำแหน่งจากยานพาหนะติดตั้ง GPS ที่มีการเก็บข้อมูลความถี่ต่ำ โดยพิจารณาความเร็วขณะใดๆ ตำแหน่งและเวลา วิธีที่นำเสนอถูกนำมาตรวจสอบประสิทธิภาพเทียบกับวิธีการพื้นฐานที่ใช้กันโดยทั่วไป โดยใช้ข้อมูลที่สำรวจจริงบนถนนในเขตเมือง ผลการศึกษาแสดงให้เห็นว่าวิธีการที่นำเสนอให้ผลการประมาณเวลาการเดินทางแม่นยำกว่าวิธีการพื้นฐานอย่างมากทั้งในภาพรวมเมื่อพิจารณาทั้งช่วงถนนและเมื่อพิจารณาเฉพาะบริเวณทางแยก การศึกษาครั้งนี้พัฒนาระบบการเก็บข้อมูลการจราจรด้วยการตรวจจับสัญญาณบลูทูธ (Blue tooth MAC Scanner, BMS) เพื่อใช้สร้างกระบวนการสร้างเวลาในการเดินทางบนช่วงถนน และสร้างแบบจำลองการทำนายเวลาการเดินทางในอนาคตอันสั้นด้วยวิธี Multilayer feedforward neural network โดยใช้ข้อมูลนำเข้าจากช่วงถนนที่สนใจและช่วงถนนโดยรอบ ข้อมูลจราจรจากการรวบรวมด้วยการตรวจจับสัญญาณบลูทูธในกรุงเทพมหานคร ถูกนำมาใช้ในการตรวจสอบการใช้งานได้ของแบบจำลอง ผลการศึกษาพบว่าวิธีการทำนายที่ได้ให้ผลดีกว่าวิธีอื่นๆในสภาพการจราจรบนช่วงถนนที่มีการผันผวนของเวลาการเดินทางปานกลางถึงมาก (CV>0.4) ซึ่งเป็นสภาพที่พบบนช่วงถนนในเมืองส่วนใหญ่

ภาควิชา	วิศวกรรมโยธา	ลายมือชื่อนิสิต	....
สาขาวิชา	วิศวกรรมโยธา	ลายมือชื่อ อ.ที่ปรึกษาหลัก	....
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Travel time information has been accepted as the core of advanced traveler information systems (ATIS) and advanced traffic management systems (ATMS). Providing the accurate travel time information to traffic operators and travelers allows them to make informed decisions, leading to more advantage for individual road users and the entire transportation system. Most of the traffic information providers normally deliver the current traffic conditions or current travel times to public assuming the state of traffic remains constant in the near future. Aimed at the more effective applications, short-term future traffic conditions have been proposed as a valuable piece of information in ATIS and ATMS, apart from instantaneous or estimated travel time for representing current traffic conditions.

This dissertation aims at formulating the approaches for travel time estimation and short-term travel time prediction using probe data. The urban roadways in CBD area of Bangkok metropolis with highly complex and nonlinear behaviors were selected as the study corridors for confirming the applicability of the proposed techniques. First, a modified algorithm for calculating travel time and travel speed on urban roadways from high-resolution GPS probe data called “Running Speed and Stopped Delay (RSSD) method” has been proposed. This technique was modified from the average speed method using the advantage of movable sensor in which the location and speed of the tracked vehicle could be automatically detected. Secondly, for the real world application, the new analytical algorithm for allocating travel time from low-resolution GPS probe data into individual road sections by integrating instantaneous speed together with tracked locations and time stamp has been proposed. The performance of the proposed model in travel time allocation was tested and compared with the widely used technique using real field data. Results indicated that the proposed technique provided a significant improvement in travel time allocation at both complete section and intersection levels compared to the baseline technique. Thirdly, a traffic data collection system from Bluetooth MAC Scanner (BMS) was developed and the framework for constructing link travel time information from Bluetooth probe data and the preliminary analysis was also provided. Next, the short-term travel time prediction model using multilayer feedforward neural networks with the information from both target section and neighboring sections as the candidates for model inputs has been proposed. The real Bluetooth dataset obtained from BMS systems installed on urban roadway networks in Bangkok CBD was used in verifying the applicability of the proposed technique. Results indicated the proposed forecast technique was superior in traffic condition with moderate and highly fluctuated travel time profiles (CV>0.4) which could be experienced on most urban road sections.

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1. INTRODUCTION

1.1 CONTEXT AND BACKGROUND

Travel time is considered as an important quantitative indicator for evaluating performance of transportation networks. It is also one of the simplest and most understood measures for road users to make informed travel decisions. Traffic operators can also utilize travel time information in evaluating their ongoing traffic operational plan. In general, there are two general types of travel time which are normally informed to the users; (1) current travel time (or real-time traffic information) and (2) short-term forecasted travel time.

Current travel time of road network has been well applied in various transportation purposes. In the view point of time horizon, current travel time provides information of the current traffic condition to road users that might help them in a short-term delivery e.g. precise travel time information could help to avoid congested sections and increase the service quality of commercial delivery. On the other hand, for long-term scheduling or pre-trip planning, the predicted travel time information is essential. In the other viewpoint of traffic condition, in an area with relatively stable traffic conditions (e.g. on freeways or rural roadways) a fairly simple estimation method can be used to estimate and forecast travel time with the satisfactory accuracy, but in areas with rapidly changing traffic conditions or have complex behaviors (e.g. on urban roadways) a robust prediction model is necessary (Van Grol, Danech-pajouh et al. 1999). The prediction of travel time is the major trend to enhance the application of travel time information in both transport and logistics fields. Moreover, the impetus of forecasted traffic information rather than relying only on current travel time information is to let the road users be proactive in the trip management at both the pre-trip planning stage and in the ongoing trip decision (Ishak and Al-Deek 2002).

As the current state of practice, traffic data collection and travel time measurement can be divided by a sampling technique into two main categories (Lin and Zito 2005)

(1) using fixed sensors installed on roadway facilities such as registration plate matching, loop detectors, infrared sensors, and radio beacon, etc. to gather data from passage vehicles at selected points, and (2) using movable sensors or observers such as the GPS or Bluetooth probe vehicle (PV) method or the floating car technique, etc.

1.2 PROBLEM STATEMENT

In past decades, research on traffic states and travel time studies have been focused on data gathered from traditional inductive loop detectors and probe vehicles. For instance, using data from single loop detectors (Dailey 1999, Jin, Wang et al. 2010, Wei, Xiao et al. 2012), dual loop systems (Rakha and Zhang 2005, Soriguera and Robuste 2011), taxi probes (Herring, Hofleitner et al. 2010), bus probes (Pu and Lin 2009, Vanajakshi, Subramanian et al. 2009), or test vehicles (Puangprakhon and Narupiti 2015, Puangprakhon and Narupiti 2017). Although the abovementioned systems are regarded as efficient approaches in traffic data collection, the disadvantages of loop detectors especially on signalized urban streets are noteworthy. Firstly, travel time and speed are the preferred pieces of traveler information (Vlahogianni, Golias et al. 2004), while loop detectors measure traffic volume and occupancy. As travel time and speed must be derived by using the traffic speed-density-volume relationships (Petty, Bickel et al. 1998, Dailey 1999), uncertainties and errors in travel time calculation are unavoidable. Secondly, since loop detectors installed at signalized intersections are mainly designed for traffic signal control, when vehicle queues persist over the detector location travel time prediction is practically impossible (Sisiopiku 1994). (Sen, Soot et al. 1996) concluded that accurate travel time estimation using loop detectors on arterial sections could be possible in case of sufficient coverage of detectors on all lanes, all sections for all movements (especially turning movements), which could be cost prohibitive.

For the probe vehicle system, PV equipped with a GPS receiver (GPS-PV) and a GSM/GPRS transmitter acts as a moving sensor that travel in a traffic stream and does not require instrumentation to be set up on the roadway. GPS-PV can directly measure speed and travel time between any two detected locations and are considered as one of the most promising data sources for travel time information (Sen, Soot et al. 1996). It is also considered as one of the reliable and cost-effective measures that has potential to provide near real time traffic data on any part of large networks and offers a possible manner to supplement fixed-point traffic sensors with high installation and maintenance cost. From the above reasons, the GPS-PV technique seems to be very appropriate for travel time estimation and prediction problems. However, one of the most important drawbacks of this measure is its small penetration rate in reality (Wang, Papageorgiou et al. 2007). Moreover, the lack of reliability, the variety of data sources, and the randomness of its spatio-temporal coverage (Herring, Hofleitner et al. 2010), make it insufficient to develop the reliable travel time estimation and prediction models on urban roadways.

Recently, with the advancement of technology, Bluetooth scanners are being considered as one of the promising techniques for transport and travel time data collection (Khoei, Bhaskar et al. 2013). The concept of Bluetooth MAC scanner (BMS) in traffic data collection is simple. It scans and records MAC-ID together with time stamps of the discoverable Bluetooth devices (BT) within its communication zone e.g. from BT signal of Bluetooth probe such as mobile phones, car navigation systems, car infotainment systems, etc. The travel time of each vehicle between two consecutive BMS locations can be directly estimated by the difference of discovered time of the same MAC-ID of Bluetooth probe vehicles (BT-PV) at those stations. Various studies on developing traffic information have been conducted by using BT-PV data collected from Bluetooth scanners. For instance, (Wang, Malinovskiy et al. 2011) showed the promising results in travel time estimation while using the BMS system compared to the travel time recorded from Automatic License Plate Recognition (ALPR) devices on both freeways and urban roads. (Bhaskar, Kieu et al. 2013) tested the BMS system on arterial roadways and showed the potential of BMS in providing urban traffic conditions. Although, the BMS system is considered as cost effective and efficient approach for gathering traffic data, the application of Bluetooth scanner system for travel time estimation and prediction on urban roadways is still the main challenges for traffic professionals due to the complex, non-linear, non-stationary behavior and the disturbance from surrounding environment such as movement of pedestrians at crossing, traffic signals, intersections and access from sideway, etc.

In terms of techniques for traffic states or travel time prediction, many researchers have attempted to develop various prediction approaches e.g. using regression models, time series models, Kalman filtering models and artificial neural network (ANN), etc. Studies from the past have demonstrated that ANN models have the potential to predict travel time on urban roadways with highly complex and complicated traffic behaviors by providing the promising outcomes when sufficient historical data can be obtained. The main advantages of ANN models or data-driven approaches over other techniques are that they do not require extensive theoretical or traffic flow modeling; many software packages are available and ready to use; and they are fast and easy to implement (Dougherty 1995). Although previous works have demonstrated the favorable prediction outcomes from ANN, some drawbacks still need to be further studied. That is, most of the research have focused on freeways where traffic behavior is less complicated than urban roadways; the predicted travel time from various studies came from simulated data which cannot truthfully represent the complicated situation in reality; most of the previous studies accounted only the effects of historical travel time from the study segment which limit the applicability of the models when travel time from previous intervals are unavailable.

1.3 RESEARCH OBJECTIVES

The main objective of this dissertation is to develop the methodology for travel time estimation and short-term travel time prediction on urban roadway networks. Toward achieving the abovementioned purpose, the objectives of this research are

(1) To develop the travel time estimation method for both data captured from GPS probe vehicles and the Bluetooth scanner system.
(2) To develop more accurately short-term travel time forecasting on urban arterial roadways using Bluetooth data.

(3) To test the applicability of the developed models in the real traffic situation.

(4) To evaluate the performance of the developed models by comparing the results with those obtained by other models.

1.4 RESEARCH SCOPE

Travel time prediction study is a wide research area. The prediction models that have been developed in previous works can be classified by many means such as in terms of roadway type, prediction horizon, source of data, data driven or model based approach, etc. This dissertation will be scoped in the following way.

(1) This research focuses only on signalized urban arterials. The other road types such as freeways, local roads, or non-signalized streets are not considered in this study.

(2) This research experiments the travel time estimation from Probe-based data. A limited scope of experiment is conducted to prove a new concept of travel time estimation called Running Speed and Stopped Delay Method for high-resolution probe data, and called speed-time-distance method for low-resolution probe data. This method of travel time estimation will be assessed against a conventional method. The proposed method will be studied in detail.

(3) This research will introduce the travel time estimation from Bluetooth probe vehicles. The methodology to handle Bluetooth data including filtering will be proposed. The detail on the data filtering and impact on resulting travel time estimation will be addressed.

(4) This research elaborates on the methodology for forecasting travel time using the Artificial Neural Network (ANN) Model. The development of the model will be carried out using several inputs and model structures. Especially, the travel times of the adjacent road sections will be considered as model inputs.

(5) For prediction, only on short-term prediction will be focused. From literature, there is no clear definition and boundary among short-term and long-term prediction. In this dissertation, 60 minutes (or 4 time steps ahead) is chosen as the longest prediction horizon for testing the applicability and performance of the proposed model.

(6) The data source is one of the main issues in travel time study as the availability of data dominantly affects the modeling approach and research methodology. In travel time prediction, data are limited to traffic data captured from Bluetooth scanners installed at signalized intersections on urban roadways in Bangkok CBD.

1.5 ORGANIZATION OF THE DISSERTATION

This dissertation is organized into seven chapters as follow:

Chapter 1 Introduction: as described in this chapter

Chapter 2 Literature review: reviews the previous short-term travel time prediction works ranging from simple methods to the complicated ones.

Chapter 3 Travel time estimation from GPS probe data: describes the concept and technique for developing traffic information on urban roadways from high and low resolutions probe data.

Chapter 4 Travel time estimation from Bluetooth probe data: presents the data used in this research and the preprocessing as well as preliminary analysis of Bluetooth data.

Chapter 5 Development of models for travel time prediction and experimental corridors: describes the concept of neighboring section relationships, the developments of ANN models for travel time prediction, the experimental corridors and dataset in this study.

Chapter 6 Travel time prediction results and discussions: present the travel time prediction results, analysis of results, and also comparison of the results obtained from the proposed methods with others traditional techniques.

Chapter 7 Conclusions and future research: summarizes the findings of this research and contributions and also provides recommendations for future works.

2. LITERATURE REVIEW

In this chapter, a review of the existing research related to travel time prediction techniques is described. The literature review can be classified under five broad categories; definition of the elements of urban networks, traffic data collection technologies, taxonomy of travel time prediction models, short-term travel time prediction, and the summary of the literature review.

2.1 DEFINITION OF THE ELEMENTS OF URBAN ROADWAYS

In this dissertation, the following definitions are used (Lui 2008). Figure 2.1 illustrates the outline of different elements of urban roadways.

An intersection is the location or a road junction where two or more roads meet or cross at the same grade or same level.

An urban link is a section of an urban road which lies between two consecutive intersections.

An urban section is a combination of one or more urban links and one or more intersections. Two types of urban section can be classified as follows:

- Type A: an intersection is connected to the start of an urban link.
- Type B: the end of an urban link is connected by an urban intersection. This urban section will be used in the rest of this dissertation.

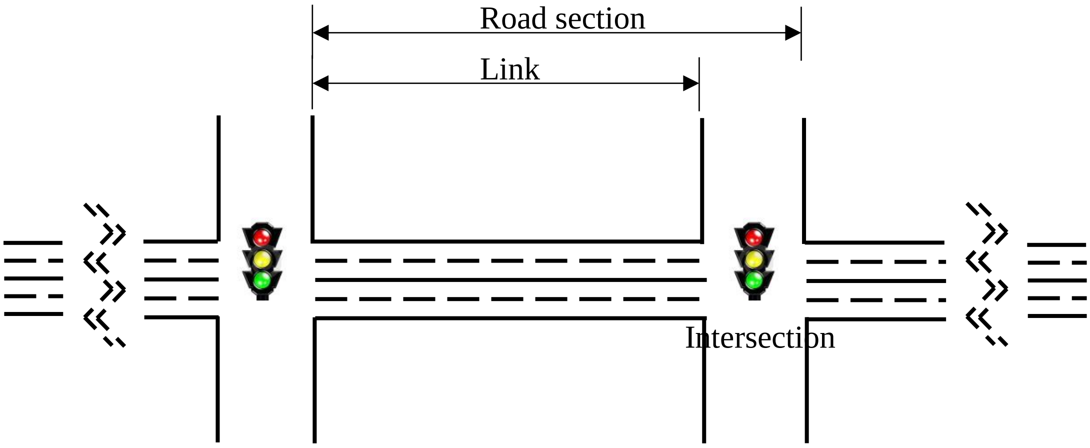


Figure 2-1 Basic elements of an urban roadway.

2.2 TRAFFIC DATA COLLECTION TECHNOLOGIES

Travel time is a fundamental measure in transportation as it is simple concept, easy to understand, and can be used in communication by a variety of stakeholders, including travelers, transportation planners, engineers, etc. In general, the broad definition of travel time can be defined as "the time necessary to traverse a route between any two points of interest".

Travel time can be directly measured by traversing time on the route(s) that connects any two or more points of interest. Travel time between any two points normally comprises the running time region and stopped delay time region (or moving sufficiently slow as to be stopped) (Turner, Eisele et al. 1998). Figure 2-2 illustrates the concepts of running time and stopped delay time.

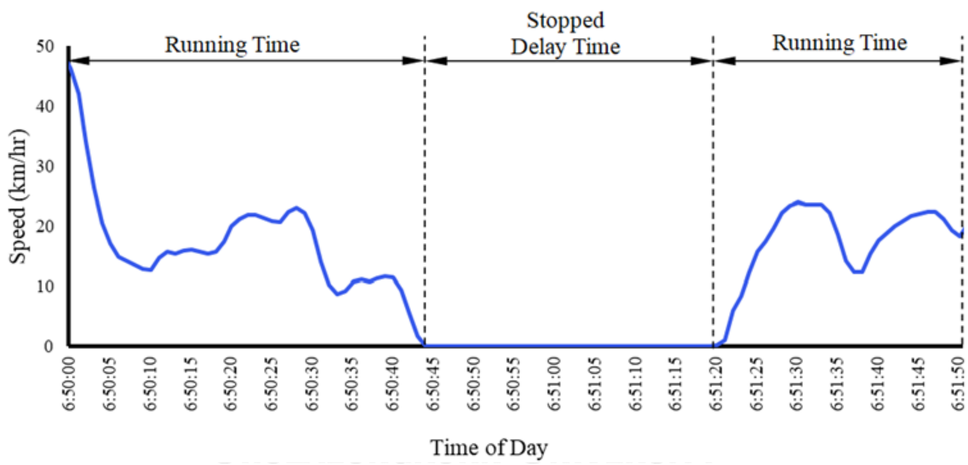


Figure 2-2 Concepts of running time and stopped delay time.

The techniques for gathering travel time information can be broadly categorized into two main groups. The first one relies on the fixed-location sensors that can collect traffic information such as volumes, headways, time mean speeds, and lane occupancy. The sensors in this group are such as inductive loop detectors (ILD), infrared sensors, Doppler microwave, and video camera, etc. The second group relies on movable or mobile sensors such as GPS, Cell Phone, toll tag, and Bluetooth devices that "track" the vehicle location and time along the travel route. One of the key advantages of the movable sensors compared to the fixed sensor system is the direct measurement of point-to-point travel time.

From literature, numerous works on both arterials and freeway employed the fixed-location sensors particularly inductive loop detectors in measuring traffic information such as traffic volume, occupancy and point speed (Coifman 2002) for the advanced traffic management systems (ATMS) and advanced traveler information systems (ATIS). Various researches have applied data gathered from loop detectors in developing travel time information in the form of both estimated and predicted travel times (Sisiopiku 1994, Anderson and Bell 1997, Palacharla and Nelson 1999, Li 2002, Stathopoulos and Karlaftis 2003, Lucas, Mirchandani et al. 2004, Robinson and Polak 2005, Guo and Jin 2006).

Although popular, the drawbacks of loop detectors in traveler information application, particularly on signalized urban roads, are notable. First, loop detectors measure occupancy and traffic volume while the preferred traveler information in ATIS is travel time and speed (Vlahogianni, Golias et al. 2004). In developing travel time and sometimes travel speed, many mathematical assumptions are required such as vehicle length and traffic speed-density-volume relationships (Petty, Bickel et al. 1998, Dailey 1999). Nonetheless, dual loop detectors were widely used in measuring traffic speed, and travel time must still be carefully derived (Coifman 2002), resulting in inevitable uncertainty and error in travel time calculation. Second, the main objective for mounting loop detectors at signalized intersections is for traffic signal control purposes that may not be suitable for providing travel time and speed information. For example, travel time prediction is practically impossible when vehicle queues persist beyond the detector location. (Sen, Soot et al. 1996) concluded that a sufficient coverage of detectors on all lanes, sections, and movements (especially turning movements) is required for the accurate estimation of travel times using loop detectors on arterial sections, which could be cost prohibitive. Third, in real-time travel time prediction, both real-time traffic measurements and real-time traffic signal timing information are necessary. These requirements become problems when traffic signal controls are not integrated in the system. Moreover, the cost prohibitiveness is a major concern in widespread deployment of fixed sensors such as loop detectors in large urban areas.

On the other hand, probe vehicles (PV) can directly measure travel speed and travel time between any two locations of interest and are considered one of the most promising data sources for travel time estimation and prediction (Sen, Soot et al. 1996). Any vehicle can be a probe as long as the vehicle can be tracked continuously or at least recognized at the starting and ending points of a route. Examples are personal vehicles instrumented with automatic identification tags, traceable by cellular phone signals (Bar-Gera 2007), equipped with global positioning satellite (GPS) devices (Quiroga 2000, Taylor, Woolley et al. 2000) or equipped with Bluetooth devices (Bhaskar and Chung 2013). The PVs equipped with a GPS receiver (GPS-PV) and a GSM/GPRS transmitter act as a moving sensor traveling in a traffic stream and may not require instrumentation to be set up on the roadway. It can directly measure speed and travel time between any two detected locations and is also considered as one of the reliable and cost-effective measurement systems that has potential to provide near real time traffic data on any part of a large network. However, one of the most important drawbacks of these systems is its small penetration rate in reality. The Bluetooth scanner is considered as one of the promising techniques for transport and travel time data collection. It scans and records MAC-ID together with time stamps of the discoverable Bluetooth devices (BT) within its communication zone. The travel time of each vehicle between two consecutive BMS locations can be directly estimated from the difference of discovered times of the same MAC-ID of Bluetooth probe vehicles (BT-PV) between those stations. The BMS system is also considered as the cost effective and efficient approach that has high potential in gathering traffic data.

2.3 TAXONOMY OF TRAVEL TIME PREDICTION MODELS

In order to understand the differences among travel time prediction approaches, the key distinguishing factors between travel time prediction models are presented as follow:

2.3.1 Difference between travel time estimation and travel time prediction

Travel time is the time spent by a vehicle traversing a given road section, including all delays encountered. Travel times on a link experienced by individuals vary. The average of the arithmetic mean of all individual travel times in the same time interval is generally used as the travel time information, which can be classified into two broad categories:

The estimated travel time is the travel time which is already experienced by the vehicles that have already departed the road section in the current or past time-periods (Van Lint 2004).

The predicted travel time is the travel time that will be experienced by the vehicle in a future time-period (Van Lint 2004).

2.3.2 Prediction horizon

The prediction horizon is the time interval (or period) after the prediction is made. There are two types of travel time prediction categorized by prediction horizon; (1) short term prediction that usually reflects the forecasting time up to one or two hours (Hinsberger, Van et al. 2007), and (2) long term prediction that refers to time up to days, weeks, months or years. In general, the prediction models with longer horizon tend to rely on statistic e.g. ARIMA or regression, or rely on theoretical assumptions e.g. Wardrop equilibrium or Dynamic User Optimum. In this dissertation, we will focus only on short term travel time prediction with the prediction horizon up to 1 hour.

2.3.3 Modeling approach

There are two main groups in travel time prediction approaches:

(1) Data driven technique employs statistical relations among historical travel time and future travel time without considering the traffic processes. In this approach, the main factors that affect the travel time prediction results are the data quality, the used technique, and the parameters used as inputs in the developments of models.

(2) Model based technique uses the traffic flow theory and traffic flow models in the traffic condition and travel time prediction. From previous researches, using the traffic flow theory seems more appropriate. However, the major drawbacks of this technique are that; it needs highly accurate models and model inputs, and the accuracy of outputs from this technique strongly depends on the quality of input data, the calibration of models, and the used models. Furthermore, application on large networks requires a lot of effort in modeling, implementation, calibration and maintenance.

Since our proposed method belongs to the first category (data driven technique), only the prediction methods related to this approach, i.e., statistical or data driven models, will be examined in this dissertation.

2.3.4 Methodology

The methodology of travel time prediction can be classified into two types;

(1) The direct method predicts travel time directly from the current and historical travel time data recorded by the sensors.

(2) The indirect method forecasts the future traffic conditions using other data from travel time such as travel speed, flow, occupancy and then using traffic flow fundamentals to estimate the future travel time from future traffic conditions.

2.3.5. Road type

Types of road can be classified into two main groups, which are (1) freeway with no interruption from the surrounding environment e.g. intersections, traffic signals, roadside parking, and (2) urban roadway with the complex and highly nonlinear behavior due to the disturbance from surroundings. In this dissertation, due to the challenges in transport research, we focus only on urban roadways.

2.4 SHORT-TERM TRAVEL TIME PREDICTION

The timeliness and accuracy level of future traffic conditions is the key feature of traffic information. The accurate information on future travel time is more beneficial than the past or current traffic information, particularly on the section where travel time is highly fluctuated. A variety of methods both in theoretical background and testing procedure for travel time prediction are available in the literature. The next section describes an overview, applications and discussion of various travel time prediction approaches, including simple prediction model, time series analysis, Kalman filtering, and neural networks technique.

2.4.1 Simple prediction models

Simple methods for travel time prediction have been developed and applied in many ITS applications. These methods are also known as ad hoc or naïve techniques and they are attractive because their simple and no site specific manner. Simple techniques can be categorized into using real-time information, using historical information, or the combination of the two (Hamed 2004).

The use of real-time or current travel time as the predicted value assumes that the travel time during any given time period is the same as that during previous time period. This technique is probably the simplest and most straightforward of all prediction techniques. It assumes that the current traffic condition is the best predictor for traffic condition in the near future. This method is also known as “random walk” technique, which can be expressed as;

$$\hat{X}_{i+j} = X_i, \qquad j = 1, 2, \ldots \tag{2-1}$$

Another simple technique is the use of historical average, assuming the travel time during any specified time period equals the smoothed historical volume for that period as obtained from earlier observations, which can be expressed as;

$$\hat{X}_{i+j} = \frac{(X_i + X_{i-1} + \cdots + X_{i-N+1})}{N} \qquad j = 1, 2, \ldots \tag{2-2}$$

The above-mentioned techniques are used as the benchmarks for evaluating performance of proposed travel time prediction models in numerous works such as in (Stephanedes, Michalopoulos et al. 1981, Park, Rilett et al. 1999, Williams and Hoel 2003, Chen and Rakha 2014, Pongnumkul, Pechprasarn et al. 2014, Fan and Gurmu 2015, Tak, Kim et al. 2016).

2.4.2 Time series analysis

A time series is a collection of observation or series of data points in time order with equally spaced time interval. The time series analysis is a statistical technique that deals with time series data. Time series model uses a set of time series data *x(t)* to catch and explain the system behavior and also to forecast the future condition at time *t+D*, where *D* is the prediction interval (Smith and Demetsky 2004). There are various forms of time series for representing different stochastic processes. The common time series forms include the auto regressive (AR) models, the auto regressive moving average (ARMA) models, the autoregressive integrated moving average (ARIMA) models, and the seasonal autoregressive integrated moving average (SARIMA) models.

Some of the previous works that employed various time series models in forecasting traffic information on both freeways and arterials are as follow:

(Williams and Hoel 2003) applied SARIMA models in addressing the traffic flow prediction problem on 2 freeway locations, one in the United States and one in the United Kingdom. Data from both freeways were gathered by inductive loop detectors. The U.K. data were from the outer loop in the southwest quadrant of the M25 motorway which represented a modern major urban circumferential freeway, while the U.S. data were from northbound I-75 inside the northwest quadrant of the I-285 perimeter freeway around Atlanta which represented a major urban radial freeway. The result indicated that One-step (a one-week lagged) seasonal ARIMA predictions consistently outperformed heuristic forecast benchmarks on both testing corridors by providing the best forecasting result based on MAD, RMSE and MAPE values. They concluded that a first seasonal difference taken at a one-week lag could be the key to proper application of ARIMA modeling to time-indexed traffic volumes.

(Billings and Yang 2006) applied autoregressive integrated moving average (ARIMA) models in addressing the arterial travel time prediction problem on urban roadways. They used the GPS probe vehicles in data collection during afternoon peak hours (3.30-5.00 pm) on one of the most heavily traveled and congested roadways in the Duluth metro (3.7-mile with 10 signalized intersections on Minnesota State Highway 194) for two weeks. The results indicated that the ARIMA models provided reasonable prediction results on most of the road sections, particularly on the section with higher speed limit. While on the sections with a shorter distance, lower speed limit, and the section with relatively high cross-street traffic, the prediction error seemed relatively large. They also stated that their proposed method could be easily modified and applied to short-term arterial travel time prediction for other urban areas.

(Chowdhury, Nath et al. 2009) proposed two new methods which were based on moving average called "Successive Moving Average (SMA)" and "Chain Average (CA)" for travel time prediction. They tested their proposed methods with simulated data generated from PNU (Pusan National University) trajectory data generator. This dataset was first collected from field data in Pusan city, South Korea using GPS sensors. Traffic patterns were then extracted, simulated, and generated as the trajectory data for testing the prediction models. They compared their methods with the two benchmark techniques; Naïve Bayesian Classification (NBC) (Lee, Chowdhury et al. 2008) and switching method (Schmitt E. J. and Jula 2007). The prediction results indicated that their proposed methods provided a more precise prediction in most test cases. They also concluded that their proposed techniques could provide an accurate prediction with low cost due to simplicity and could eliminate unwanted fluctuations in the data set in comparison with the conventional moving average method.

(Khoei, Bhaskar et al. 2013) studied the travel time prediction on three urban signalized arterials in Brisbane. In their study, Bluetooth detectors installed along the urban corridors by the Brisbane City Council were used for traffic data collection (Bluetooth probe data) from November 2011 to June 2012 (8 months). From 8 months dataset, the travel time was classified into 3 categories: school holiday, public holiday, and working day. They applied SARIMA model with a seasonality of 24 hours recurrent trend in travel time prediction from 5 minutes up to 90 minutes prediction horizons. The prediction results indicated that the SARIMA model produced good results for short-term travel time prediction up to 30 minutes ahead. In longer prediction horizons, the prediction errors increased accordingly due to the high variability in the day to day travel time trend. They also concluded that their proposed model performed much better in arterial corridors with normal shaped congestion peaks created by sufficient data points and with more similar recurrent trends in their historical travel time databases.

The researches mentioned above indicate the potential of applying time series analysis in tackling the travel time prediction problems. However, an issue to consider is the assumption that historical patterns will remain the same in the future. The accuracy of these models is a function of similarity between real-time situations and historical patterns. Variations in historical data or deviations in the relationship between real-time and historical data could lead to significant inaccuracy in the prediction results.

2.4.3 Kalman filtering

The Kalman filter, which is called linear quadratic estimation (LQE) in the control theory, was first proposed by R.E. Kalman in 1960. In Kalman filtering algorithm, series of measurements observed over time which contain statistical noise and inaccuracies are used to estimate unknown variables by estimating a joint probability distribution over the variables for each timeframe. There are two main features of Kalman formulation and solution to the problem, the first one is vector modeling of the random processes under consideration, and the second is the recursive processing of noisy measurement or input data. Kalman filtering models consist of two main equations. The state equation estimates the current state variables, along with their uncertainties, and the measurement equation transfers the estimated state variables into observed variables once the outcome of the next measurement is observed. Then, the difference between observed and predicted variables is used to update the next state variables. Kalman filter models can fully respond to dynamic conditions using time-varying parameters which make it different from the methods using only historical data for prediction.

Some of the previous works that employed Kalman filter as a forecasting technique to address traffic prediction problems on both freeways and arterials are as follows:

(Nanthawichit, Nakatsuji et al. 2003) developed a method for traffic state estimation and short-term travel time prediction on freeways by integrating probe vehicle data with data collected from conventional inductive loop detectors. In their research, the state equation was represented by the macroscopic traffic flow model. The observation equation was constructed using data from both probe and inductive loops. Then, the estimated states were updated with information from both fixed detectors and probe vehicles. Their proposed method was tested under various traffic conditions based on simulated data from INTEGRATION software. The results from the traffic state estimation indicated that the method using both fixed detector and probe data provided the smallest errors. The error could be reduced significantly (70-85% for speed and density) compared to the use of the macroscopic model only. Their proposed travel time prediction method also performed well compared to the autoregressive function with the KFT method proposed by (Chen and Chien 2001).

(Xiaobo 2004) developed three dynamic recursive prediction models: a dynamic exponential smoothing model (DESM), an improved dynamic exponential smoothing model (IDESM), and a dynamic moving average model (DMAM), by incorporating the Kalman filtering model (KFM) into both an exponential smoothing model (ESM) and a moving average model (MAM). The models were tested on data from a selected highway in Southern New Jersey that was simulated using CORSIM simulation software. The prediction results under various traffic conditions (e.g., free-flow condition, recurrent and non-recurrent congested traffic conditions) showed that the IDESM outperformed other models in prediction of accuracy and stability. The author also suggested that the IDESM is easy to implement in the real world network for short-term travel time prediction.

(Yang 2005) studied the arterial travel time prediction using the Kalman filtering and estimation technique. They used the Global Positioning System (GPS) test vehicle technique to collect travel time data after the graduation ceremony events on the Duluth Entertainment and Convention Center (DECC), Minnesota. In Yang's study, three test vehicles were used to report travel time data. These vehicles were sent to the field and followed the pre-specified path, thereby running on three or five minutes headway. Then the discrete-time Kalman filter was applied to predict travel time exiting the study area. The results showed that the prediction error was acceptable (judged by traffic engineers) with MARE 17.61%. They pointed out that using shorter prediction time interval with higher number of intervals provided better prediction results than using the longer interval with lower number of intervals. They also suggested the use of interpolation technique for increasing the number of intervals in order to reduce the prediction time interval.

(Zhu, Kong et al. 2009) applied the Kalman filtering method in travel time prediction on large-scale urban arterial roads. The researchers proposed a new prediction method based on Kalman filter by estimating the state transition matrix from temporal and spatial perspectives separately. To estimate the parameters in the method, the hierarchical clustering analysis was used to gain the spatial factors of roads. In model testing, a large number of float car data collected from arterial roads in Beijing was used to evaluate the accuracy of the proposed prediction method. The prediction results indicated the mean absolute relative error of 14.66% with a minimum of 6.37% and a maximum of 19.56%. The researchers also stated that their proposed prediction method could dynamically reflect the traffic fluctuation during the rush hours which could greatly improve the accuracy of the prediction. They also informed that their proposed method using the float car data was used in the Traffic Information System to supply service (based on the data of 2009).

The researches cited above indicate the potential and effectiveness of using Kalman filtering in travel time prediction both on freeway corridors and on urban arterial roadways. Unlike time series analyses where historic data are used for prediction, the Kalman method uses adaptive parameters responsive to dynamic conditions. Therefore, theoretically, the Kalman filtering method could provide a prediction that quickly reflects the traffic fluctuations. Kalman filtering can also be applied with data from multiple sources in order to improve the prediction accuracy. Although the Kalman filtering technique has superior prediction capabilities than the time series techniques, it has been criticized for doing so only on a limited time interval.

2.4.4 Artificial Neural Networks

Artificial Neural Network (ANNs) can be defined as the technique for processing information that is inspired by the human brain system. The brain is principally composed of enormous number of neurons that are massively connected together to solve a specific problem. ANNs mimic the biological neurons functions to perform the sophisticated and intelligent computations similar to the human brain system. Neural networks are statistical models capable to capture and represent the complex relationship between input and output. ANNs resemble the human brain systems by acquiring knowledge through training process, and storing connecting weights from the training process. The ANN model comprises several building blocks called neurons. Each neuron is composed of two units: the first one is sums of the weight coefficients and inputs, and the second unit is a nonlinear transfer function known as an activation function. The summed (and weighted) input is brought into the activation function to produce an output. If the output is not the same as the desired output, then an apparent error will be present. The error is fed back to the model and the weights are re-adjusted. This training process is repeated until the model performance is acceptable. Once the model has already been trained, the model weights are set and ready for use in the prediction task. The key capabilities of ANNs include pattern recognition, classification, detection, adaptive filtering, estimation, and prediction, etc. Since the rapid development of computational technology in last decades, the neural network has become a major technique in addressing various transportation problems (Dougherty 1995).

Some of the previous works that applied various structures of ANNs in traffic prediction on both freeways and arterials are as follows:

(Bae 1995) applied the multilayer feedforward neural networks (MFNNs) with 1 hidden layer and 8 hidden neurons to interpret auto travel time from bus travel times which were gathered by the automatic vehicle location (AVL) system from equipped buses, acting as probe vehicles, for estimating bus arrival times and auto travel times. The inputs for MFNNs comprised both dynamic and static field data that could affect bus travel times, such as link length, number of lanes, parking availability, bus travel time passengers, etc. The prediction results indicated that the proposed MFNNs models provided better outcomes compared to the regression technique, particularly, on the network with nonlinear behavior.

(Kisgyorgy and Rilett 2002) applied an ANN with two different approaches to predict travel time on a freeway corridor in San Antonio, Texas. The first approach used the Modular Neural Networks (MNN) that involved three steps: pre-processing the data, identifying the clusters, and identifying the model structure of the ANN for each cluster, to predict speed from its measured value and then to calculate the future travel time using a standard formulation. In the second approach, the travel time was predicted directly with the ANN. In the third approach, travel time was predicted from actual speeds data. The results indicated that the model where travel times were directly predicted by neural networks from detector data provided best results. However, because of the lack of continuous collection of travel time data, this model could not be used in practice.

(Ishak, Kotha et al. 2003) used three ANN topologies which were Jordan/Elman, partially recurrent networks, and time-lagged feedforward networks for short-term traffic prediction in the range of 5 to 20 minute-horizons on freeways using data obtained from inductive loop detectors under different networks and traffic conditions. The various combinations among data of target location, upstream and downstream locations were considered as model inputs. The results indicated that the optimized performance of the dynamic neural networks outperformed a statistical non-linear time series approach in most cases. Results also pointed out that no single topology consistently outperformed the others for all prediction horizons. Finally, authors provided the comparative evaluation of performance between optimal and non-optimal settings and suggested that the applied procedure could be used to identify the prediction reliability of information dissemination systems.

(Lui, He et al. 2009) used the neural network model to address the problem of travel time prediction on urban arterials using data from loop detectors. They proposed a generic segment model based on the State Space Neural Network for travel time prediction on a basic segment of urban arterials. For a longer arterial covering several controlled intersections, it can be conducted by assembling each individual segment model. This method led to the significant reduction in number of parameters of the neural network, which made it simpler and easier to be implemented in practice. To verify their proposed model, an urban arterial in the Netherlands was selected as the test bed. The results indicated that the proposed model was capable of dealing with complex nonlinear urban arterial travel time predictions with satisfying accuracy.

However, although generally said that their proposed model was capable for travel time prediction problems, the larger difference between predicted and actual travel time occurred in the transition states when congestion was developed and dissolved.

The researches cited above indicate that neural networks have proven to be a powerful method in the area of travel time forecasting. Neural networks can perform highly nonlinear mappings between input and output spaces, as the neural network approach is nonparametric. Therefore, one does not need any assumptions about the functional form of the underlying distribution of the data. Neural networks can be applied to forecast multiple period mean travel times more accurately than other competing approaches, such as time series and Kalman filtering.

(Karlaftis and Vlahogianni 2011) reviewed numerous works in modern transportation studies and concluded that NN have mainly been used as data analytic methods in transport research due to various reasons e.g. the ability to work with multi-dimensional data, flexibility in modeling, adaptability, and good predictive ability.

The characteristics of time series analysis, Kalman filtering technique, and artificial neural networks in travel time prediction are summarized in Table 2.1 (Vlahogianni, Golias et al. 2004). These characteristics mainly are concerned with the statistical hypotheses made (stochastic versus deterministic, stationary or not) or any statistical predefined input parameter that could affect the structure of the model (linear or non-linear), the difficulty/complexity in modeling multivariate data, the data requirements in terms of quantity and quality (data continuity). Finally, the last two rows give a short description of the main advantages and disadvantages of the methodologies regarding the efforts made in modeling traffic data.

Table 2-1 Summary of characteristics for the widely used models in travel time prediction.

	Time series	**Kalman filtering**	**Neural networks**
Hypothesis on the statistical nature of data	Stochastic	Stochastic Gaussian nature of initial conditions	Not required
Hypothesis on the temporal regularity (stationarity)	Weak stationarity	Not required	Not required
Hypothesis on-linearity or non-linearity	Input parameter*	Input parameter*	Not required
Multivariate modeling	Difficult	Straightforward	Easily incorporated
Data - quantity	Extensive	Extensive	Extensive
Data - quality	Continuity	Continuity	Not required
Results - extraction	Explicit	Explicit	Implicit
Results - accuracy	Low but capable	Medium	Best
Main advantages	Well-established theoretical background	Multivariate nature	Non-stationary and non-linear environment, wide mapping capability
Main disadvantages	Weak stationarity, low accuracy in extreme value	Gaussian hypothesis	Data extensive, complex internal structure

Input parameter: the decision of linear or non-linear modeling must be predefined because it largely affects model structure.

2.5 SUMMARY OF LITERATURE REVIEW

This chapter covers an overview of the traffic data collection technologies, taxonomy of travel time prediction models, and short-term travel time prediction studies.

Most existing data collection technologies fall into two categories, the fixed location sensor and mobile sensor (probe). The most widely used fixed location sensor is the inductive loop detector (ILD). Fixed location sensors are important traffic data sources but the deployment and maintenance cost is usually high and the aggregated data is not the most suitable input for real time ITS applications. It is not cost effective for traffic data collection on urban arterial roads. Mobile sensors are developed along with ITS and become the most important data sources and demonstrate the high potential for ITS applications.

The general forms of travel time information in ITS application can be grouped into two categories: the estimated travel time already experienced by the vehicles, and the predicted travel time that will be experienced by the vehicles in the future time periods.

The travel time prediction horizon can be categorized into short-term prediction (with less than 1 hour prediction horizon), and long-term prediction (more than 1 hour up to years).

In travel time prediction, there are two main techniques in modeling; 1) model based approach using the traffic flow theory and traffic flow models in the traffic condition, and 2) data driven approach which employs statistical relations among historical travel time and future travel time without considering the traffic processes.

Methodologies for travel time prediction fall into two methods: 1) direct method that predicts travel time directly from the current and historical travel time data, and 2) indirect method that forecasts the future traffic conditions using other data such as travel speed, flow, occupancy then using traffic flow fundamentals to estimate the future travel times from future traffic conditions.

Two different road types were mainly focused in literature the freeways with uninterrupted behavior and urban arterials with highly complex and nonlinear behavior.

Previous studies imply that there are three main techniques in addressing traffic forecasting problems, which are time series analysis, Kalman filtering, and ANNs. Although there is no sole conclusion on which technique is always superior to the others, the potentials of ANNs in transport study are noteworthy, e.g. the ability to work with multi-dimensional data, flexibility in modeling, adaptability, and good predictive ability.

In this dissertation, the data driven approach (ANNs) with historical travel time of target and neighboring sections as inputs was selected for tackling the short-term travel time prediction problems on urban roadways using data from probe vehicles. Details of model development are given in Chapter 5. The results of short-term travel time prediction are presented in Chapter 6.

The proposed techniques for travel time estimation from high resolution and low resolution GPS probe data are given in Chapter 3. Details of travel time estimation from Bluetooth data are provided in Chapter 4.

3. TRAVEL TIME ESTIMATION FROM GPS PROBE DATA

In this chapter, the methods for travel time estimation from GPS-probe data are presented. The organization of this chapter starts with the simple techniques in approximating travel time and speed from the high-resolution GPS-probe data, followed by the error in travel speed estimation from simple techniques. Then the travel time allocation problem that represents low-resolution data in real world application is addressed. The techniques for tackling travel time allocation problems both the widely used and proposed techniques are described next, followed by the field experiment on travel time allocation. At last, concluding remarks of this chapter is presented.

3.1 APPROXIMATION OF TRAVEL TIME AND SPEED FROM HIGH-RESOLUTION GPS-PROBE DATA

3.1.1 Calculation by the average speed method

Travel time is defined as the time spent to travel between any two points. In general, the travel time is composed of running time and stopped delay time. The running time is time that the vehicle is in motion, while stopped delay time can be defined as time when the vehicle is completely stopped or moving considerably slow as to be stopped, typically less than 8 km/hr or 5 mph (Turner, Eisele et al. 1998).

Based on the definition of travel time, section travel time (T_S) or travel time spent for traversing any road section can be expressed in terms of running and stopped delay time as:

$$T_S = t_R + t_D \tag{3-1}$$

$$T_S = \frac{L}{v_R} + t_D \tag{3-2}$$

where T_S denotes the section travel time, t_R is running time, t_D is stopped delay time, L is distance traveled or length of the road section, and v_R is the average running speed.

GPS reciever is capable to gather coordinates, speeds and time. The speed and the position from GPS recievers are independent since the speed is calculated from the receiver's poll psudorange data (distance between the sattelite and the GPS reciever) and psudorate data. This allows us to calculate traveling distance from GPS speed and also permits us to calculate the segment speed (Quiroga and Bullock 1998).

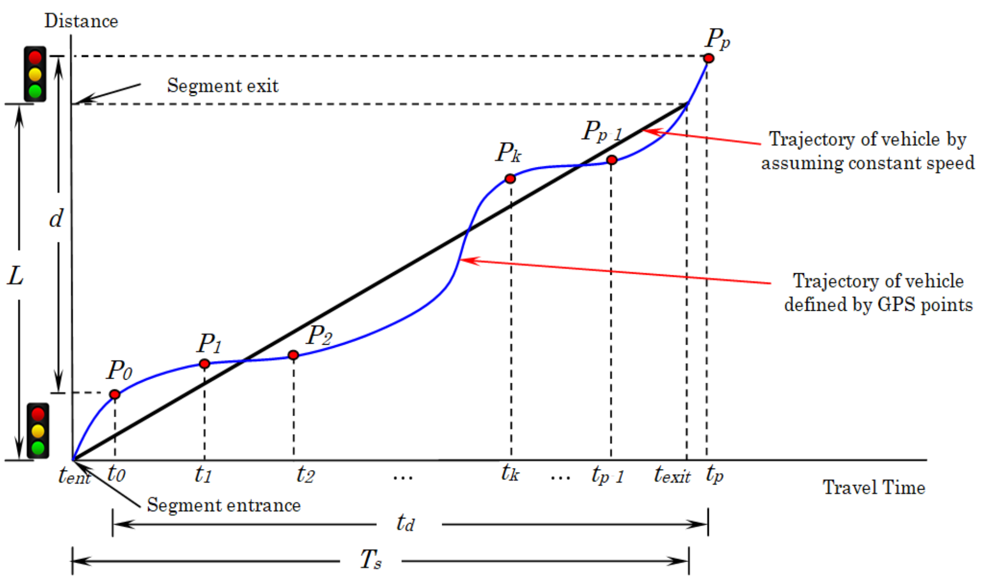


Figure 3-1 Time-space diagram of GPS points along the traveled segment

Let d be the distance traveled covered by probe vehicle during time t_0 and t_p. From Figure 3.1, distance traveled can be expressed as:

$$d = \int_{t_0}^{t_p} v dt \approx v_0\left(\frac{t_1 - t_0}{2}\right) + \left[\sum_{k=1}^{p-1} v_k\left(\frac{t_{k+1} - t_{k-1}}{2}\right)\right] + v_p\left(\frac{t_p - t_{p-1}}{2}\right) \tag{3-3}$$

This trapezoidal approximation is reasonable in case the time interval among GPS points is small enough and the distance between two adjacent GPS points are much smaller than the section length or distance traveled.

The average speed (u_d) associated with distance traveled (d) can be expressed as:

$$u_d = \frac{d}{t_d} = \frac{d}{t_p - t_0} \tag{3-4}$$

where t_d denotes travel time spent for traversing through distance d.

In case the first and the last GPS points corresponded to the road section are sufficiently close to the entrance and exit points of the section respectively, the distance traveled (d) and section length (L) should be very similar. As a result, the average section speed (u) from u_d can be estimated and equation (3-4) can be rewritten as:

$$u \approx \frac{1}{t_p - t_0}\left\{ v_0\left(\frac{t_1 - t_0}{2}\right) + \left[\sum_{k=1}^{p-1} v_k\left(\frac{t_{k+1} - t_{k-1}}{2}\right)\right] + v_p\left(\frac{t_p - t_{p-1}}{2}\right)\right\} \tag{3-5}$$

Generally, the section length (L) is known; consequently, section travel time then becomes

$$T_S \approx \frac{L}{u} \tag{3-6}$$

3.1.2 Calculation by the running speed and stopped delay method (RSSD)

As illustrated in the previous section, travel time is composed of two parts: the running time and stopped delay time. Recalling equation (3-4), the distance traveled covered by the probe vehicle can be computed by:

$$d = t_d \times u_d \tag{3-7}$$

As the distance traveled arises only from the running period, the equation can be rewritten so that the distance traveled is a function of running speed as:

$$d = t_{R,d} \times v_{R,d} \tag{3-8}$$

where $t_{R,d}$ denotes the running time spent for traversing distance (d) and $v_{r,d}$ denotes the average running speed associated with the distance traveled (d).

Equation (3-5) can then be rewritten in terms of running speed and stopped delay as:

$$v_{r,d} \approx \frac{1}{[(t_p - t_0) - t_{D,d}]} \left\{ v_0 \left(\frac{t_1 - t_0}{2} \right) + \left[\sum_{k=1}^{p-1} v_k \left(\frac{t_{k+1} - t_{k-1}}{2} \right) \right] + v_p \left(\frac{t_p - t_{p-1}}{2} \right) \right\} \tag{3-9}$$

where $t_{D,d}$ denotes the stopped delay time while the vehicle is traversing through distance (d).

On the arterial road network which generally comprises signalized intersections, the road section is typically partitioned at the intersection(s). At those points, transferring of a vehicle from one to another section occurs after the vehicle has passed the signal (intersection) and occupied the next road section. It is theoretically recognized that while a vehicle is transferred from one road segment to the nearby segment, the vehicle speed needs to be more than zero. In other words, it must be in the running state (stopped vehicle cannot move). Furthermore, in case that the sampling time interval of GPS is small, the speed of the vehicle traversing between the last GPS point in the upstream segment and the first GPS point in the downstream segment is generally more than zero (no stopped delay time between two contiguous GPS points which lie on different segments).

Let's reconsider the concept of travel time estimation. The section travel time (T_S) is estimated from the relationship between the known traveled distance (d) and section length (L) (shortened or lengthened the known distance around the edge of the segment to the section length) together with the average speed (u) (which comprises the running speed and stopped). However, from the above argument, it is reasonable to employ the running speed instead of the average speed in performing travel time estimation. The time changes as a result of shortened or lengthened distance are governed only by the running period. With this manner, the section travel time can be rewritten in terms of running time and stopped delay time as:

$$T_S \approx \frac{L}{v_{R,d}} + t_{D,d} \tag{3-10}$$

Consequently, the average section speed can be computed by

$$u \approx v_{R,d} \frac{t_{R,d} + (T_S - t_d)}{T_S} \approx v_{R,d} \frac{(t_d - t_{D,d}) + (T_S - t_d)}{T_S} \tag{3-11a}$$

$$u \approx v_{R,d} \frac{T_S - t_{D,d}}{T_S} \approx v_{R,d} (1 - \frac{t_{D,d}}{T_S}) \tag{3-11b}$$

It could be noticed from equation (3-11b) that in case of no stopped delay time during traversing road section, the value of running speed must be equivalent to the average speed.

3.2 ERROR IN TRAVEL SPEED ESTIMATION FROM GPS-PROBE DATA

3.2.1 Average speed method

From the concept of travel time that comprises running time and stopped delay time, the average speed on each section, u can be approximated from the relationship between section length and the section travel time as follow:

$$u \approx \frac{L}{t_{exit} - t_{ent}} = \frac{L}{T_S} \tag{3-12}$$

The upper bound for error of speed (ε_u) in terms of positional accuracy of individual GPS point (ε) and section travel time (T_S) can be expressed by assuming the errors associated with t_{ent} and t_{exit} are independent (practically, ε_u values may be lower if the errors associated with t_{ent} and t_{exit} are both of the same sign and magnitude) and using the error propagation theory as:

$$\varepsilon_u \approx \frac{\sqrt{2}\varepsilon}{t_{exit} - t_{ent}} = \frac{\sqrt{2}\varepsilon}{T_S} \tag{3-13}$$

The error of the average speed computed from equation (3-5) can also be expressed using the error propagation theory by assuming constant sampling time interval (Δt) between two contiguous GPS points as:

$$\varepsilon_u \approx \frac{\sqrt{p-0.5}}{p}\varepsilon_v \approx \frac{\sqrt{\Delta t(T_S - 0.5\Delta t)}}{T_S}\varepsilon_v \tag{3-14}$$

where p denotes the number of GPS points within the segment (in addition to p_0), ε_v is the error in speed associated with each GPS point.

Due to equation (3-13) and equation (3-14), a measurement error in section speed occurs from the error in positional and speed measurement respectively. Therefore, by combining equation (3-13) and (3-14), the threshold which makes equation (3-5) preferable for estimating the average section speed can be expressed as:

$$\varepsilon_v < \frac{\sqrt{2}\varepsilon}{\sqrt{\Delta t(T_S - 0.5\Delta t)}} \tag{3-15}$$

Table 3-1 Limiting error ε_v from the baseline approach as function of T_S and ε. (Assuming Δt = 1 s.) [Equation (3-15)]

T_S (s)	Limiting error ε_v in speed measurement (km/h)				
	ε = 0.1 m	ε = 0.5 m	ε = 1 m	ε = 3 m	ε = 10 m
10	0.17	0.83	1.65	4.96	16.52
20	0.12	0.58	1.15	3.46	11.53
50	0.07	0.36	0.72	2.17	7.24
100	0.05	0.26	0.51	1.53	5.10
200	0.04	0.18	0.36	1.08	3.60
500	0.02	0.11	0.23	0.68	2.28
1000	0.02	0.08	0.16	0.48	1.61

Table 3.1 demonstrates some sample values of ε_v calculated from equation (3-15) for several combinations among ε and T_S by assuming constant sampling time interval Δt = 1 sec. As could be noticed from Table 1, ε_v has a direct proportion to ε which indicates that as the positional accuracy of GPS device increases (ε decreases), the accuracy on speed must also increase (ε_v decreases) in order to maintain the advantage of equation (3-5) over equation (3-12). Moreover, ε_v is inversely proportional to T_S and Δt which signifies that as the section travel time or sampling time interval increases, the effect of positional error will be lower. In our study, we used the GPS devices which had 3 m positional accuracy and 0.36 km/h speed accuracy as the data collecting instruments. From Table 1, by assuming ε = 3 m, the limiting error for ε_v is much larger than 0.36 km/h. This means that equation (3-5) provides more accurate segment speed estimation result than equation (3-12).

3.2.2 Running speed and stopped delay method (RSSD)

As demonstrated in equation (3-11b), an average speed can be approximated using the relationship among running speed, stopped delay time, and total travel time. Consequently, from equation (3-9) and (3-11b), an error of the average speed calculated from the RSSD technique can be computed using the error propagation theory and by assuming that sampling time interval Δt between two contiguous GPS points is constant, which can be expressed as:

$$\varepsilon_u \approx \varepsilon_R (1-\frac{t_{D,d}}{T_S}) \approx \frac{\sqrt{\Delta t(T_S - t_{D,d} - 0.5\Delta t)}}{T_S - t_{D,d}} (1-\frac{t_{D,d}}{T_S})\varepsilon_v \tag{3-16}$$

It was noted that in reality the detected vehicle speeds from GPS data normally comprise discrepancies due to the limitation of device accuracy. As a result, even though the vehicle is in the stopped delay period, the detected speeds from GPS at those points are generally fluctuated and not perfectly equal to zero. However, the error from discrepancies during these stopped delay times could be mitigated by setting up the threshold for detecting the stopped delay behavior of vehicles (e.g. by setting 0.5 km/h as the threshold and considering all the speed values lower than 0.5 km/h as the absolutely stop behavior, 0 km//h) and filtering out the error in speed measurement during this period. This procedure leads to higher accuracy to the RSSD technique since some errors were disregarded during this process.

By comparing equation (3-13) and (3-16), the threshold which makes equation (3-11b) preferable for estimating average speed can be expressed as:

$$\varepsilon_v < \frac{\sqrt{2}\varepsilon}{\sqrt{\Delta t(T_S - t_{D,d} - 0.5\Delta t)}} \tag{3-17}$$

Table 3.2 demonstrates sample values of ε_v calculated from equation (3-17), in terms of congestion level or ratio between the stopped delay time and travel time, ($t_{D,d} / T_S$) assuming the sampling time interval is 1 sec and the positional error of GPS is 3 m. It could be observed that in the uncongested segment or the segment without stopped delay time, the ε_v values calculated from the average speed technique (equation (3-15)) are equal to the ones from the RSSD technique (equation (3-17)). However, as the congestion increases (ratio of stopped delay time per section travel time ($t_{D,d} / T_S$) increases), the effect of positional error increases, leading to higher limitation of error in speed associated with each GPS point (ε_v) for providing the advantages of speed estimation by equation (3-11) over equation (3-12).

Table 3-2 Limiting error ε_v from RSSD approach as function of T_S and $t_{D,d}$.(Assuming Δt = 1 s. and $\varepsilon = 3\,m$)[Equation (3-17)]

T_S (s)	Limiting error ε_v in speed measurement (km/h)			
	$\frac{t_{D,d}}{T_S} = 0$	$\frac{t_{D,d}}{T_S} = 0.2$	$\frac{t_{D,d}}{T_S} = 0.4$	$\frac{t_{D,d}}{T_S} = 0.6$
10	4.96	5.58	6.51	8.16
20	3.46	3.88	4.50	5.58
50	2.17	2.43	2.81	3.46
100	1.53	1.71	1.98	2.43
200	1.08	1.21	1.40	1.71
500	0.68	0.76	0.88	1.08
1000	0.48	0.54	0.62	0.76

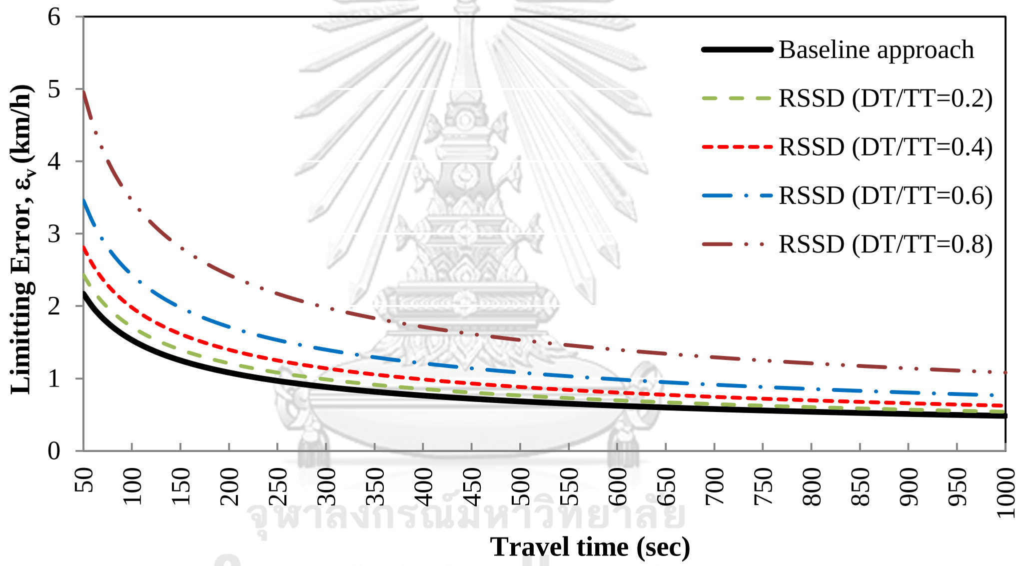


Figure 3-2 Limiting error in speed associated with each GPS device from the baseline and RSSD approaches. (Assuming $\Delta t = 1\,s$ and $\varepsilon = 3\,m$)

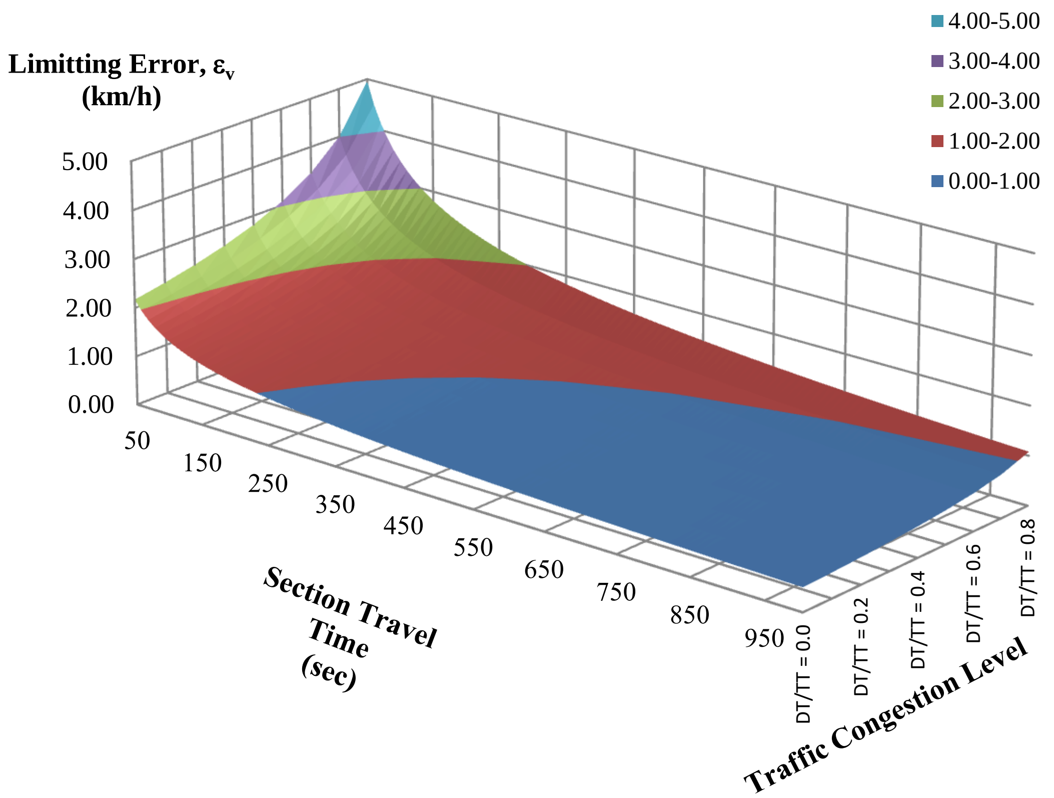


Figure 3-3 Surface plotting of limiting error in speed associated with each GPS device in various traffic congestion levels from the RSSD approach. (Assumming $\Delta t = 1\,s$ and $\varepsilon = 3\,m$)

Furthermore, the advantages of RSSD over the average speed approach in addressing speed estimation can be demonstrated by the limiting error in speed associated with each GPS device as presented in Figure 3.2 and 3.3. In the case that no stopped delay time (DT = 0) is experienced during traversing throughout the road segment, the limiting of GPS speed errors from both techniques are equivalent, as they are represented by the bold line in Figure 3.2. However, as the congestion level increases (ratio of stopped delay time to travel time (DT/TT) increases), the limiting error of GPS for the RSSD technique increases while the baseline method provides the same values as in the case of uncongested condition (as the limiting error of the baseline technique does not consider the effect of delay time, as illustrated in equation (3-15)). The abovementioned points out that in congested traffic condition the RSSD technique allows the use of lower accuracy devices than that of the baseline approach to maintain the accuracy level of travel speed estimation over equation (3-12). In other words, with the same device, travel speed estimation from the RSSD technique offers higher accuracy of the estimation than by the baseline approach, particularly in highly congested traffic conditions.

3.3 TRAVEL TIME ALLOCATION PROBLEMS

3.3.1 Background of problems

In the past decades, numerous research on travel time study in both freeway and arterial settings were carried out using probe-based data from various sources e.g. taxi probes (Herring, Hofleitner et al. 2010), bus probes (Pu and Lin 2009, Vanajakshi, Subramanian et al. 2009) test vehicles ((Billings and Yang 2006, Puangprakhon and Narupiti 2015), or synthetic data simulated from traffic simulation software ((Nanthawichit, Nakatsuji et al. 2003). Up to now, most of the previous studies require high resolution data, e.g. sampling every 1 second or less, to address the complete section travel time estimation or prediction problems (Zheng and Zuylen 2013). Conversely, in reality, the probe data fed to the traffic data collection center come from a variety of sources with different sampling time intervals such as taxies, logistics vehicles, public buses or private cars, etc. Therefore, the transmission rates can be varied from very high frequency to low resolution depending on the data providers (the sampling time interval up to 60 seconds could generally be observed). Additionally, the polling positions or sampling points in probe-based data are randomly distributed and do not necessarily correspond to the end points of the section on the road segment. As a consequence, the allocation of travel time between two consecutive sampled GPS points across the end points of the section is considered as one crucial task in the section travel time estimation procedure.

One of the simplest and easy-to-implement ideas for travel time allocation is done by assuming the constant driving speed between two consecutive sampling points. Then, the decomposed travel time in each section can be allocated by direct interpolation between the stamped times and reported positions of each vehicle. This technique provides reasonable estimation results in the traffic with nearly constant speed profiles such as on freeways or motorways with the under-saturated traffic condition. However, in the urban context where the road network typically consists of traffic signals, intersections, and numerous access points and thus the vehicle speed profiles are generally fluctuated and far from constant, the estimation based on the constant speed assumption technique has difficulty in providing precise outcomes (Neumann 2013).

For the above reason, various techniques have been proposed to address the travel time allocation problem. For instance, (Hellinga, Izadpanah et al. 2008) proposed the model which considers the probability of stopping and congestion delays based on the positions of vehicles along a road segment. Although the overall result from simulated data showed that this approach performed well compared to the benchmark technique, the section travel time was overestimated on the segment without traffic signals and the limitation on the number of stops in each section and this was a drawback of this technique. (Hofleitner and Bayen 2011) demonstrated the use of the statistical traffic flow theory in travel time decomposition problems. Their technique showed good agreement with the next Generation Simulation (NGSIM) data. Still, this technique is quite complex and requires many assumptions e.g. stationary traffic, probability of delay, etc. to allocate the travel time into individual sections. Although a number of works attempted to construct more complex models for representing the urban traffic, a finding from (Zheng, Van Zuylen et al. 2010) proved that the more complicated models did not always offer better outcomes than the simple and widely used technique (time-distance relationship technique). Conversely, in some cases, e.g. in the less frequent polling time interval or in the sparse data, the simple model tends to offer the healthier result than the complicated ones. This could be resulted from complex movement and delay behaviors on urban roadways that face many unexpected influencing factors, e.g. a bus waiting at a bus stop, double-parked vehicles or other causes. Therefore, (Zheng and Zuylen 2013) overcame the complexity of modeling by utilizing the Artificial Intelligent (AI) method in travel time allocation for urban roads. They employed the three-layer neural network with positions, section IDs, time stamps and speeds as the model inputs for complete section travel time estimation. The result from synthetic data illustrated that their approach outperformed the analytical model from (Hellinga, Izadpanah et al. 2008), particularly when the traffic demand was increasing. They also suggested that the position could be the critical factor influencing the accuracy of the ANN model while adding of instantaneous speed as the input could improve the accuracy marginally. Yet, the ANN technique requires a lot of historical data for training and the ambiguous process going underneath with regards to the decisions of ANN is questioned.

As aforementioned, accurate prediction on delays and trajectories of vehicles along the urban roads is not an easy task. However, the condition of the traffic movement at any point can basically be informed by the instantaneous speed detected from the probe vehicle. Therefore, (Puangprakhon and Narupiti 2014) demonstrated the integration of the instantaneous speed data together with time and position in the travel time allocation procedure. In their approach, the speeds at the end points of the section and travel times were approximated and tuned until convergence using the speed-time-distance relationship. Verification through the results from field data also confirmed the better-quality of the results from this technique over the simple distance-time method in all scenarios. Moreover, the speed-time-distance techniques can easily be implemented and efficiently address the travel time allocation problem as proved by more precise complete section travel time estimation results. Research by (Neumann 2013) pointed out the importance of individual decomposed travel time study particularly at the local level (e.g. an individual intersection) and also suggested that the travel time decomposition could be a crucial negative factor affecting the accuracy of probe-based section travel time as errors from each decomposed travel time do not accumulate but could balance out when being recombined into the complete section travel time. Therefore, study on quality of the decomposing technique at the local level is a necessitated task for ensuring the quality of travel time estimation at both local and complete section levels.

3.3.2 Problem statements

Section travel time or time spent for traveling through each section is considered as one of the most understood indicators for representing the condition of traffic on road networks. In probe-based data, the travel time between two consecutive observed points can be directly considered as the travel time between those points. However, in general, the locations of sampled points from probe vehicles are randomly located on the road and usually do not correspond with the end points of the section. Therefore, in measuring section travel time, the time between two consecutive sampled points across the end points of the section needs to be allocated into an individual section as depicted in Figure 3.4. There are three possible cases from two observed points from probe-based data; two observed points lie on the same section (Figure 3.4(a)), two observed points lie on adjacent sections (Figure 3.4(b)), and two observed points lie on different sections with at least one section in between (Figure 3.4(c)). In the first case, since both observed points lie on the same section, travel time between those points can be directly measured from the sampling time interval without travel time allocation problems. While in the second and third cases, the measured travel time between two observed points $(t_2 - t_1)$ is allocated or decomposed into existing sections ($t_{L1,dec}, t_{L2,dec}, \ldots, t_{Ln,dec}$) between those points.

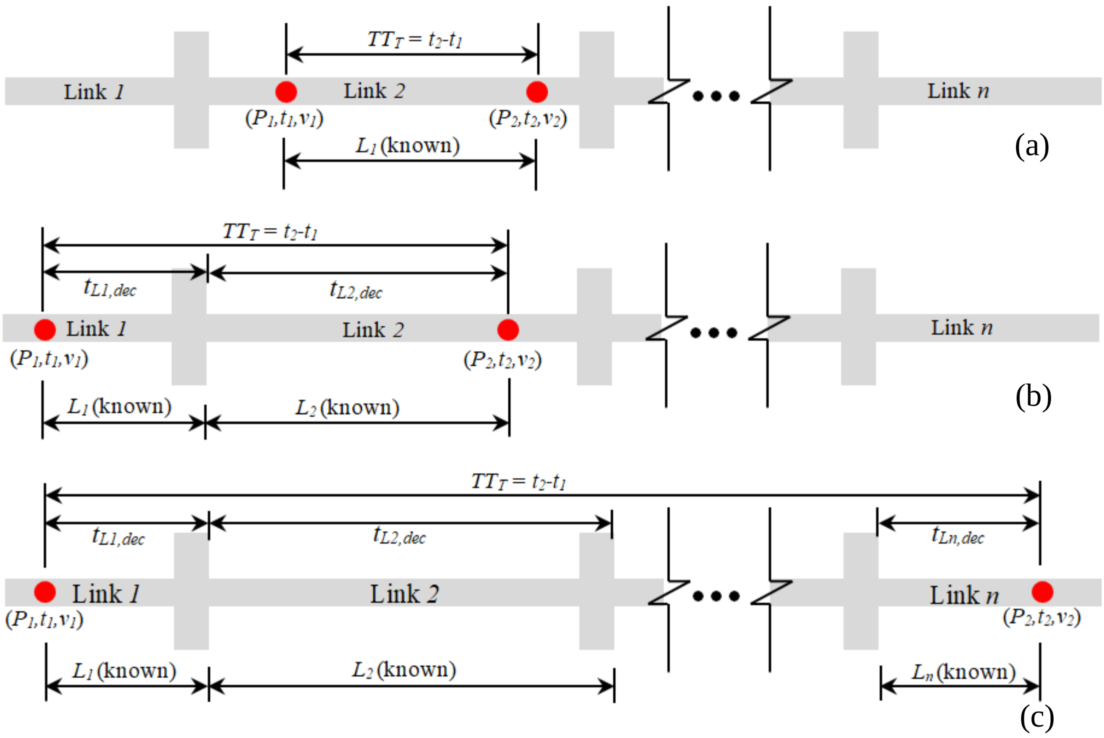


Figure 3-4 Three possible travel time allocation cases from probe-based data. (a) sampled points lie on the same section; (b) sampled points lie on adjacent sections; (c) sampled points lie on different sections with at least one section in between.

3.4 TRAVE TIME ALLOCATION TECHNIQUES

3.4.1 Distance-time relationship method

Travel time allocation by the distance-time relationship assumes "the speed of the probe vehicle is constant during traversing between two consecutive sampled points". The decomposed travel time in each component section can be approximated by interpolating among locations and recorded times from sampled data regardless of instantaneous speed of those points. From Figure 3.4, Let n be the number of incorporated sections between two consecutive sampled points, time stamps at the first and second points are t_1 and t_2 respectively, TT_T is the travel time or time difference between those two points (calculated by $t_2 - t_1$), which is generally equivalent to the probe sampling time interval, L_i is the distance between two sampled points projected on section i. The decomposed travel time of section i, $t_{Li,dec}$, can be estimated by:

$$t_{Li,dec} = TT_T \frac{L_i}{\sum_{i=1}^{n} L_i} \qquad (3\text{-}18)$$

3.4.2 Speed-Time-Distance relationship method (Proposed Methods)

The state or movement of traffic at each sampled location can be reflected by instantaneous speed recorded in probe data. Previous research from (Zheng and Zuylen 2013) has demonstrated the improvement of travel time estimation when the instantaneous speed was integrated into the estimation process. Therefore, not only information from time stamped and sampled location of probe vehicles, but also the instantaneous speed of those positions are assimilated into the approximation procedure of the speed-time-distance approach. In this technique, firstly, the speed at the end point of the section is approximated by direct interpolation assuming linear relationship between speeds and location of two sampled points. Then, the estimation of individual section travel time using the speed and distance relationship is estimated and a tuning of individual section travel time is compared with the sampling time interval. Afterward, the speed at the end point of the section is re-calculated from the adjusted individual section travel time from the previous step. All the above mentioned processes are repeatedly performed until the individual section travel time is convergent. The procedure for allocating travel time into an individual section by the speed-time-distance approach can be outlined into six steps and is illustrated in Figure 3.5.

- Step 1: Approximation of speed at the end of section.

Assuming a linear relationship between instantaneous speed and recorded location from two consecutive sampled points across the end points of the section, the speed of the vehicle at the end points of the section, v_e, can be estimated using the proportion among instantaneous speeds and distances as follows:

$$v_e = v_1 + \Delta v(\frac{L_1}{L_1 + L_n}) = v_2 - \Delta v(\frac{L_2}{L_1 + L_2}) \qquad \text{(3-19)}$$

where Δv is the difference of instantaneous speeds between two sampled points, computed by ($v_2 - v_1$), v_1 and v_2 are instantaneous speeds recorded at first and second points, respectively. It should be noted that v_e will be used as the dividing term in the next step. For that reason, in the special case where $v_e = 0$ (in case of $v_1 = v_2 = 0$), the small speed value (e.g. 1 km/h) should be applied to v_e for solvable purpose instead of 0 km/h.

- Step 2: Approximation of decomposed travel time from the speed-distance relationship

Due to the clear relationship among travel speed, travel time and traversing distance, (Δx during time t_1 and t_2) can be expressed in terms of speed profile as $\Delta x = \int v dt$ (in the case that dt is small enough). Consequently, the decomposed travel time of each section can be roughly estimated by applying the above relationship as follows:

$$t_{Li,dec} = \begin{cases} 2L_i/(v_e + v_1) & \text{for } i = 1, n \\ L_i / v_e & \text{otherwise} \end{cases} \tag{3-20}$$

- Step 3: Calculation of time difference between sampling time interval and estimated travel time

The travel time between two consecutive sampled points must correspond to the sampling time interval. Thus, the time difference between decomposed travel times from the previous step and a sampling time interval can be expressed as follows:

$$\Delta t = TT_T - \sum_{i=1}^{n} t_{Li,dec} \tag{3-21}$$

- Step 4: Tuning the decomposed travel time to sampling time interval

As discussed previously, summation of decomposed travel times calculated in Step 2 needs to be equivalent to the sampling time interval. For that reason, in the tuning procedure, time difference calculated in Step 3 is added to the decomposed travel time in each section according to the ratio between individual section decomposed travel time and total decomposed travel time as illustrated in Eq. (3.22). It should be noted that to ensure that the adjusted decomposed travel times always have positive values and lie within the sampling time interval, the minimum and maximum boundaries $0 \le t_{Li,dec} \le TT_T$ should be applied.

$$t'_{L_i,dec} = \min\{\max\{t_{L_i,dec} + \Delta t\left(\frac{t_{L_i,dec}}{\sum_{i=1}^{n} t_{L_i,dec}}\right), 0\}, TT_T\} \tag{3-22}$$

- Step 5: Re-estimation of speed at the end points of the section from adjusted decomposed travel time

From the speed-time-distance relationship, the speeds at the end points of the section calculated from adjusted decomposed travel time in each section ($v_{e,i}$) can be estimated using Eq. (3-23). It should be noted that the lower and upper boundaries for $v_{e,i}$ should be applied to ensure that the adjusted speeds in this step have positive values and are not more than the rational driving speed. In this paper, the speed limit was employed as the upper boundary. However, another appropriate value could be used instead; for instance, free flow speed.

$$v_{e,i}\begin{cases}\min\left\{\max\left\{(2L_i/t'_{Li,dec})-v_i,0\right\}, speed\ limit\right\} & for\ i=1,n\\ \min\left\{\max\left\{(L_i/t'_{Li,dec})-v_i,0\right\}, speed\ limit\right\} & otherwise\end{cases} \tag{3-23}$$

- Step 6: Re-adjusting speed at the end point of section

The adjusted speed at the end point of section (v'_e) can be approximated from the adjusted decomposed travel time in each section ($v_{e,i}$) by weighing with the distance proportion as follows:

$$v'_e=\sum_{i=1}^{n}(v_{e,i}(L_i/\sum_{i=1}^{n}L_i)) \tag{3-24}$$

Substitute v'_e calculated from Eq. (3-24) into Eq. (3-20) in place of v_e and recalculate Step 2 to Step 6 until the adjusted decomposed travel time of each section ($t'_{L,dec}$) is convergent.

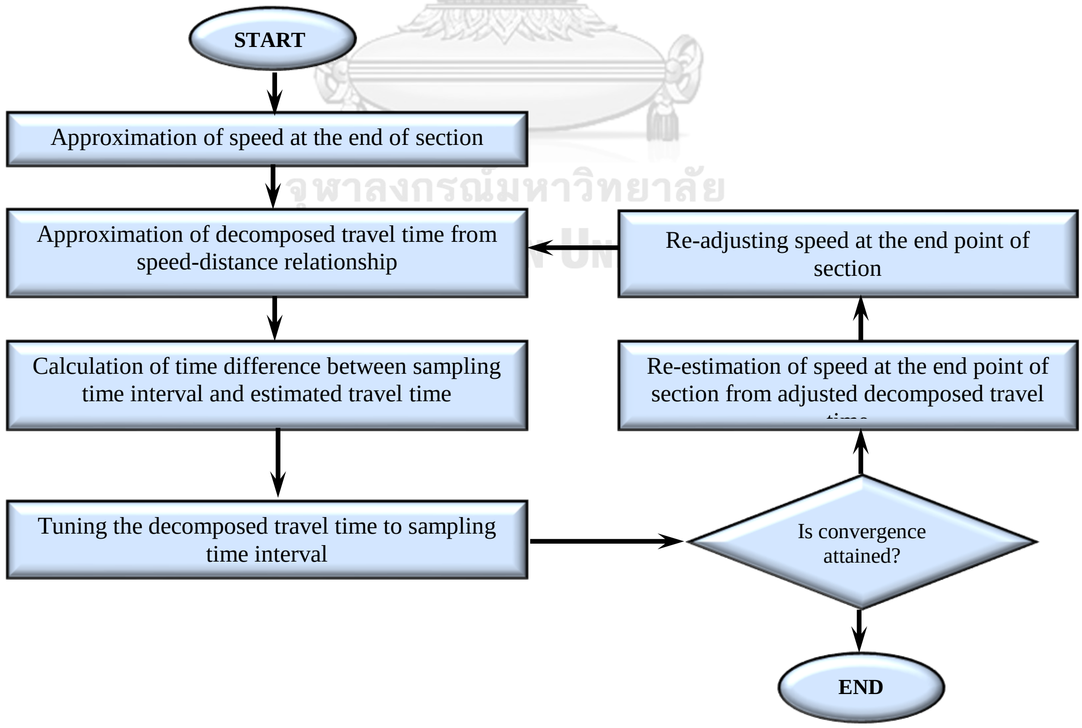


Figure 3-5 Calculation flowchart for travel time allocation of the proposed technique.

3.5 EXPERIMENTAL STUDY ON TRAVEL TIME ALLOCATION

3.5.1 Study corridor and data gathering technique

In order to validate the proposed technique, the 4.07 km in-bound urban roadway comprising 6 sections with different length varying from 0.2 to 1.24 km partitioned by 5 signalized intersections in Bangkok Metropolis was selected as the test corridor for gathering high resolution probe data. The field data were collected from 15 GPS equipped probe vehicle runs throughout the study site with a sampling time interval of every 1 second. The time period for data collection was from 6:00 am to 4:00 pm to ensure that both congested and uncongested traffic conditions were included in the dataset. From high resolution probe data, the testing scenarios were simulated to the sparsely distributed data into three testing campaigns for representing the more often used sampling time interval in reality; sampling every 15, 30 and 60 seconds, respectively.

As the bias on the estimation results could occur if only one sampling position on the section was used, in this study various initial conditions of samplings were used. Therefore, the re-sampling technique was applied in this study for diminishing the bias in the sampling process. From each re-sampling time interval, for instance sampling every 30 seconds, the combination of different starting times can be expressed as follows:

Combination 1: j, j+30, j+60, j+90,…

Combination 2: j+1, j+31, j+61, j+91,…

…

Combination 30: j+29, j+59, j+89, j+119,…

The expected section travel time from vehicle k which traversed through section i can be calculated by averaging the results from all combination cases as:

$$TT_{k,i} = \frac{1}{m}\sum_{j=1}^{m} tt_{k,j} \tag{3-25}$$

where m is the number of combination cases (or sampling moment), $tt_{k,j}$ is the estimated travel time of section i using data gathered from vehicle k with the sampling moment j.

3.5.2 Performance indicators

To display the effectiveness of the proposed technique, the estimation results from the speed-time–distance technique in both complete section and local contexts were assessed and compared with the baseline technique by means of various indicators. The Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) were applied as the accuracy indicators for complete section travel time estimation, since MAPE can express the error in generic percentage whereas RMSE presents the differences between values from estimation and observation.

$$MAPE = \frac{100}{n}\sum_{k=1}^{n}\left|\frac{TT_{k,i,est} - TT_{k,i,obs}}{TT_{k,i,obs}}\right| \tag{3-26}$$

$$RMSE = \sqrt{\frac{\sum_{k=1}^{n}(TT_{k,i,est} - TT_{k,i,obs})^2}{n}} \tag{3-27}$$

where $TT_{k,i,est}$ denotes the estimated travel time of section i using data recorded from vehicle k, $TT_{k,i,obs}$ is the observed travel time of section i from vehicle k, and n is the total number of probe runs throughout section i.

In comparing the two approaches, the Percentage of Improvement (*PoI*) was selected as the indicator for performance measurement. The *PoI* of travel time estimation from the proposed technique compared to the benchmark technique on segment j, can be calculated as follows:

$$PoI_j = \frac{RMSE_{baseline,j} - RMSE_{proposed,j}}{RMSE_{baseline,j}} \tag{3-28}$$

where $RMSE_{baseline,j}$ denotes the RMSE on segment j from the estimation using the baseline method (simple time-distance method), $RMSE_{proposed,j}$ denotes the RMSE on segment j from the estimation using the speed-time-distance method.

3.5.3 Results and discussions

As discussed previously, the investigation on the validation and performance of travel time allocation techniques can be evaluated in both complete section and local levels. Therefore, in this section, the results are presented and discussed in both complete section and intersection levels for examining the correctness of the proposed technique compared with the baseline approach. For representing the application of probe vehicles in reality, the testing scenarios were simulated from the high resolution observed data (ground truth) and divided into three testing campaigns with sparsely sampling time intervals from 15, 30 and 60 seconds, respectively.

Complete section travel time estimation

Based on data collected from 15 probe runs throughout the studied corridor which comprises 6 sections and 7 intersections, the accuracy on travel time allocations from both the proposed (speed-time-distance relationship) and baseline techniques (time-distance relationship) in complete section travel time estimation is illustrated in Table 3.3.

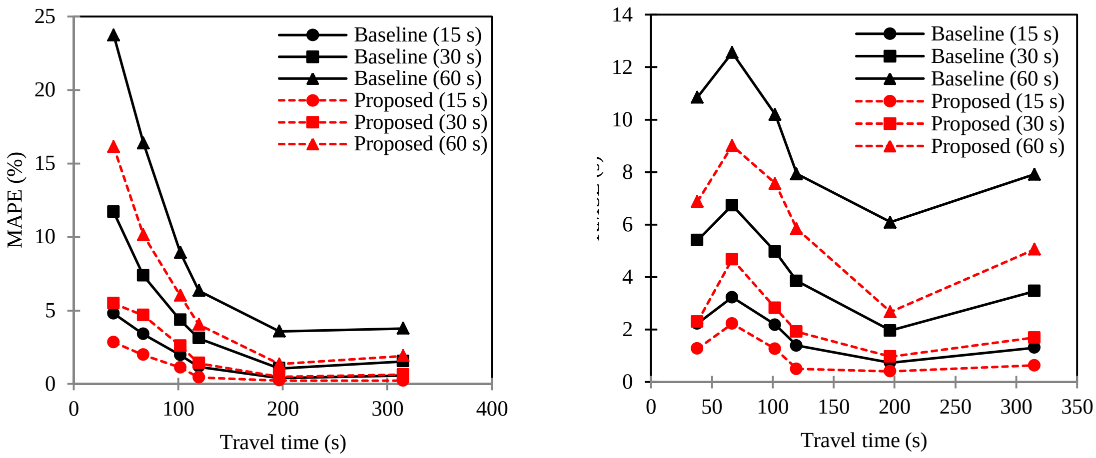
From Table 3.3, it can be observed that the less frequent sampling time interval decreases the correctness of estimation from both models. In the proposed technique, as the sampling time interval increases from 15 to 60 seconds, average MAPE increases from 1.14 to 6.59%, and average RMSE also increases from 1.05 to 6.17 seconds. On the other hand, the baseline technique provides poorer estimation results as reflected by the steep increase on average MAPE from 2.04 to 10.46% and average

RMSE from 1.85 to 9.26 seconds, while the sampling time interval rises from 15 seconds to 60 seconds respectively. In addition, as depicted by PoI values, the accuracy of estimation is significantly boosted in all test campaigns when employing the proposed technique, compared to the baseline approach.

Table 3-3 Performance measurements at complete section level of proposed and baseline method in different sampling time intervals.

Section			**AB**	**BC**	**CD**	**DE**	**EF**	**FG**	**Average**
Average observed travel time (s)			66.67	102.00	38.20	315.13	196.67	119.73	
Average observed speed (km/h)			17.56	28.08	20.25	28.43	20.62	15.43	
Sampling time 15 seconds	MAPE (%)	Baseline	3.38	1.96	4.79	0.56	0.39	1.16	2.04
		Proposed	1.97	1.11	2.84	0.22	0.24	0.44	1.14
	RMSE (s)	Baseline	3.23	2.18	2.23	1.31	0.74	1.39	1.85
		Proposed	2.23	1.26	1.27	0.63	0.41	0.5	1.05
	PoI (%)		31.02	42.15	42.99	51.76	44.92	64.18	46.17
Sampling time 30 seconds	MAPE (%)	Baseline	7.37	4.35	11.7	1.54	1.06	3.1	4.85
		Proposed	4.67	2.6	5.47	0.64	0.49	1.41	2.55
	RMSE (s)	Baseline	6.74	4.97	5.4	3.46	1.96	3.85	4.40
		Proposed	4.68	2.82	2.31	1.69	0.97	1.92	2.40
	PoI (%)		30.56	43.22	57.35	51.09	50.62	50.20	47.17
Sampling time 60 seconds	MAPE (%)	Baseline	16.38	8.94	23.73	3.77	3.58	6.34	10.46
		Proposed	10.13	6.01	16.13	1.91	1.35	4.03	6.59
	RMSE (s)	Baseline	12.56	10.19	10.86	7.92	6.09	7.93	9.26
		Proposed	9.01	7.57	6.89	5.06	2.68	5.84	6.17
	PoI (%)		28.23	25.74	36.58	36.09	56.09	26.35	34.85

As shown in Figure 3.6, the total time spent in each section affects the accuracy level of section travel time estimation in the case that MAPE is employed as the indicator for accuracy. In this case, since the accuracy is represented by the error time per total travel time, in the longer section or section with higher travel time, the accuracy from both techniques are higher than in the shorter ones, indicated by lower MAPE values, as illustrated in Figure 3.4(a). This occurred because the portion of the known travel time (travel time in this section does not need to be allocated, as illustrated in Figure 3.4(a)) is a lot greater than the unknown cases (Figure 3.4(b), (c), which need to be allocated) in the more time consuming section. In comparison, the relationship among section travel times and the time difference between estimated and observed values indicated by RMSE are fluctuated as illustrated in Figure 3.6(b). This could be caused by the local characteristics (e.g. traffic movement behaviors at each intersection) and the error combination from both ends of section as discussed previously. Even so, the proposed technique still provides superior results to those from the baseline approach as seen by the lower RMSE in all test scenarios.



(a) (b)

Figure 3-6 Relationship between MAPE, RMSE and section travel time from the proposed and baseline method in various sampling time intervals.

Travel time allocation at local level (intersection level)

As described previously about the effects of balancing out of errors from both ends of section and also effects of portion of known travel time within the section (as illustrated in Fig. 3.4(a)), which could create biases in the complete section travel time estimation, this section introduces the analysis at local level (intersection level) for diminishing the bias and provides the closer look at the effectiveness of travel time allocation by the baseline and proposed techniques.

In this section, the results and discussions on travel time allocation from both techniques at the local level (or at the intersection instead of complete section) are demonstrated. The section starts with the definition of local level and time region used in this study, followed by the travel time allocation results at each intersection, then the results according to the different movement behaviors at each intersection are demonstrated and discussed.

- Definition and time region for evaluating local level travel time

In this study, the time region for evaluating local level or intersection level was defined and shown in Figure 3.7. Figure 3.7 displays an example of the speed and time tracked from the probe vehicle during traversing through section AB. The time spent for traversing within this section can be determined by the time difference between entrance and exit time of the section (the entrance time is when the vehicle passed intersection A and the exit time is when the vehicle passed intersection B which were 08:08:00 and 08:09:19 respectively). In the case that the sampling time interval is 15 seconds, the time region used for evaluating the accuracy of travel time allocation at local level at intersection A will cover the region from 15 seconds before and after the time that the vehicle passed intersection A (from 08:07:45 to 08:08:15 as depicted in Figure 3.7). This is because, in the analysis part, this time period will cover all the combinations of sampling time at intersection A that are used for testing the accuracy of travel time allocation as previously described. Therefore, in this example, totally 15 combinations from 15 sampling cases starting from the first case recorded at 08:07:45 and 08:08:00 , second case at 08:07:46 and 08:08:01,…, and the fifteenth case at 08:08:00 and 08:08:15 will be combined together and used for evaluating the accuracy of both techniques at the local level of intersection A.

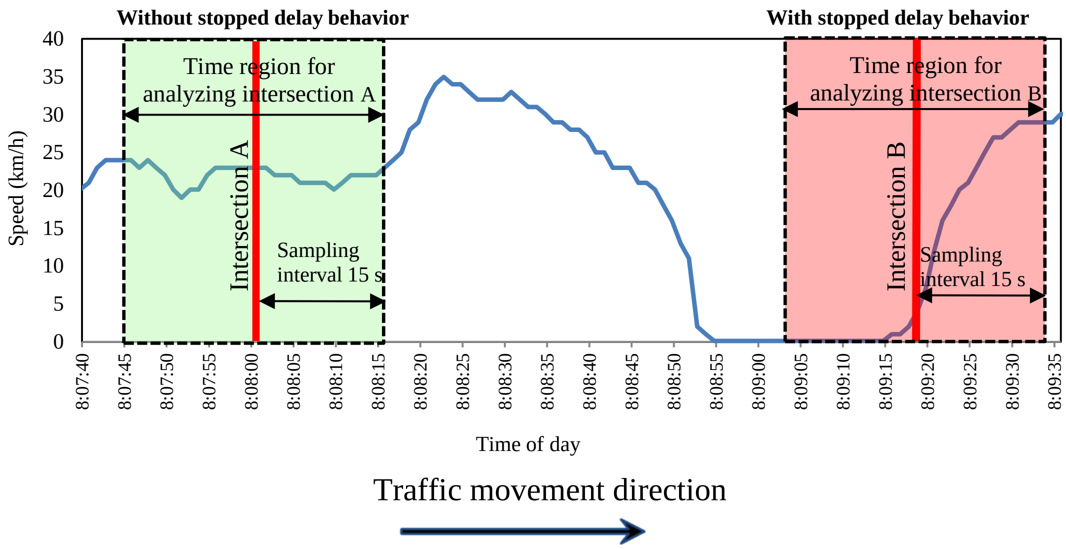


Figure 3-7 Time region for local level (intersection level) analysis in the case that the sampling time interval is 15 seconds.

- The evaluation of travel time allocation at the local level

As illustrated in Table 3.4, travel time allocation resulted from the proposed technique is superior to that of the baseline approach in all intersections and sampling intervals. The estimation error is smallest in the shortest sampling interval, but increases as the sampling interval increases. MAPE values in Table 3.4 are significantly greater than in Table 1 as all the allocation cases in local context are unknown as depicted in Figure 3.4(b) and 1(c), unlike in complete section level in Figure 3.4(a). Additionally, the average *PoI* values ranging between 30-40% also show considerably better results than the proposed technique in the local context.

- Effects of stopping behavior at intersection region

The movement behavior of the vehicle within the area of intersection (within the time region as depicted in Figure 3.7) could affect the accuracy level of both models due to different basic assumptions. Therefore, besides the overall picture at each intersection given in Table 3.4, an in-depth analysis by considering stopping behavior from the vehicle speed profile is performed. In this study we defined the "intersection with stopping behavior" as the intersection where the probe vehicle has at least one stopped delay within one sampling interval prior to or after the recorded time at the intersection point (as depicted by red region in Figure 3.7).

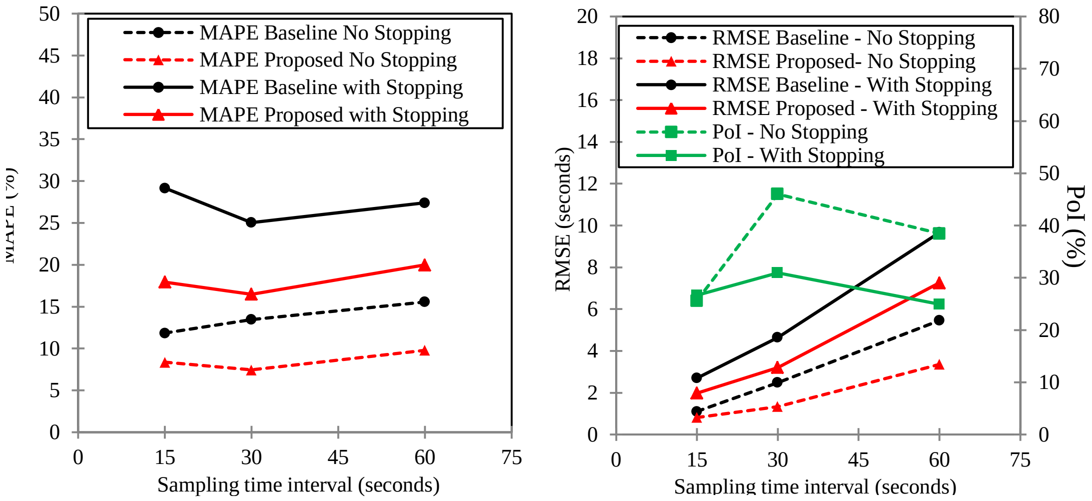
As shown in Figure 3.8, the estimation errors from both techniques are significantly higher at the intersection with stopping behavior (which generally contained a highly fluctuated speed profile). Still, the proposed technique offers better outcomes in all cases. This is because the baseline approach allocates travel time by assuming a constant speed profile among two consecutive probe points and this is far from the real traffic behavior particularly with stop and go movement. On the other hand, the proposed technique could reflect the fluctuation of the speed profile by assuming a linear relationship among recorded instantaneous speeds and speed at the end points of the section using the speed-time-distance relationship in the tuning process to find speed at the end points of the section from travel time allocation.

In Figure 3.8, although the proposed technique can represent better speed variation than the baseline approach, the *PoI* values at the intersection without stopping behavior are higher than the stopping ones. This is because the RMSE (or dividing term) of the "no stopping cases" are significantly lower than the "stopping case". Therefore, even though the proposed technique can reduce higher quantity of RMSE in the “stopping cases”, the effect from the smaller dividing term in “no stopping cases” will lead them to the higher *PoI* value.

Table 3-4 Performance measurement at intersection level of proposed and baseline method in different sampling time intervals.

Intersection			A	B	C	D	E	F	G	Average
Sampling time 15 seconds	MAPE (%)	Baseline	33.21	15.53	20.22	16.35	7.72	7.92	16.59	16.79
		Proposed	23.64	10.53	15.09	7.83	5.64	5.77	9.12	11.09
	RMSE (s)	Baseline	3.30	1.28	1.79	1.37	0.68	0.75	1.42	1.51
		Proposed	2.63	0.88	1.37	0.74	0.45	0.58	0.77	1.06
	PoI (%)		20.46	31.16	23.64	46.03	33.41	23.11	46.10	31.99
Sampling time 30 seconds	MAPE (%)	Baseline	31.52	18.51	21.37	22.87	11.81	9.51	21.92	19.64
		Proposed	23.35	14.17	14.78	11.20	5.40	4.92	12.04	12.27
	RMSE (s)	Baseline	5.85	3.48	4.05	3.73	2.23	1.62	4.07	3.58
		Proposed	4.67	2.37	2.44	2.17	0.93	0.95	2.11	2.23
	PoI (%)		20.16	31.86	39.81	41.75	58.32	41.10	48.21	40.17
Sampling time 60 seconds	MAPE (%)	Baseline	31.73	23.32	22.38	34.94	22.97	12.61	22.55	24.36
		Proposed	23.81	18.55	18.32	25.44	10.03	6.70	18.67	17.36
	RMSE (s)	Baseline	10.74	7.81	8.45	11.49	7.92	4.32	8.89	8.52
		Proposed	8.46	6.50	6.45	8.48	3.68	2.14	6.98	6.10
	PoI (%)		21.19	16.82	23.65	26.16	53.59	50.54	21.50	30.49

*Average decomposed travel times in each section (upstream and downstream sections) at intersection are 7.5, 15 and 30 seconds for sampling time interval 15, 30 and 60 seconds respectively.



(a) MAPE (b) RMSE and *PoI*

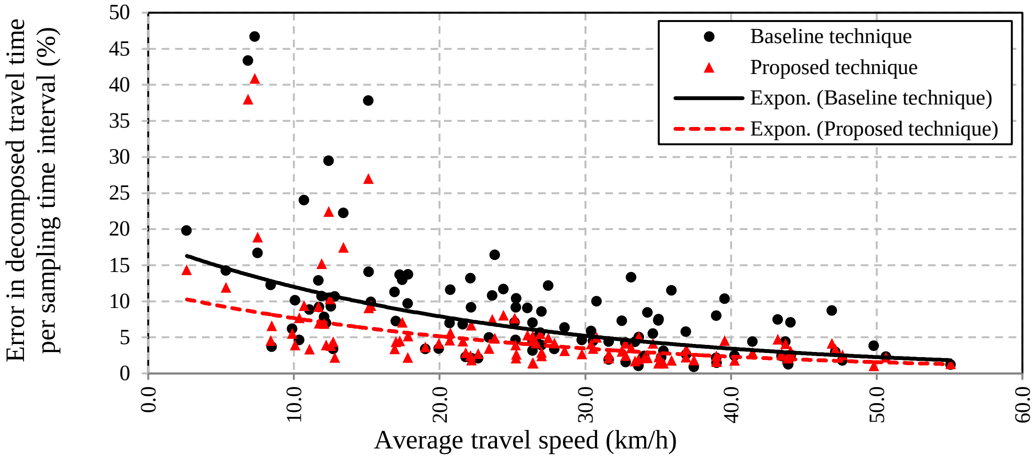
Figure 3-8 MAPE, RMSE and PoI of decomposed travel time from the baseline and proposed technique categorized by stopping behavior.

- Effects of the average speed within time region of each intersection

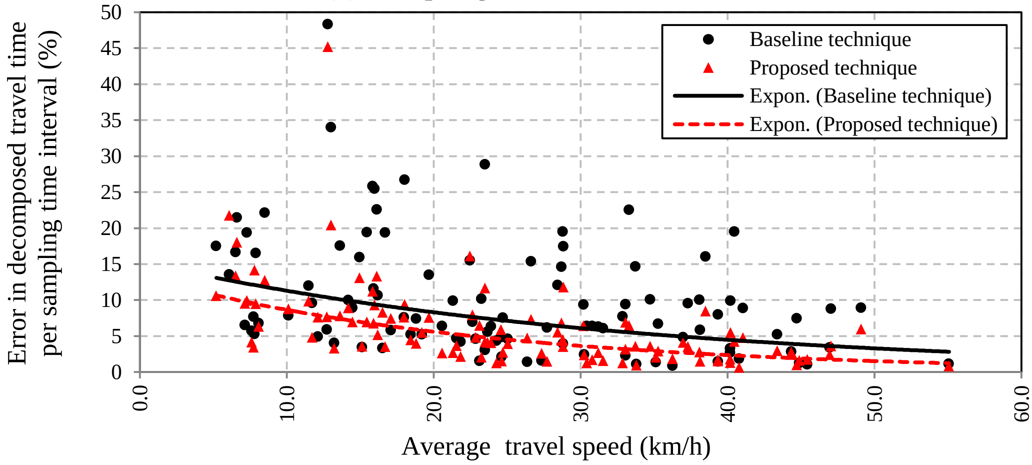
The average travel speed at intersection could be used to represent the state of traffic at that location, the higher movement speed the better traffic conditions. Therefore, the relationship between the average travel speed within the intersection region and the error from each allocation technique were presented. In Figure 3.9, the percentage of error from travel time allocation per size of sampling interval is represented in the vertical axis (e.g. if allocation error is 3 seconds and sampling time interval is 15 seconds, the error in decomposed travel time per sampling time interval will be 20 %), while the horizontal axis indicates the average travel speed of the probe vehicle inside the intersection region. From Figure 3.9, the errors of travel time allocation from both techniques decrease when the average travel speed at the intersection region increases. This points out the advantages of both techniques in the uncongested traffic condition. Besides, the speed profile in the uncongested condition (higher average speed) is smoother and close to the constant value due to the better agreement with the results from the baseline technique with constant speed assumption. However, in all sampling time intervals and all states of traffic, the proposed technique yields the superior results.

- Effects of the speed fluctuation within the time region of each intersection

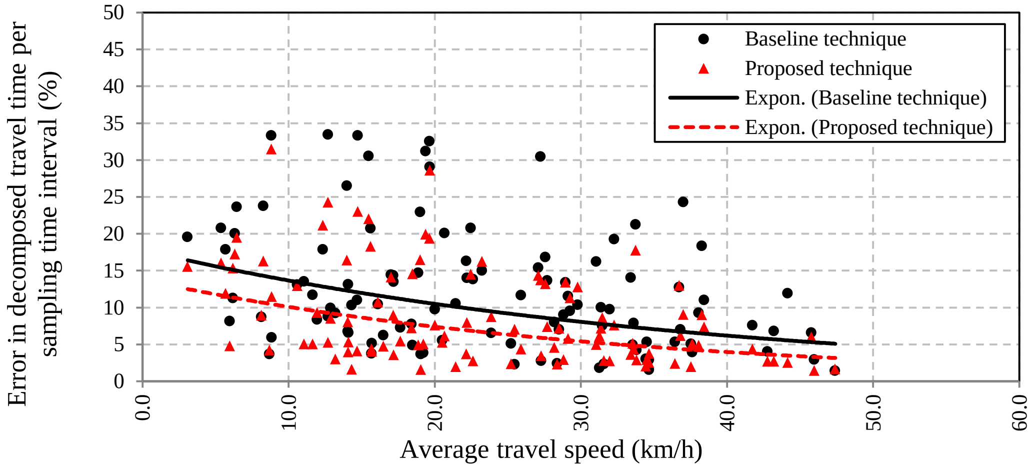
A closer consideration is made on the effects of speed fluctuation at the intersection level on the accuracy of both techniques. The relationship between the travel time allocation errors and the standard deviation of speed is illustrated in Figure 3.10. The standard deviation of speed on the horizontal axis can be calculated from all recorded instantaneous speeds (recorded every 1 second) within the intersection region, while the vertical axis can be determined as described in the previous section. From Figure 3.10, as the speed fluctuation increases (higher standard deviation), the error of estimation from the baseline technique increases massively; e.g. from 5% to 20% approximately when the standard deviation in speed changes from 5 km/h to 25 km/h, while the error from the proposed technique is still at the same level (approximately 5%). Results illustrated in this section imply the superior outcomes from the proposed technique particularly in the region with highly fluctuated speed e.g. at signalized intersection, congested condition or interrupted flow.



(a) Sampling time interval 15 sec

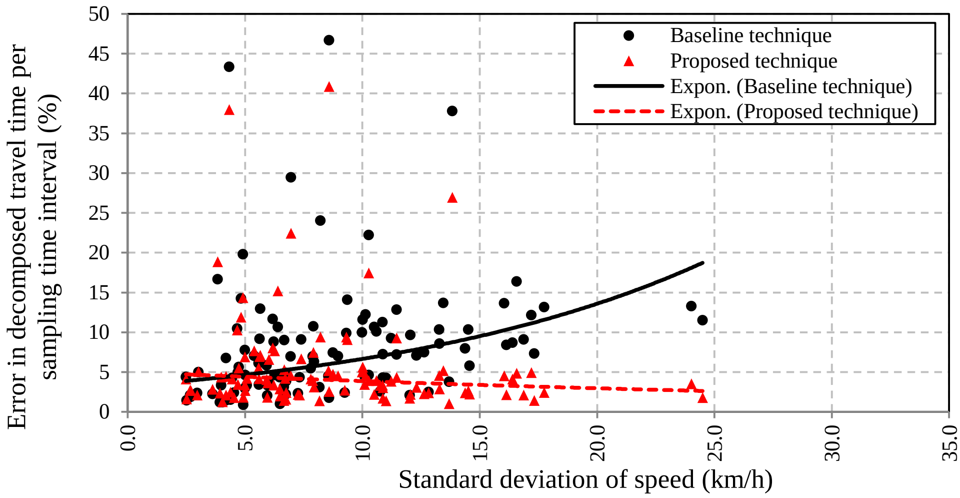


(b) Sampling time interval 30 sec

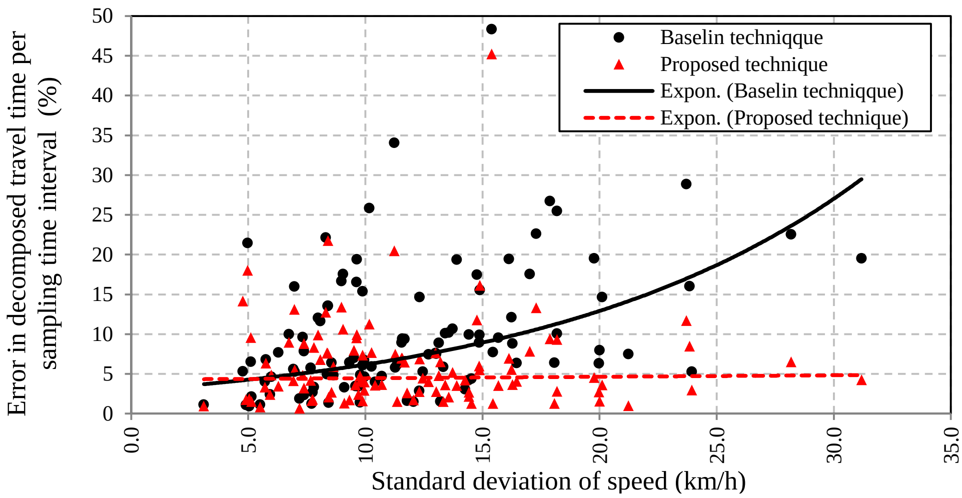


(c) Sampling time interval 60 sec

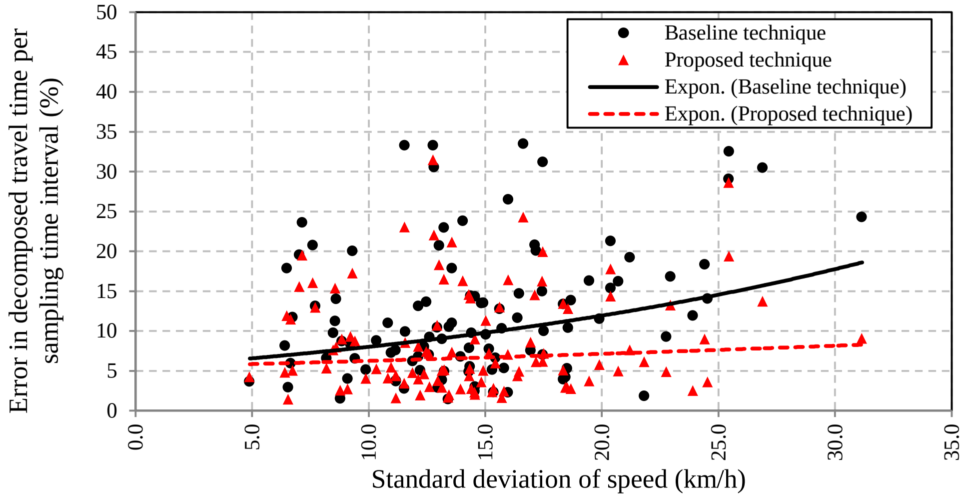
Figure 3-9 Relationship between the average travel speed within intersection region and travel time allocation error.



(a) Sampling time interval 15 sec



(b) Sampling time interval 30 sec



(c) Sampling time interval 60 sec

Figure 3-10 Relationship between standard deviation of speed within intersection region and travel time allocation error.

3.6 CONCLUDING REMARKS

This chapter provides contents about travel time estimation using information from GPS-probe data both with high and low-resulution.

For the real world application, we have proposed the new analytical algorithm for allocating travel time into individual sections by integrating instantaneous speed together with tracked locations and time stamp. From traffic state information represented by instantaneous speed data, the proposed model applies the speed-time-distance relationship for model tuning and then allocates travel time into each section. The performance of the proposed model in travel time allocation was tested and compared with the widely used technique in both complete section and local levels using high resolution (ground truth) field data.

It is found that the proposed technique provides a significant improvement in travel time allocation at both complete section and intersection levels compared to the benchmark technique. Moreover, from the in-depth analysis at the local level, the stopping (traffic) behavior within the intersection region affects the level of accuracy on both models. Accuracy from both techniques is lower at the intersections with stopping behavior due to its complicated movement behavior. Still, the proposed technique outperforms the baseline approach in both intersections with low and high stopped delays. The average speed of vehicle within the intersection region, which represents the local traffic state, also influences the model accuracy. Intersections with the higher average speed can achieve the higher accuracy level in both methods. Furthermore, analysis on the effects of speed fluctuation at the local level points out the outstanding performance of the proposed model in addressing the complicated movement behavior compared to the baseline approach.

Although this chapter demonstrates the process of estimating travel time from GPS-probe data and shows acceptable test result with real field data, the main problems of GPS-probe data in constructing traffic information are the very low penetration rate and sparse distibution in practice. Therefore in this dissertation the GPS-probe data will not be considerd in the developed travel time prediction model. Instead, The Bluetooth-probe data will be used. Details of Bluetooth-probe data and the technique for estimating travel time is described in the next chapter.

4. TRAVEL TIME ESTIMATION FROM BLUETOOTH PROBE DATA

Based on a recent survey, researches on travel times study over past several years have mainly been focused on data collected from traditional inductive loop detectors and GPS probe vehicles system as the techniques for gathering traffic data. Even though the abovementioned approaches are regarded as efficient methods in traffic data collection, the requirement of mathematical and theoretical assumptions in converting data from loop detectors to section travel time and the low penetration rates of GPS probe vehicle in real situation are the main drawbacks of those systems, respectively.

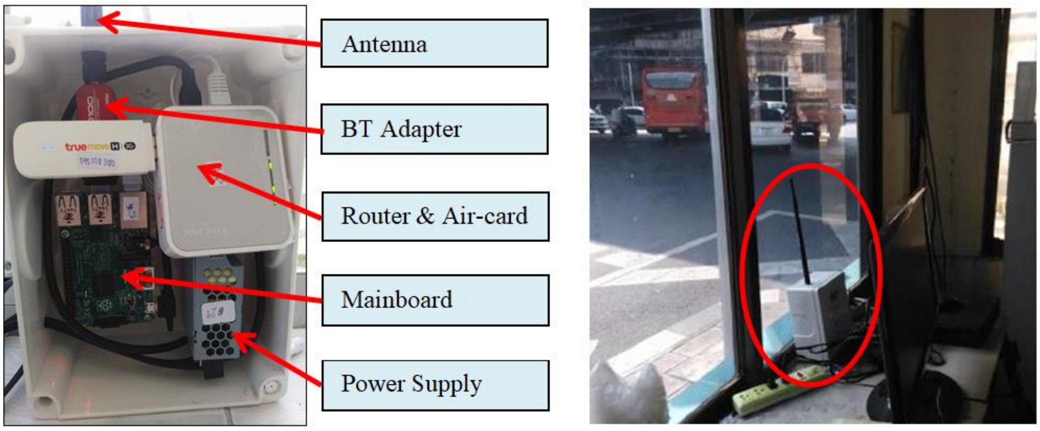
Recently, with the advancement in telecommunication technology, Bluetooth MAC (Media Access Control) scanners (BMS) have been introduced and become more popular in transport studies as a cost efficient approach for gathering data and making traffic database (Puckett and Vickich 2010). Various studies on traffic information have been successfully conducted using Bluetooth scanners as the data collection devices. For instance, (Wang, Malinovskiy et al. 2011) showed the promising results in travel time estimation using the BMS system compared to the travel time recorded by Automatic License Plate Recognition (ALPR) devices. (Bhaskar and Chung 2013) have tested the BMS system on arterial roadways and showed the potential of BMS in providing urban traffic conditions. (Barcelo, Montero et al. 2010, Blogg, Selmer et al. 2010, Barcelo, Montero et al. 2012) have demonstrated the ability of the BMS system in extracting the Origin-Destination (O-D) of trips. Although, from literature, the BMS system is considered as a cost effective and efficient approach for gathering traffic data, the raw data from the BMS system commonly contain noise and outliers particularly on urban roadway networks due to the complex, non-linear, non-stationary behavior and disturbance from surrounding environment such as movement of pedestrians at crossing, traffic signals, intersections and access from sideway (Nantes, Miska et al. 2014, Puangprakhon and Narupiti 2017). As aforementioned, in developing travel time information, the robust methodology for removing noise and outliers is an important task. This chapter demonstrates the development of the BMS data collection system in Thailand and frameworks for eliminating outliers and constructing section travel time information on urban roadways from the BMS system for Advanced Traveler Information Systems (ATIS).

The chapter is outlined as follows. In the next section, an overview of the Bluetooth scanner system and Bluetooth data is described. Thereafter, a method for extracting travel time from Bluetooth data is presented. Subsequently, the travel time estimation result from real field data is shown.

4.1 BLUETOOTH SCANNER SYSTEM

4.1.1 Bluetooth MAC scanner (BMS)

Bluetooth or IEEE 802.15.1 is a device for short wireless range communication and data transmission. It is cheap and very popular for short range transmission among modern electronic devices (Abedi et al. 2013). In order to apply Bluetooth technology in traffic data collection, the BMS with the capability to scan and record Bluetooth MAC addresses from Bluetooth devices (each electronics device contains their own unique identifier known as a Media Access Control address, assigned by the manufacturer) within the communication zone is needed. In this study, a total of 40 BMSs have been developed. Each of them comprises 5 main components, which are (1) main board (RASBERRY PI 2 Model 2) that can run the field software based on Linux operating system for processing and storing MAC addresses of the discovered devices, (2) Bluetooth adapter (Parini-UD 100) for broadcasting the short range communication to other Bluetooth devices, (3) antenna (TP link (9 dBi) to extend the Bluetooth communication range for traffic data collection purpose, (4) router (TP-Link 3020 with 3g air-card) to transmit the discovered data to the server, and (5) power supply unit. The assembly of BMS unit and the installation are illustrated in Figure 4.1.



(a) (b)

Figure 4-1 Bluetooth MAC scanner (a) main components of Bluetooth scanner and (b) installation in a police box at an intersection with AC power supply.

4.1.2 Travel time from Bluetooth MAC scanners

As aforementioned, BMS can detect the active Bluetooth devices within its communication zone (with radius around 100 meters in this study). The obtained travel time between 2 BMSs is a zone-to-zone travel time rather than point-to-point travel time. Figure 4.2 illustrates the concept of travel times between two BMSs which can be categorized into three types (Bhaskar and Chung 2013).

First, travel time from the stop line of the upstream to the stop line of the target section (*S2S*). This type is theoretically considered as section travel time, it is governed by the free-flow travel time and delay only from the target section. However, *S2S* travel time is hard to detect from the BMS system in reality because BMS can only discover the device IDs within its communication zone and cannot localize the real position of those devices.

Second, travel time from entrance to entrance of BMS zones (*En2En*). This travel time contains partial delay of the upstream section, free flow travel time and partial delay of the target section. It is noted that, in general, vehicles tend to experience more delay and spend a lot of time before approaching the stop line at the signalized intersection. Therefore, this travel time could comprise enormous effect from the upstream section and might indicate the congestion of the target section around the downstream intersection well. *En2En* travel time can be directly approximated from the captured data by calculating the difference between first detected time of each Bluetooth device at upstream and downstream intersections.

Third, travel time from exit to exit of the BMS zone (*Ex2Ex*). This travel time is governed mostly by the delay and free-flow travel time of the target section. This type of travel time can be extracted from BMS data by considering the difference between the last detected time of the BT device at each BMS. Analysis from previous research (Bhaskar and Chung, 2013) also pointed out that *Ex2Ex* travel time should be used instead of *En2En* travel time in travel time estimation for ITS applications. Therefore, in the remaining parts of this chapter, *Ex2Ex* travel time will be used to represent the travel time of the target section (or study section).

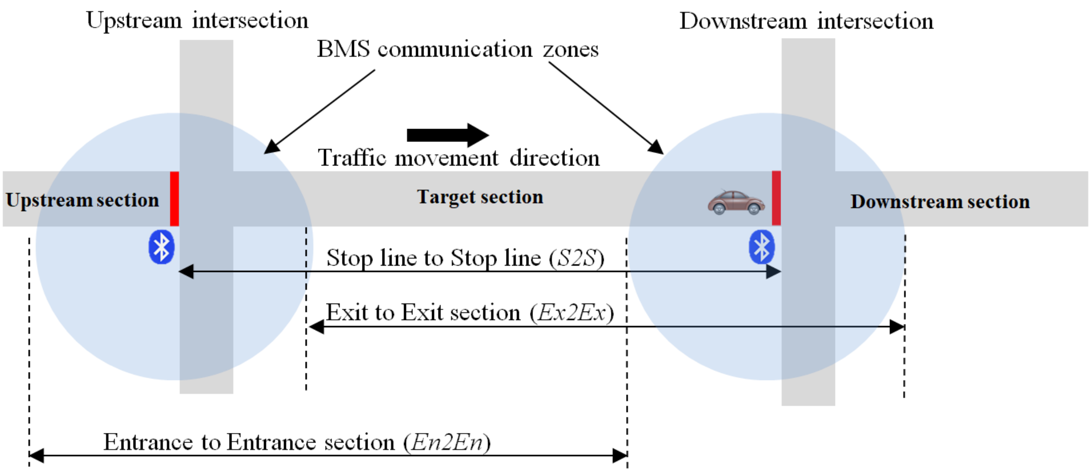


Figure 4-2 Three different section travel times from the BMS system

4.2 FRAMEWORK FOR CONSTRUCTING TRAVEL TIME INFORMATION FROM BLUETOOTH DATA

In this study BT data were collected from the BMS system installed on urban roadways in Bangkok CBD. The framework for estimating section travel time from Bluetooth data is depicted in Figure 4.3 which includes the following steps:

Data Matching: This step aims to match the same Bluetooth MAC-ID captured at two consecutive BMSs together. The travel time between BMSs or the time spent by each vehicle to pass between BMSs can be calculated by the difference of detected time of the same MAC-ID at those BMSs (*Ex2Ex* travel time).

In this step, the time gap for separating trips needs to be set up since on urban roadways each BT device can detour and return to the same BMS zone for multiple times after traveling to the next zone. In such situation, the device can be found for multiple times in the first zone and only one time at the second (adjacent) zone, resulting in multiple travel time values. For our study the 10 minutes time gap is set as the threshold to separate trips; that means the record is considered as the last detected time of the trip at BMS when there are no other records from the same BT device discovered in the same BMS zone within 10 minutes from the last detected time (if another record of the identical MAC-ID is discovered at the same BMS after 10 minutes from the last detected time it will be considered as another trip). In this case, the section travel time from the same device is determined as the minimum travel time value from all matching trips of this MAC-ID.

Data Filtering: The objective of the filtering process is to remove the questionable and outlier data from the samples that are obtained in the matching stage. This process comprises 3 sub-tasks as follows:

- Removing questionable ID: After the matching process, travel times from questionable BT devices such as the cloned devices (e.g. from logistic company, etc.) with the same ID that can be found at several locations at the same time are removed.
- Removing questionable trips: This step aims at removing outlier trips by setting upper and lower boundaries to track the trip that is faster and slower than usual trips, for instance, the trips with faster travel speed than the available speed limit on roadways, or trips that use another route instead of a direct route for passing the distance between two BMSs, or from stopping vehicles. In this study, the trips that traveled

faster than the speed limit of road sections and spend more than one hour on any sections were removed.

- Removing outlier trips: This step is to apply Median Absolute Deviation (MAD) filter or Hampel identifier (Gather and Fried 2004, Tsubota, Bhaskar et al. 2011, Kieu, Bhaskar et al. 2012, Khoei, Bhaskar et al. 2013) which is a robust measure to eliminate data variation. In Hampel's test statistical tables are not necessary. This method is not sensitive to outliers and has no restriction to the abundance of data set (Kuppusamy and Kaliyaperumal 2013).

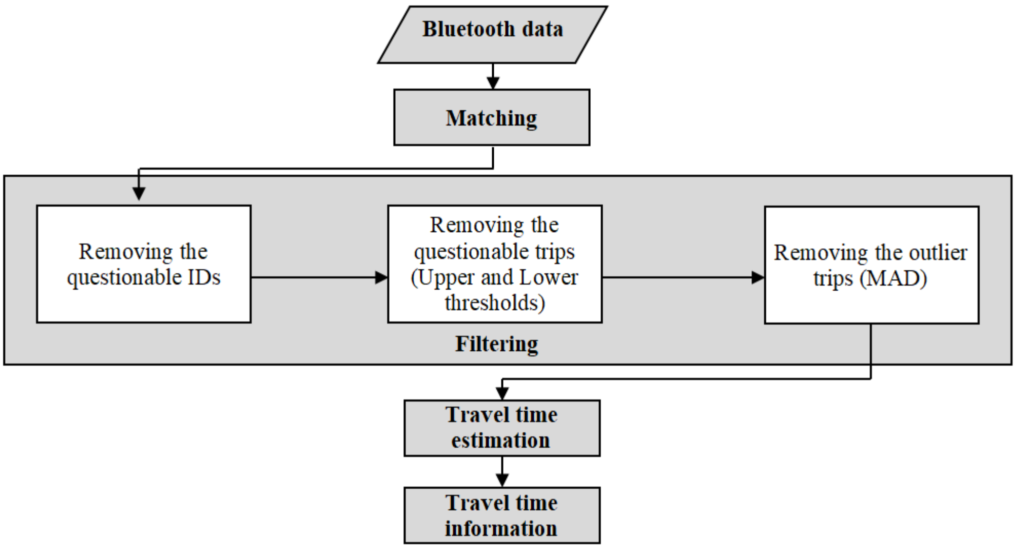


Figure 4-3 Framework for travel time estimation from BT data.

Let's assume that travel time values are univariate data, the MAD is the median of the absolute deviations from the data's median.

$$MAD = median\left| X_i - median(X) \right| \quad (4\text{-}1)$$

$$\sigma = k \cdot MAD \quad (4\text{-}2)$$

where k is a constant scale factor which depends on the type of the distribution (in case of a normal distribution k is 1.4826). In this research the 15 minutes moving time window (equal to 15 minutes interval for travel time information reporting in this study) was selected for calculating MAD. The upper and lower boundaries for filtering outlier trips can be calculated by adding and subtracting $f\sigma$ from MAD as illustrated in Eq. (4-3) and (4-4). The suggested *f* values from previous studies range from 1 to 5 (Davies and Gather 1993, Pearson 2002). The small *f* provides higher confidence in the travel time profile but some of the valid points can be considered as noise and disregarded. Conversely, higher *f* yields lower confidence in the travel time profile with some noisy points considered as valid. For this study, the *f* = 2 is applied in Eq. (4-3) and (4-4) as recommended by (Kieu, Bhaskar et al. 2012, Bhaskar, Kieu et al. 2013, Bhaskar, Kieu et al. 2015). The trip travel times beyond these boundaries are considered as outlier values and will be removed.

$$Upper\ Bound = median + f\sigma \tag{4-3}$$

$$Lower\ Bound = median - f\sigma \tag{4-4}$$

Travel time estimation: In this study, one day (24 hours) was divided into 96 intervals (15 minutes per interval) from 0:00:00-0:14:59, 0:15:00-0:29:59, …, 23:45:00-23:59:59. The estimated travel time of each interval i (TT_i) can be calculated by averaging all filtered the trip travel times within that interval as follows:

$$TT_i = \frac{1}{n}\sum_{t=1}^{n} s_t \qquad \text{for } i = 1, 2, 3, \ldots, 96 \tag{4-5}$$

where s_t is the value of valid filtered travel time and n is the number of valid data point in a particular interval *i*.

4.3 EXPERIMENTAL SITE AND DATA GATHERING SYSTEM

4.3.1 Study site

The urban roadways in Bangkok CBD were selected as the study location for testing the applicability of the BMS system in travel time collection and estimation. The trial was conducted 24 hours per day for a total of 33 days from the 4th February 2016 to 7th March 2016. A total of 40 BMSs have been placed inside the police box at the signalized intersections for gathering the Bluetooth signal form Bluetooth devices within their communication zones (approximately 100 meters from the location of BMS as recommended for traffic applications (Bhaskar and Chung 2013). The installation locations of all 40 BMSs are depicted in Figure 4.4, and names and positions of BMSs are described in Table 4.1.

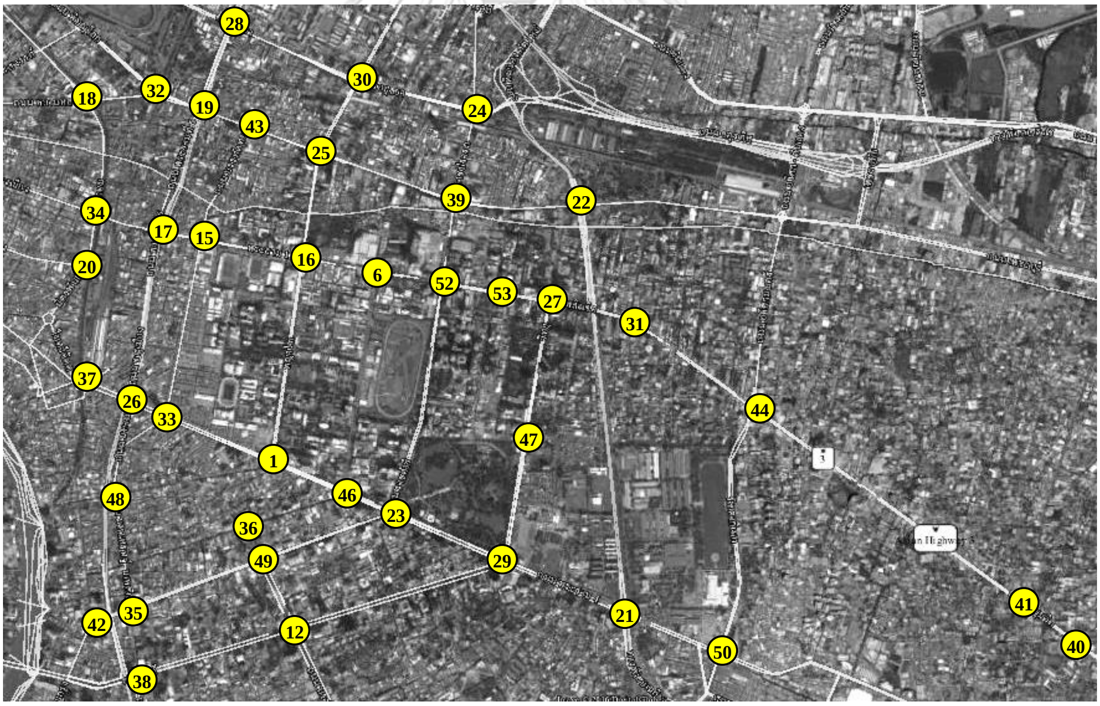


Figure 4-4 Installation locations of Bluetooth MAC scanners in Bangkok CBD

Table 4-1 Names of intersections and position of each BMS installation.

Scanner	Intersection name	Latitude	Longitude	Scanner	Intersection name	Latitude	Longitude
1	Samyan	13.73292	100.52870	32	Yommarach	13.75735	100.52052
6	Chaloem Pao	13.74538	100.53588	33	Saphan Laueng	13.73577	100.52155
12	Narinthorn	13.72204	100.53018	34	Kasatsruk	13.74872	100.51661
15	Chareon Phol	13.74743	100.52387	35	Surasak	13.72362	100.52065
16	Pathumwan	13.74613	100.53082	36	Narathiwas	13.72858	100.52704
17	Phong Phraram	13.74813	100.52078	37	Hua Lumpong	13.73800	100.51640
18	Saphan Khaw	13.75664	100.51601	38	Surasak-Sathorn	13.71887	100.51980
19	Urupong	13.75614	100.52357	39	Phatunam	13.75001	100.54099
20	Noppawong	13.74563	100.51623	40	Ekkamai Tai	13.72037	100.58421
21	Tai Duan	13.72295	100.55258	41	Thong Lor	13.72371	100.57931
22	Tai Duan Phetburi	13.74989	100.54992	42	Bangrak	13.72229	100.51661
23	Sala Daeng	13.72960	100.53661	43	Phetphraram	13.75510	100.52674
24	Makkasan	13.75610	100.54241	44	Asoke	13.73638	100.56138
25	Ratchathewee	13.75351	100.53151	46	Henry Dunant	13.73090	100.53359
26	Maha Nakorn	13.73680	100.51919	47	Sarasin	13.73417	100.54584
27	Pleonjit	13.74336	100.54749	48	Maha Nakorn-Si Phraya	13.73063	100.51816
28	Sri Ayudharya	13.76197	100.52563	49	Silom-Narathiwas	13.72629	100.52807
29	Witthayu	13.72667	100.54449	50	Phraram 4	13.72029	100.55910
30	Phayathai	13.75797	100.53438	52	Rachprasong	13.74455	100.54018
31	Nana	13.74190	100.55296	53	Chidlom	13.74409	100.54387

4.3.2 Data gathering system

In this research, the inquiry cycle for each BMS has been programmed at 1 second, which means that the BMS sends the inquiry messages and scan the replied signal from Bluetooth devices within its communication zone every 1 second. As a Bluetooth enabled device traveled along the road network, the BMS logged the unique Bluetooth MAC address together with detected time and detected location of that device. Recorded data from the BMS system were then sent to the server via 3G telecommunication network. Table 4.2 illustrates an example of recorded data from BMSs. The first column represents the record number; second column is the MAC-ID of the discovered Bluetooth device which is 48 bits long and normally comprises a sequence of twelve hexadecimal digits (six groups of two hexadecimal digits separated by colons); third column is the detected time of BT devices; and forth column is the number of BMS station which represents the location of the BMS on network (as illustrated in Figure 4.4).

Table 4-2 Data recorded from BMSs

Record number	BT MAC-ID	Detected Time	BMS ID
1	AC:7A:4D:A3:E4:XX	4/2/2016 5:04:40	47
2	AC:7A:4D:A3:E4:XX	4/2/2016 5:04:41	47
3	AC:7A:4D:A3:E4:XX	4/2/2016 5:04:42	47
4	64:D4:BD:D8:71:XX	4/2/2016 5:04:42	47
5	64:D4:BD:D8:71:XX	4/2/2016 5:04:43	47
6	64:D4:BD:D8:71:XX	4/2/2016 5:04:46	47
7	AD:C5:EE:02:F5:XX	4/2/2016 5:04:42	16
8	AD:C5:EE:02:F5:XX	4/2/2016 5:04:43	16
9	00:1D:FD:07:B0:XX	4/2/2016 5:04:42	16
10	64:D4:BD:D8:71:XX	4/2/2016 5:04:49	47
.	.	.	.
.	.	.	.

Remarks: the last two digits in column 2 are blinded due to privacy concerns.

4.4 RESULTS AND DISCUSSIONS

4.4.1 Amount of data from each Bluetooth scanner

The summary of MAC-ID and Unique MAC-ID detected from 40 BMSs installed at intersections on urban roadways in Bangkok CBD during weekdays on February 4-5, 2016 is presented in Table 4.3. It could be observed that the total number of recorded MAC-ID at each location ranges from 5,573 at BMS 20 to 245,700 at BMS 28, with an average of 94,367, on Thursday 4th February 2016 (excluding BMS No. 17 and 29 due to malfunction problems). The number of Bluetooth devices or unique MAC-ID discovered at each location ranges from 988 to 8,383 devices per day, or 4,647 devices per day on average. On Friday 5th February 2016, the number of total and unique MAC-ID records at each BMS were comparatively the same values as the records on 4th February 2016. These results show that the BMS has potential to capture Bluetooth devices within its communication zone on urban road networks for developing further traffic information. However, as previously mentioned, the BMSs at locations 17 and 29 failed to detect and record data compared to the others. This could happen from various reasons such as malfunction of software, hardware or BMS components, communication problems, or environmental constraints, etc.

4.4.2 Distribution of Bluetooth data along the day

From 40 BMSs installed in Bangkok CBD, the distribution of captured Bluetooth data throughout the day during 4-5th February 2016 is depicted in Figure 4.5. It is observed that from 0:00 to 05:00 of both days the detected BT points (less than 100,000 points per hour) were significantly lower than other periods of day. This event is consistent with the actual traffic behavior that the number of travelers and road users during the late nighttime to the early morning is commonly less than the number of daytime, resulting in a smaller number of detected Bluetooth data points. During daytime, the peak periods can be observed at two intervals: morning peak during 07:00-08:00 on both days and evening peak during 18:00-19:00 on February 4th and during 17:00-18:00 on February 5th. The captured data points during morning and evening peak hours of both days were more than 200,000 points/hour. This value was around three times more than the value in the late night period. When comparing between morning and evening peaks, the number of detected BT points in morning peaks was slightly smaller than the number in evening peaks on both days. Once considering the spreading of data points throughout the day, it is observed that the data distributions from both days spread in the same manner. This behavior indicates the feasibility of using the BMS system as a tool to collect traffic data on urban roadways for developing further travel information such as travel time or travel speed information.

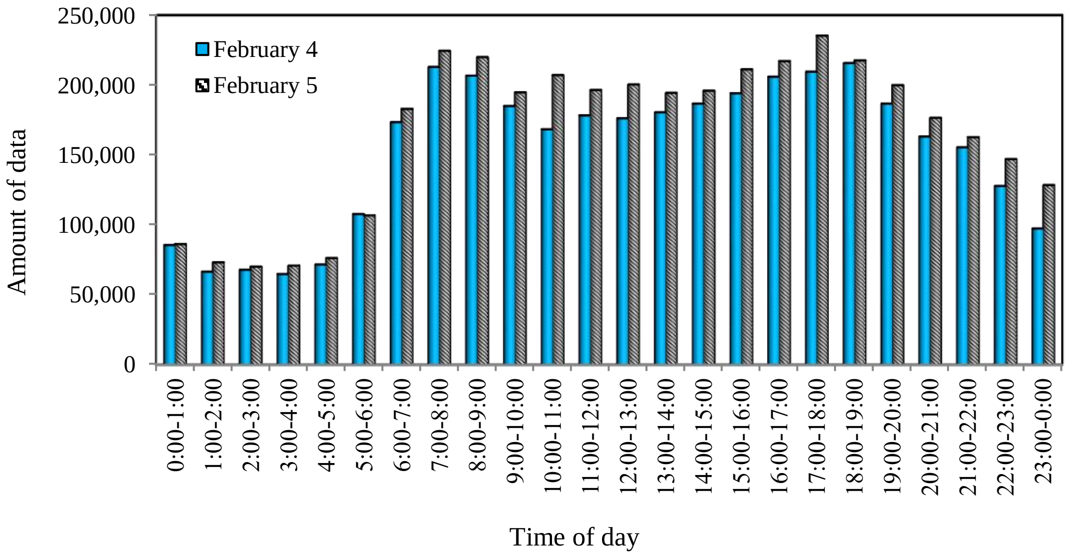


Figure 4-5 Number of captured Bluetooth points per hour during 4-5 February 2016.

Table 4-3 Total Mac-ID and Unique Mac-ID gathered by each Bluetooth Scanner.

Scanner #	Data on Thursday 4/2/2016		Data on Friday 5/2/2016	
	Total MAC-ID	Unique MAC-ID	Total MAC-ID	Unique MAC-ID
1	147,480	5,308	158,445	5,447
6	19,689	2,218	23,438	2,202
12	66,172	5,147	63,910	5,298
15	122,453	5,015	113,822	5,059
16	77,840	4,039	71,976	4,089
17	193	42	150	43
18	116,794	5,374	105,560	5,054
19	6,969	1,505	9,089	1,802
20	5,573	988	4,343	911
21	171,107	8,383	164,833	8,470
22	125,014	7,568	126,371	7,683
23	235,118	5,795	237,036	5,872
24	77,880	5,123	96,723	5,129
25	63,326	5,306	62,534	5,352
26	172,843	7,189	177,968	7,206
27	16,546	2,892	18,217	2,924
28	245,700	7,226	258,109	7,888
29	1	-	88	-
30	63,206	4,929	66,918	5,008
31	58,121	2,312	88,497	4,357
32	91,501	6,763	100,559	7,137
33	51,873	4,555	63,682	4,800
34	97,059	5,454	97,082	5,806
35	25,598	1,919	61,141	4,208
36	238,580	3,188	234,968	3,236
37	80,090	4,873	84,430	5,104
38	84,791	6,724	97,477	7,043
39	60,925	4,751	58,901	4,791
40	59,842	4,521	62,266	4,618
41	81,656	4,785	48,810	2,778
42	86,559	2,770	93,819	2,830
43	94,965	5,953	78,813	6,181
44	52,886	4,859	66,398	5,287
45	29,445	1,804	32,685	1,914
46	91,998	4,620	105,814	4,828
48	182,739	3,651	210,317	4,423
49	37,780	3,239	40,548	3,501
50	236,251	7,203	286,293	7,268
52	51,199	3,914	63,106	3,879
53	58,363	4,714	80,117	4,513
Average*	**94,367**	**4,647**	**100,395**	**4,839**

*Average from 38 BMSs except BMS No.17 and 29 due to malfunction issue.

4.4.3 Effects of the filtering process on travel time estimation

The travel time data of section 16-15 from Phatumwan intersection (BMS 16) to Chareonphol intersection (BMS 15) with a distance of 767.5 meters is presented in Figure 4.5. Figure 4.6 depicts the snapshot of raw travel time calculated from captured BT devices after the matching process (before filtering) (Figure 4.6a) and the filtered travel time using the proposed method (Figure 4.6b), respectively. Figure 4.6(c) presents the estimated travel time for each time interval (15 minutes/interval as mentioned in Eq. (4-5)).

In Figure 4.6(a), it can be observed that the amount of travel time data detected from BT devices between 00:00-05:00 is relatively small compared to the other times of the day, consistent with that discussed in the previous section. However, when considering the dispersion of data points, it is observed that there are some outlier points that significantly deviate from the main group. The occurrence of these outliers can happen from various reasons; for instance, from the stopping vehicle along the way, from the vehicle that takes short-cut or other routes then back to the study area again, or from non-vehicle trip, etc. In developing section travel time information, these outliers need to be deleted from the dataset for constructing unbiased data and estimation model. Figure 4.6(b) depicts the remaining travel time data after applying Hampel identifier or MAD filtering as previously proposed in Eq. (4-1 to 4-4) to remove the outliers. From the figure, it is clear that the largely dispersed data points from the main group were eliminated after filtering process. After filtering, this dataset were used in the travel time estimation process as aforementioned in Eq. (4-5).

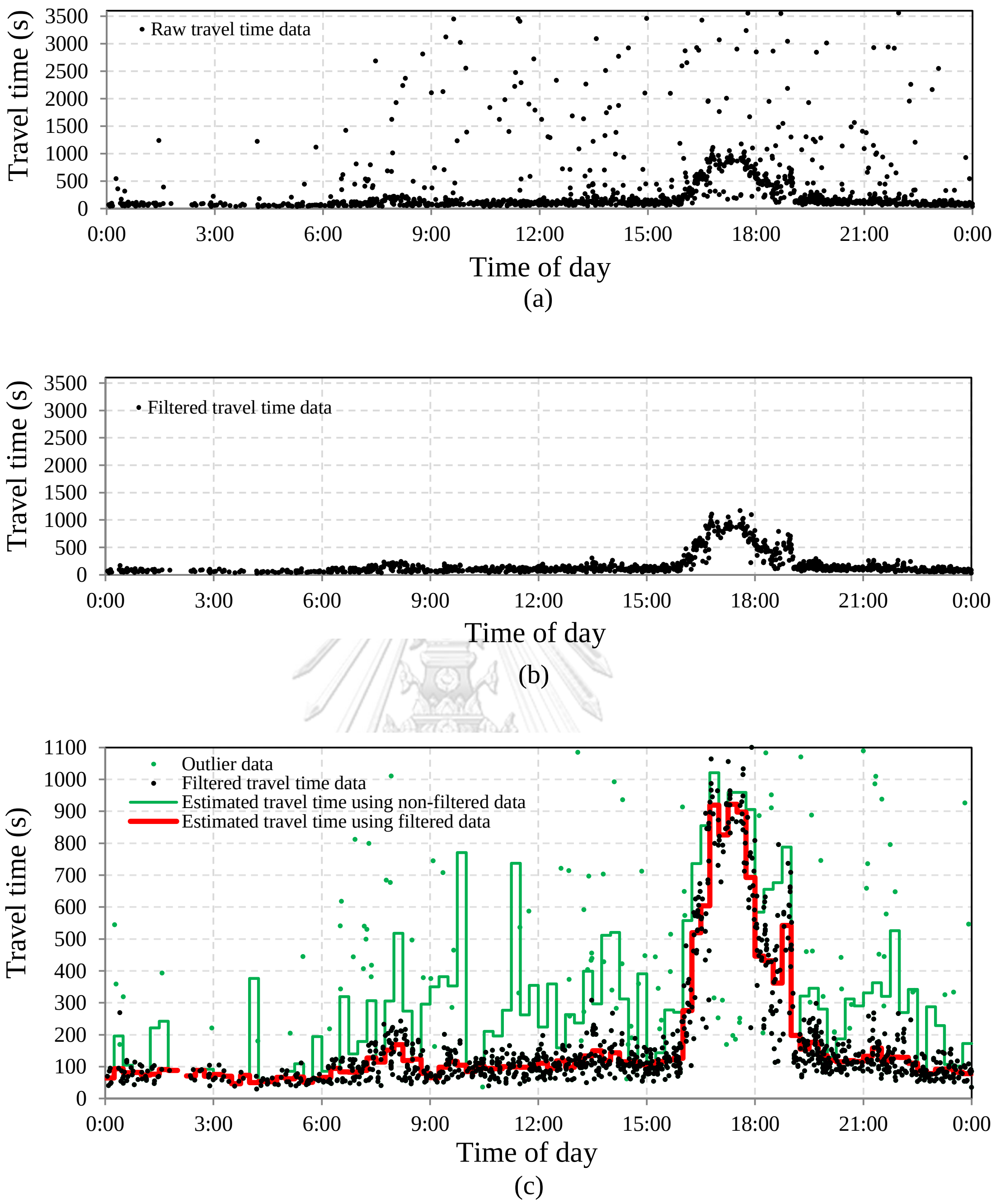


Figure 4-6 Travel time from Pathumwan intersection (BMS 16) to Chareon Phol intersection (BMS 15) on 4th February 2016 (a) travel times before filtering (b) travel times after filtering by MAD (c) estimated travel time for each interval (every 15 minutes).

Figure 4.6(c) depicts the estimated travel time of each interval (every 15 minutes) form both filtered and non-filtered dataset to point out the effects of outliers on travel time estimation results. It could be noticed that the estimated travel time from filtered data yields results that are consistent with actual traffic behavior with small fluctuation among adjacent intervals particularly on the off-peak periods. On the other hand, the estimated travel times from the raw dataset (with outliers) demonstrates the highly fluctuated results even in the off-peak periods, and such behavior is quite contradictory to actual traffic behavior. These results indicate the cruciality of the filtering process in developing travel time information for urban roadway networks and also point out the potential of using MAD in the data filtering process.

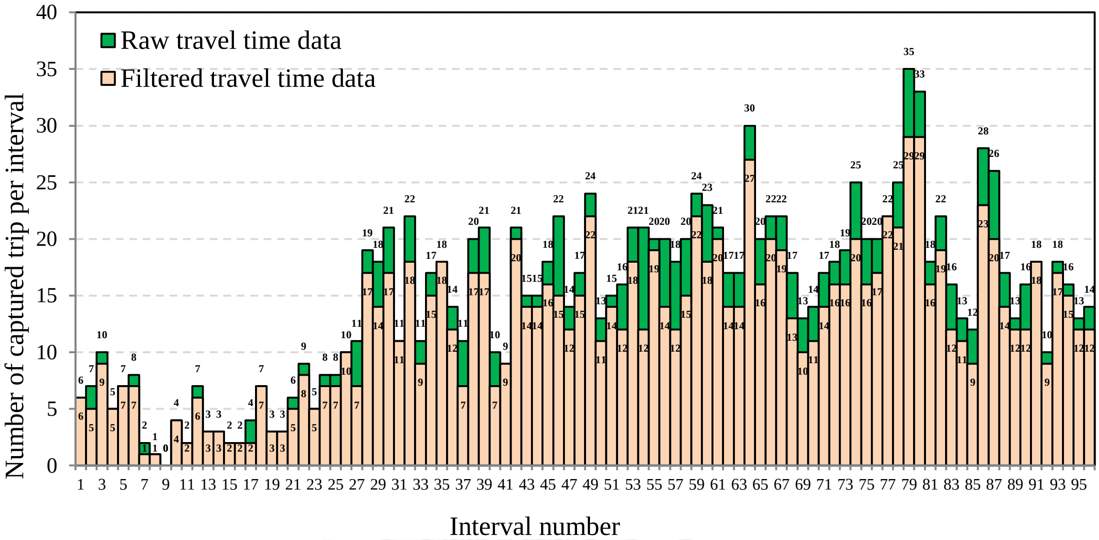


Figure 4-7 Number of trips/interval from section 16-15 during 4th February 2016.

Figure 4.7 depicts the number of trips in each time interval (15minutes) before and after the filtering process captured from section 16-15 (BMS 16 to BMS 15) on 4th February 2016. It could be noticed that the number of captured trips from both filtered and unfiltered data are quite low from midnight to early morning compared to the number during daytime period. The missing data problem was found in the 9th (02:00-02:15) interval, but it did not affect the study as later the night time was disregarded in the further consideration. In practice, the travel time estimation for the missing data often considers the travel time data of the previous interval as the representative of the missing one. The highest number of raw trips (35 trips/15 minutes) was captured in the 79th (19:30-19:45) interval and there were 29 trips/15minutes left after the filtering process or approximately 2 trips/minute. The total number of raw trips captured from 96 intervals were 1,419 trips (14.78 trips/interval) and 1,205 trips (12.55 trips/interval) after filtering. It should be noted that just a small number of trips (only

2.23 trips/interval or around 15.08%) were considered as the outliers and were deleted in the filtering process while the travel time estimation result from the filtered dataset was significantly better and more consistent with the real traffic behavior. This also points out the potential of using Hampel identifier or MAD filtering in diminishing outliers from Bluetooth data.

Details of the captured trips per interval, average travel time (Avg TT) and speed, and the standard deviation of travel time (stdev) before and after the filtering process of various sections from 06:00-22:00 of 4^{th} February to 7^{th} March 2016 were summarized in Table 4.4.

Table 4-4 Average of captured trip per interval, average standard deviation of travel time, average travel time and speed before and after the filtering process of various sections.

Road section	Length (km)	Without filtering				Filtered data			
		Avg. captured trip/interval	Avg. stdev	Avg tt (sec)	Avg speed (kph)	Avg. captured trip/interval	Avg. stdev	Avg tt (sec)	Avg speed (kph)
01-16	1.491	4.03	487.22	773.38	6.94	3.18	139.92	537.47	9.99
16-01	1.491	5.54	468.28	568.15	9.45	5.51	90.97	349.29	15.37
01-33	0.841	12.08	466.27	390.45	7.75	10.20	60.71	198.32	15.26
33-01	0.841	5.21	514.48	529.81	5.71	5.23	80.81	252.58	11.98
01-46	0.568	8.52	499.78	426.25	4.80	6.81	75.94	202.51	10.10
46-01	0.568	8.43	493.24	370.37	5.52	8.57	65.21	160.32	12.75
01-48	1.173	1.60	445.90	1277.97	3.31	1.42	293.98	1161.37	3.64
48-01	1.173	5.27	501.18	585.84	7.21	5.30	109.20	340.98	12.39
06-16	0.551	7.95	375.73	387.73	5.12	6.84	78.12	230.03	8.63
16-06	0.551	1.95	354.63	547.53	3.63	1.89	36.60	317.48	6.25
15-16	0.761	2.50	419.92	741.41	3.70	1.82	78.65	499.36	5.49
16-15	0.761	9.53	435.42	347.54	7.88	9.53	42.07	149.78	18.30
16-25	0.794	5.93	460.39	632.54	4.52	4.71	96.37	431.41	6.62
25-16	0.794	10.50	397.03	342.08	8.35	10.36	66.61	179.69	15.90
25-30	0.587	10.81	367.06	376.56	5.61	9.44	82.40	242.69	8.71
30-25	0.587	20.96	291.26	259.76	8.14	20.78	66.79	180.52	11.71
25-39	1.066	4.76	610.57	822.71	4.67	3.88	252.68	558.17	6.88
39-25	1.066	5.55	525.19	654.53	5.87	5.57	105.61	396.55	9.68
25-43	0.562	8.83	536.88	473.56	4.27	7.07	73.52	214.47	9.43
43-25	0.562	13.14	418.83	366.94	5.51	13.22	81.25	215.16	9.40

*Considered only data from 06:00 to 21:00 of 4^{th} February to 7^{th} March 2016

4.4.4 Effects of data fluctuation on travel time estimation

For a more in-depth analysis, Figure 4.8 shows the difference between travel time estimation in each interval using pre- and post-filtering data on the 4th and 5th February 2016. It can be seen that the travel time estimation results from both pre- and post-filtering data are not significantly different in the intervals with low standard deviation. As the standard deviation of the raw dataset increases, the difference among travel time estimation results increases accordingly. This can imply that, once the data in each interval is not significantly different or clustered together, the filtering process almost treats all the data as valid values with no outlier. On the other hand, when the data are very fragmented, some data points that greatly deviate from the median are considered as outliers and are taken out, then filtered data could produce reasonable estimation outcomes as aforementioned in the previous section. However, in some intervals with high standard deviation, if no abnormal data that significantly diverge from the group median is found, all the data within that interval will be considered as the valid values with no outlier as could be noticed in the region with 0 (or close to 0) percent difference of estimated travel times between pre- and post-filtering data.

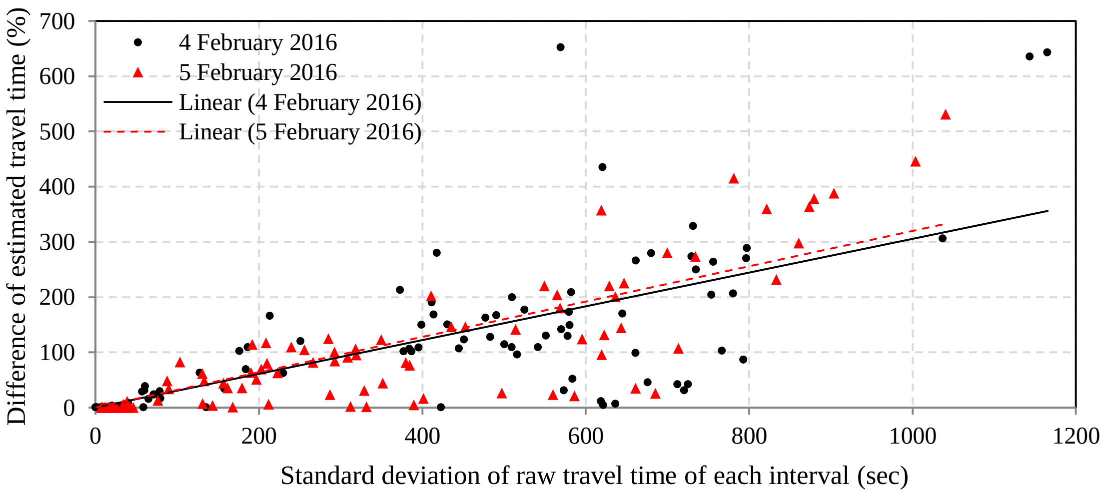


Figure 4-8 Difference between estimated travel time from raw and filtered data vs standard deviation within interval from BMS 16 to 15 during 4-5 February 2016.

4.5 CONCLUDING REMARKS

A Bluetooth MAC scanner is one of the advanced and cheapest technology that has potential for implementation as an area-wide traffic data collection system. The successful implementations of the BMS system on freeways from many countries have been reported recently. On the other hand, the application of BMS on urban roadways is becoming the challenging topic for all traffic professionals due to the complicated behaviors and disturbances from surroundings. This chapter presents the development of traffic data collection system from BMSs starting from the basic components of BMS, the possible installation place for collecting traffic data on urban roadways, details of captured data, and also suggested framework for constructing travel time information from Bluetooth probe data.

Results from the field data collection from 4th February to 7th March 2016 of 40 BMSs show the sufficient number of collected raw data, approximately 100,000 data points per BMS per day or around 4,700 Bluetooth devices per BMS per day after grouping together by MAC-ID. The analysis on data spreading along time of day points out that during 00:00-05:00 the amount of captured data was considerably lower than on the amount during daytime, and this could create the missing data problem in some road sections. However, the amount of captured data was higher and approximately sufficient for developing reliable traffic information during daytime, which is a period that highly requires traffic information for disseminating to road users.

The data filtering by the Hampel identifier can successfully remove outliers that greatly deviate from the group median, resulting in the more reasonable travel time estimation results and proved consistency with real traffic behaviors. The in-depth analysis also points out that only small amount of data were considered as outliers and were taken out in the filtering process, but this could significantly improve the estimation results.

5. DEVELOPMENT OF MODELS FOR TRAVEL TIME PREDICTION AND EXPERIMENTAL CORRIDOR

The main objective of this dissertation is to develop the methodology for short-term travel time prediction on urban roadway networks using data captured from the Bluetooth scanner system. Thus, this chapter provides details for developing and testing the travel time prediction model. The chapter starts with explanation on criteria for developing the travel time prediction model, then the concept of neighboring sections. The third is an overview of the travel time prediction methodology using Artificial Neural Network or ANN. After that, details of the experimental corridor and dataset for travel time prediction are explained. The fifth section is about the scenarios for testing. The final section is the concluding remarks of this chapter.

5.1 CRITERIA FOR DEVELOPING THE TRAVEL TIME PREDICTION MODEL

This dissertation aims at developing an accurate and robust short-term travel time prediction model for signalized arterial roadways which can be implemented in practice. Before the model is presented, there are several criteria that should be clarified;

1) The model should be general and can be implemented at any location, at least in terms of the input-output relationship and model structure.
2) The model should be practically implemented based on the available and feasible data gathered from the Bluetooth scanner system.
3) The model should be able to provide acceptable output in various traffic conditions

5.2 THE BASIC CONCEPT OF NEIGHBORING SECTIONS FOR TRAVEL TIME PREDICTION MODEL DEVELOPMENT

In order to develop the travel time prediction models from the historical data by incorporating the effects of neighboring sections, we need to express the idea of neighboring sections. Figure 5.1 illustrates the signalized arterial roads which consist of 14 uni-directional road sections and two signalized intersections. If we consider the section number 1 as a *target section*, its neighboring sections can be classified into three broad categories as follows:

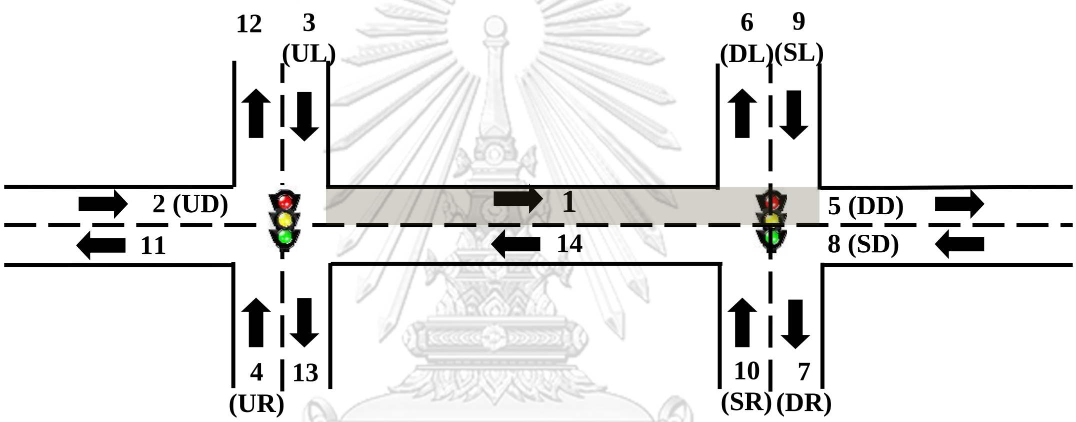


Figure 5-1 Signalized arterial roads.

Upstream sections are the sections that send traffic to the target section. From Figure 5.1 the upstream sections comprise;

- Section number 2 is the road section that transfers its traffic to the target section by through movement. In this dissertation, we will call this section as upstream-direct section (UD).
- Section number 3 is the road section that transfers its traffic to the target section by left turn movement (alternatively, it can be considered as this section is on the left hand side of the target section). In this dissertation, we will call this section as upstream-left section (UL).
- Section number 4 is the road section that transfers its traffic to the target section by right turn movement (alternatively, it can be considered as this section is on the right hand side of the target section). In this dissertation, we will call this section as upstream-right section (UR).

Downstream sections are the sections that receive traffic from the target section. From Figure 5.1 the downstream sections comprise;

- Section number 5 is the road section that receives the traffic from the target section by through movement. In this dissertation, we will call this section as downstream-direct section (DD).
- Section number 6 is the road section that receives the traffic from the target section by left turn movement (alternatively, it can be considered as this section is on the left hand side of the target section). In this dissertation, we will call this section as downstream-left section (DL).
- Section number 7 is the road section that receives the traffic from the target section by right turn movement (alternatively, it can be considered as this section is on the right hand side of the target section). In this dissertation, we will call this section as downstream-right section (DR).

Signal sharing sections are the sections that share the traffic signal time with the target section. From Figure 5.1 the signal sharing sections comprise;

- Section number 8 is the road section that shares the traffic signal time with the target section and is located on the opposite side of the target section. In this dissertation, we will call this section as share-direct section (SD).
- Section number 9 is the road section that shares the traffic signal time with the target section and is located on the left hand side of the target section. In this dissertation, we will call this section as share-left section (SL).
- Section number 10 is the road section that shares the traffic signal time with the target section and is located on the right hand side of the target section. In this dissertation, we will call this section as share-right section (SR).

In this dissertation, we have proposed that the travel times of these neighboring sections could have a relationship with and affect the travel time of the target section. Therefore, all the aforementioned neighboring sections will carefully be considered as inputs into the travel time prediction model.

5.3 OVERVIEW OF TRAVEL TIME PREDICTION METHODOLOGY USING ARTIFICIAL NEURAL NETWORK

Artificial Neural Network (ANNs) can be defined as the technique for processing information that is inspired by the human brain system. The brain is principally composed of enormous number of neurons that are massively connected together to solve a specific problem. ANNs mimic the biological neurons functions to perform the sophisticated and intelligent computations similar to the human brain system.

Numerous researches from the past point out the ability of ANNs in section travel time prediction; for instance, using the multilayer feedforward with back propagation (Park and Rilett 1999, Kisgyorgy and Rilett 2002, Huisken and Van Berkum 2003), the dynamics time-delayed neural networks (Shen L. and Huang M. 2011), state-space neural networks (Van Lint, Hoogendoorn et al. 2002, Van Lint, Hoogendoorn et al. 2005, Abu-Lebdeh and Singh 2011) in travel time and traffic prediction. However, as neural networks are not transferable but location specific, previous models from literature cannot be deployed in other sites. Therefore, in this dissertation the neural network model for travel time prediction needs to be specifically developed for studying corridors in Bangkok CBD.

Based on previous studies, using neural networks in travel time prediction can significantly improve the accuracy and the robustness of prediction outcomes. Although studies from the past have proposed various types of neural network structures for travel time prediction but there are no concrete conclusions on which one is the best. In this study, the multilayer feedforward neural network is selected as the main neural network structure for developing the travel time prediction model due to its simplicity in modeling, it is the major structure type used in previous literature, the successful test with various datasets from both simulation and from field study, and the capability of integration of spatial and temporal patterns into the model.

The next sub-sections provide information of the neural network model from the basic components, definitions to the principles for selecting model components.

5.3.1 Multilayer feedforward neural networks (MFNN)

Artificial Neural Network (ANN), or neural network, is one of the techniques for data mining. It is the mathematical model that simulates the human brain system to create tools that are capable of learning patterns recognition and knowledge extraction, as well as the abilities that are found in the human brain.

MFNN is one of the most widely used structures of ANNs in various applications. In MFNN, an interconnection of nodes in which the flow of calculations is in single direction starts from the input layer to the output layer. The number of layers can be computed by the number of layers of nodes. In general, a neural network consists of the following elements (Dougherty 1995).

Nodes (artificial neurons, processing elements, or processing units)*:* The basic element of ANNs is the *neuron* or *node*. Node receives the value of input (that is normalized between 0 to1 or -1 to 1) and computes the output(s) according to the selected transfer function. Figure 5.2 shows the basic function of node or artificial neuron. The neuron outputs is calculated as:

$$a = \Phi(\sum x_i w_i + b) \tag{5-1}$$

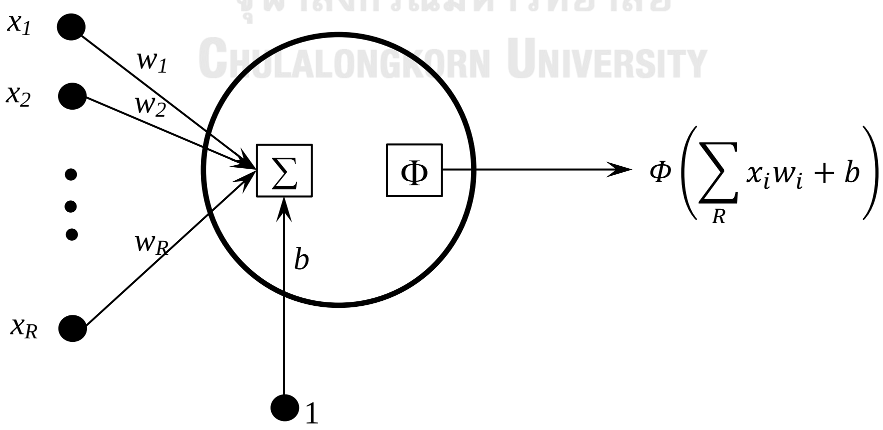


Figure 5-2 Artificial neuron

Connection weights: neural network comprises many nodes linked together by connections with varying weights that make the outputs of some nodes as the inputs.

Bias: The bias is a function that has a constant input of 1. The bias can decrease or increase the net input of the activation function depending on its value (negative or positive).

Transfer function/Activation function: The transfer function translates the input signals to output signals. There are four common types of transfer functions that are used in the neural network: Unit step (threshold), sigmoid, piecewise linear, and Gaussian.

Layers: It is usual to organize the neurons in layers, with all nodes in neighboring layers connected to each other. In neural network, there are three common types of layer: input layer, output layer, and one or more hidden layers.

The common topology of multilayer feedforward neural network is illustrated in Figure 5.3.

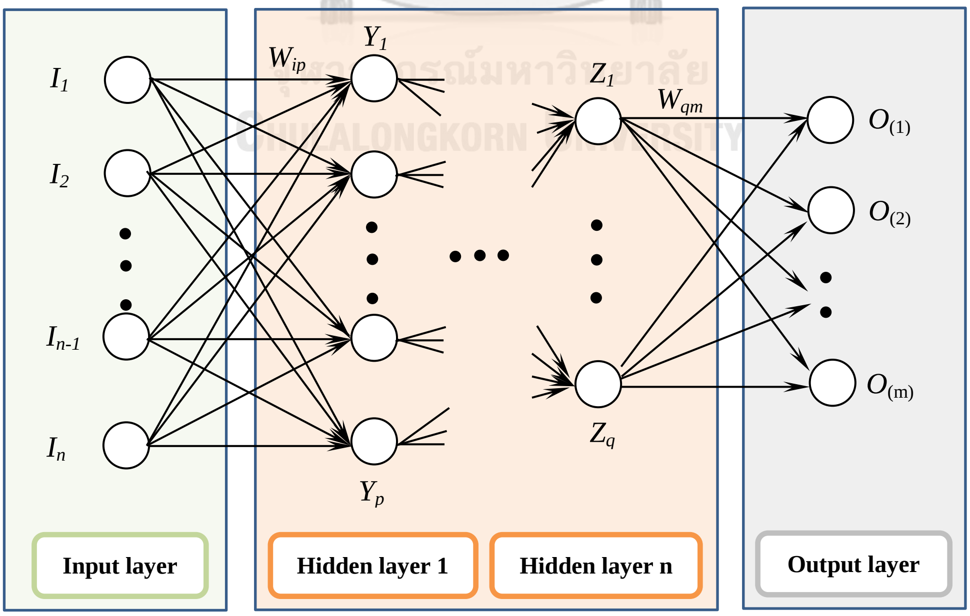


Figure 5-3 Schematic diagram of a multilayer feedforward neural network

5.3.2 Model inputs for travel time prediction

The number of input neurons on neural network corresponds to the number of variables used in forecasting future travel time. In this dissertation, to predict the travel time of the target section(s), relevant information that is expected to influence the target section(s) travel time are considered as the model inputs. In this study, the model inputs can be grouped as follows:

(1) The estimated travel time from previous interval(s): the previous research shows that the predicted travel time of the target section is dominantly influenced by its recent historical travel time. In this study, the travel times from 15, 30, 45, and 60 minutes prior to the current time are considered as candidates for model inputs.

(2) The estimated travel time of neighboring sections: as aforementioned in section 5.3, the effects of neighboring sections could play important roles in travel time prediction on urban roadways. In this study, the estimated travel times from previous intervals (15, 30, 45, and 60 minutes in the past) of upstream, downstream and signal sharing sections are considered as candidates for model inputs.

5.3.3 Input variable selection

The Input Variable Selection (IVS) is a broad research area in artificial neural network modeling. The IVS methodologies can be grouped into three main classes (Blum and Langley 1997, Guyon and Elisseeff 2003) including; (1) wrapper algorithm that integrates IVS as part of the optimization of the model structure, (2) embedded algorithm that IVS is directly integrated into the training algorithm of ANN, and (3) filtering algorithm that contrasts to the previous classes by distinctly separating the IVS from the ANN training and adopting the statistical analysis in measuring the relevance of individual input variables. In this dissertation, rank correlation most commonly used in multivariate statistics and data mining (May, Dandy et al. 2011) was used as the IVS method. The Pearson correlation, R, is defined by

$$R_{XY} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y - \bar{y})^2}} \tag{5-2}$$

where n is the sample size, x_i, y_i are the single samples indexed with i, $\bar{x}, \bar{y}$ are the sample means

Input variable ranking based on Pearson correlation is one of the most widely used techniques in IVS. The selection of variables can be done by sorting for the first k variables that have the highest correlation values, or using all variables whose correlations are significantly different from zero. A rule of thumb for the large sample size (*n*) is that the variables with absolute correlation higher than $2/\sqrt{n}$ are significant (May, Dandy et al. 2011).

In this dissertation, all the candidate parameters were gradually entered as the model inputs by descending sorting of the correlation value. The overall process for developing the travel time prediction model is depicted in Figure 5.4.

5.3.4 Selection of neurons in hidden layers

The literature indicates that a multilayer feedforward neural network with one hidden layer is sufficient for approximating any complex non-linear function with any desired accuracy (Cybenko 1989, Hornik, Stinchcombe et al. 1989) and can provide acceptable outputs in travel time prediction (Faghri and J. Hua. 1992, Dougherty 1995, Vanajakshi and Rilett 2004, Naik 2010). In this dissertation, a widely used three-layer feedforward networks that have a single hidden layer sandwiched between input and output layers was used as the main structure for constructing the travel time prediction model. However, the conclusive rules for selecting the number of hidden neurons are not available. Therefore, the hidden neurons from 1-50 were tested, by a widely-used trial-and-error approach, to identify the most appropriate number of hidden neurons within hidden layers. Each model was tested with the training dataset that was gathered from real-field data during February 4-29, 2016 for multiple times (5 times). The appropriate model (appropriate number of hidden neurons and number of inputs) was based on the model that provides the least MAPE value.

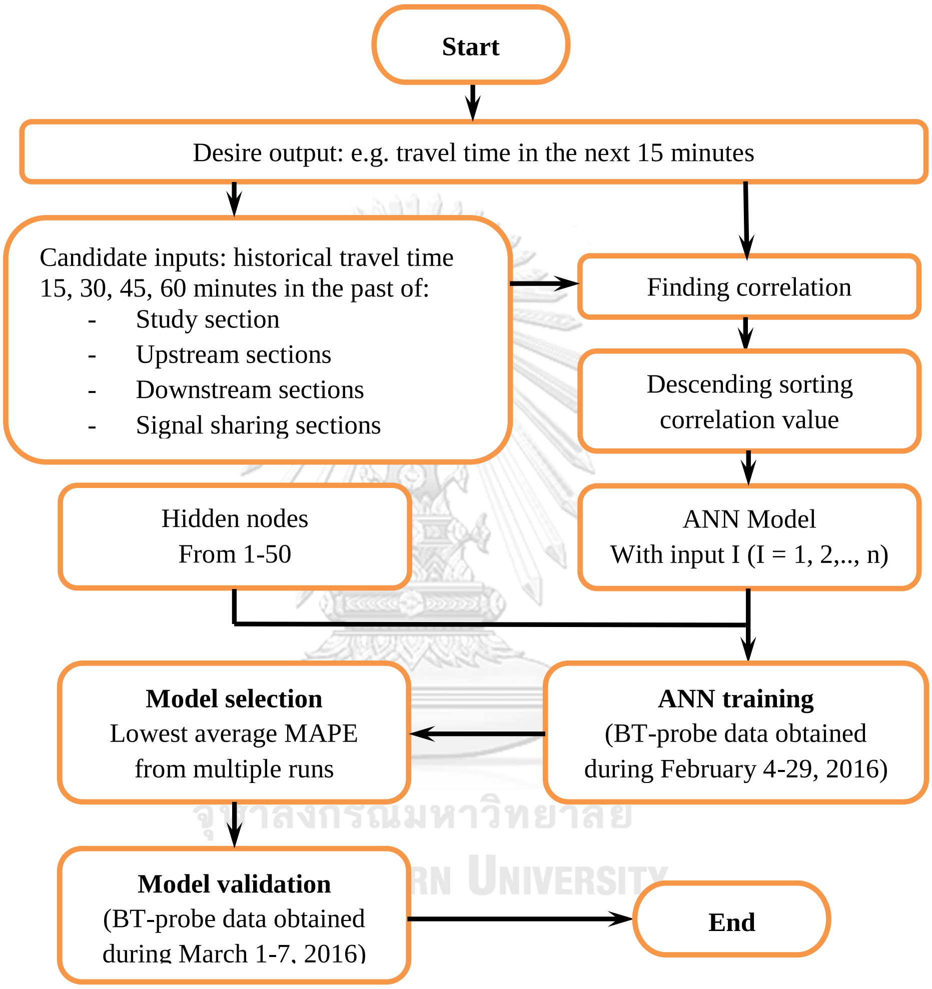


Figure 5-4 Overall processes for developing the short-term travel time prediction model

5.3.5 Selection of training algorithm

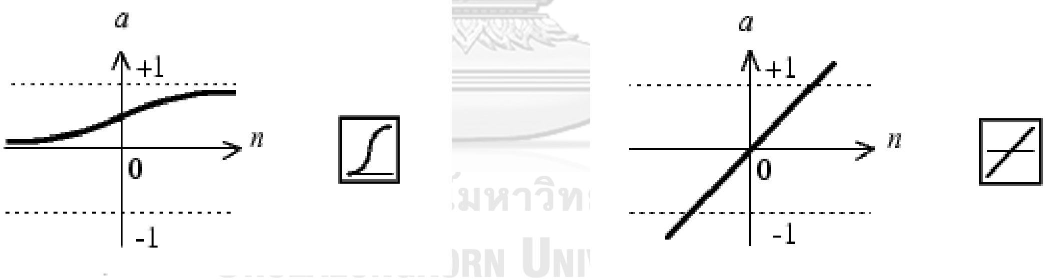
The back propagation training algorithm is the widely used technique in artificial neural networks in minimizing errors between observed values and outputs from prediction. This technique is a very popular optimization task in finding the optimal weight sets in the training process (Nawi, Khan et al. 2013). There are several nonlinear normalization approaches available for back propagation training such as the quasi-Newton, steepest gradient, conjugate gradient and the Levenberg-Marquardt (LM) algorithms. In this dissertation, the neural network models for travel time prediction were developed based on MATLAB programming as the main platform and therefore the built-in, LM algorithm based back propagation training, was used in neural network training.

5.3.6 Selection of activation functions

There are several activation functions available and have been used in previous studies. In this dissertation, two types of activation functions were used which are;

(1) Log-sigmoid function to transform value ranging from plus and minus infinity to value between 0 and 1(depicted in Figure 5.5(a)) as the activation function for hidden layer(s) as depicted in Figure 5.6.

(2) Linear function as depicted in Figure 5.5b for the output layer as depicted in Figure 5.6.



(a) (b)

Figure 5-5 Activation functions (a) log-sigmoid transfer function (b) linear transfer function.

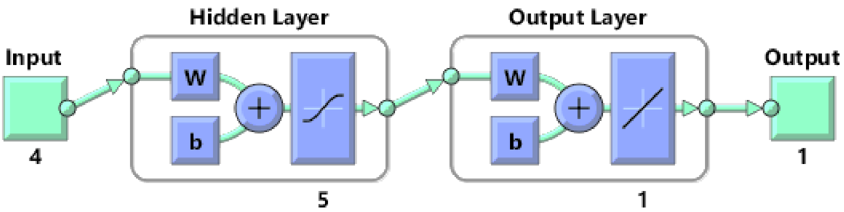


Figure 5-6 Use of log-sigmoid and linear transfer function in ANNs

5.4 EXPERIMENTAL CORRIDOR AND DATASET FOR TRAVEL TIME PREDICTION

As aforementioned in Chapter 4, a total of 40 Bluetooth scanners were installed at signalized intersections on urban roadways in Bangkok CBD for capturing signal from Bluetooth devices within their communication zones. During the data collection period, the missing data problem occurred in many periods and locations for various reasons such as (1) the runout of power supply for Bluetooth scanners which was a major problem during data collection, (2) the communication and data transmission problems from the mobile network, (3) no detection of Bluetooth devices in some intervals, etc. Therefore, it was necessary to carefully consider only the road section with low missing data problems and with enough captured data to use in this travel time prediction study.

5.4.1 Study corridors and target sections

From preliminary analyses on the availability of data, a corridor comprises 20 arterial sections partitioned at signalized intersections with different segment length ranging from 0.5 km to 1.49 km were selected as the study site. The main reason for selecting these sections was because these sections contained the more available Bluetooth probe data compared to other zones. The map of the study corridor is shown in Figure 5.7. Details of each section in the corridor are illustrated in Table 5.1. It could be observed from Table 5.1 that the amount of captured data per 15 minutes of each section varies ranging from 1.42 to 20.78 vehicles/15 minutes. The average captured rate from all section is 7.07 vehicles/15 minutes.

From the study corridors, four urban road sections were selected as target sections for the travel time prediction study which were section 01-16, 16-01, 16-25 and 25-16. Details of neighboring sections of each target section are illustrated in Table 5.2.

- *Section 01-16* from Samyan to Pathumwan intersection which is a 4-lane road of 1,491 meters long with 3 signalized intersections within the section. The right-turn movement is prohibited at the downstream intersection of this section. The data capturing rate of this section is 3.18 vehicles/15 minutes, and the average travel time and speed of section are 537.47 seconds and 9.99 km/h, respectively.
- *Section 16-01* from Pathumwan to Samyan intersection which is a 4-lane road of 1,491 meters long with 3 signalized intersections within the section. The data capturing rate of this section is 5.51 vehicles/15 minutes, the average travel time and speed of section are 349.29 seconds and 15.37 km/h, respectively.
- *Section 16-25* from Pathumwan to Rachathewi intersection which is a 2-3-lane road (two lanes at the beginning of the section and expanded to three lanes at the end of the section) of 794 meters long. The right-turn movement is prohibited at the downstream intersection of this section. The data capturing rate of this section is 4.71 vehicles/15 minutes, and the average travel time and speed of section are 431.41 seconds and 6.62 km/h, respectively.
- *Section 25-16* from Rachathewi to Pathumwan intersection which is a 4-6-lane road (four lanes at the beginning of the section and expanded to six lanes at the end of the section) with 794 meters long. The data capturing rate of this section is 10.36 vehicles/15 minutes, and the average travel time and speed of section are 179.69 seconds and 15.90 km/h, respectively.

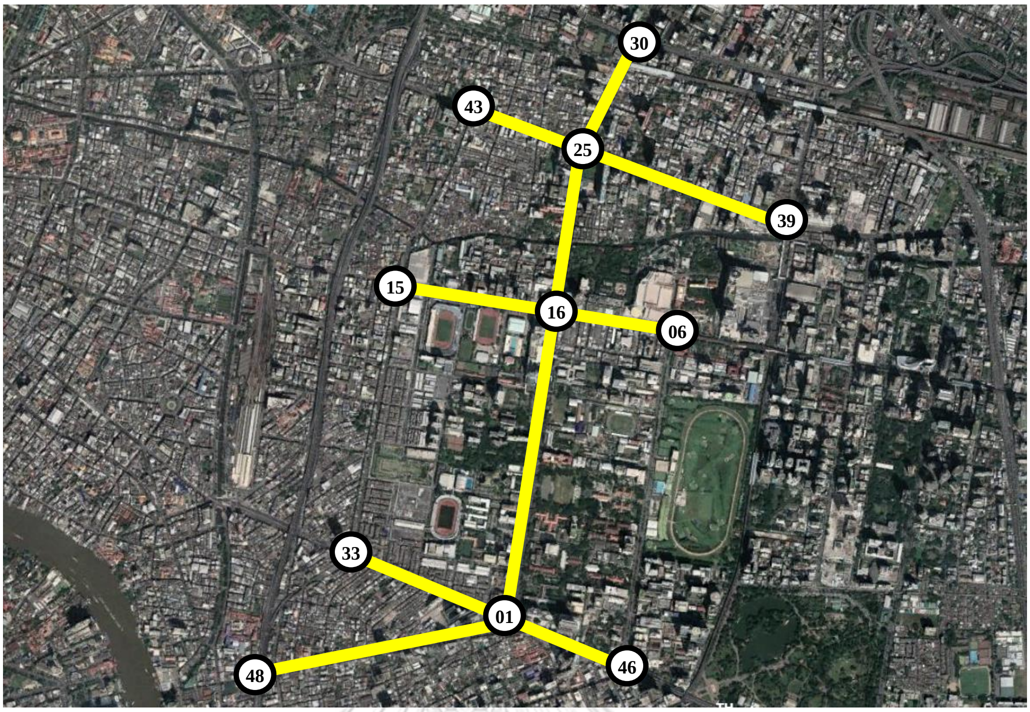


Figure 5-7 Study corridor

Table 5-1 Details of each section in the study corridor.

Road section	Length (km)	Bluetooth-Probe data			
		Avg. captured trip/15 minutes	Avg TT (sec)	Stdev of TT (sec)	Avg speed (km/h)
01-16*	1.491	3.18	537.47	139.92	9.99
16-01*	1.491	5.51	349.29	90.97	15.37
01-33	0.841	10.20	198.32	60.71	15.26
33-01	0.841	5.23	252.58	80.81	11.98
01-46	0.568	6.81	202.51	75.94	10.10
46-01	0.568	8.57	160.32	65.21	12.75
01-48	1.173	1.42	1161.37	293.98	3.64
48-01	1.173	5.30	340.98	109.20	12.39
06-16	0.551	6.84	230.03	78.12	8.63
16-06	0.551	1.89	317.48	36.60	6.25
15-16	0.761	1.82	499.36	78.65	5.49
16-15	0.761	9.53	149.78	42.07	18.30
16-25*	0.794	4.71	431.41	96.37	6.62
25-16*	0.794	10.36	179.69	66.61	15.90
25-30	0.587	9.44	242.69	82.40	8.71
30-25	0.587	20.78	180.52	66.79	11.71
25-39	1.066	3.88	558.17	252.68	6.88
39-25	1.066	5.57	396.55	105.61	9.68
25-43	0.562	7.07	214.47	73.52	9.43
43-25	0.562	13.22	215.16	81.25	9.40
Average		**7.07**	**340.91**	**98.87**	**10.42**

Considered only data from 06:00 to 21:00 of 4th February to 7th March 2016
*Target sections for travel time prediction; TT=travel time, Stdev=standard deviation of travel time

Table 5-2 Study sections and their neighboring sections.

Target sections	Upstream sections			Downstream sections			Signal sharing sections		
	UD	**UL**	**UR**	**DD**	**DL**	**DR**	**SD**	**SL**	**SR**
01-16	48-01	33-01	46-01	16-25	16-15		25-16	15-16	06-16
16-01	25-16	06-16	15-16	01-48	01-46	01-33	48-01	46-01	33-01
16-25	01-16	15-16	06-16	25-30	25-43		30-25	39-25	43-25
25-16	30-25	39-25	43-25	16-01	16-06	16-15	01-16	06-16	15-16

5.4.2 Dataset for developing the travel time prediction model

The 33-day Bluetooth data from February, 4 2016 to March 7, 2016 in the study corridor was used to test and verify the accuracy of the proposed technique in addressing section travel time prediction problems. Details of raw data and travel time estimation technique from Bluetooth probe data were described in Chapter 4.

From 24 hours of 33 days data (approximately 5 weeks), only the data collected during 06:00 – 21:00 were chosen as the full dataset in this study. The main reasons are (1) the traffic condition during daytime is generally more fluctuated than in the nighttime particularly around morning and evening peaks that need to be predicted and informed to road users, (2) the highest number of people who like to get traffic information is in the daytime period, (3) the majority of detected Bluetooth data is in daytime which makes data more reliable than nighttime.

In the model development process, full dataset as abovementioned was separated into 2 groups. First group comprised data from 26 days from February 4-29, 2016 and was used as training dataset in the model training and learning process. The second group comprised 7 days (1week) data from March 1-7, 2016 and was used as validating dataset (or testing dataset) to test the applicability of the travel time prediction model.

5.5 TESTING SCENARIOS

In this dissertation, test scenarios were separated into three cases which were;

Scenario 1: Only the historical data of the target section were available for developing the ANN model. In this case, the travel time prediction models were developed using only historical travel time from the target section as the model inputs (commonly used in the ANN model).

Scenario 2: Data of target and all neighboring sections were obtainable. In this case, the travel time prediction models were developed using both historical travel time from target and neighboring sections as the model inputs.

Scenario 3: The historical data from the target section were absent, but the data of all neighboring sections were available. In this case, the travel time prediction models were developed by using only historical travel time from neighboring sections as the model inputs.

From three testing scenarios mentioned above, all the target sections, which were section 01-16, 16-01, 16-25, and 25-16, would be tested to find the appropriate prediction models that predicted their future travel time in the 15, 30, 45, and 60 minutes horizon.

5.6 CONCLUDING REMARKS

This chapter described the details of the ravel time prediction model on urban roadways using the ANN technique by integrating the neighboring sections as the candidates for model inputs. Details of experimental corridor, dataset used in analysis and testing scenarios were also presented.

In this study, the multilayer feedforward neural network model with one hidden layer was selected as the main structure for the travel time prediction model. The candidate inputs for the travel time prediction model were historical travel times of the target section and its neighboring sections including; upstream, downstream and signal sharing sections. The input selection for the prediction model was based on the order of the correlation coefficients between desired output and each input parameter. The appropriate number of hidden neurons for each model was tested by the trial and error technique ranging from 1 to 50 hidden neurons.

The study corridor was on urban roadways in Bangkok metropolitan, comprising totally 20 sections which could be grouped into 4 target sections and their neighboring sections. The Bluetooth probe dataset, gathered 24 hours a day during February 4, 2016 to March 7, 2016, was used in this study.

From 24 hours for 33 days dataset, only the data obtained during 06:00 to 21:00 were selected as the full dataset in this study. The full dataset was then divided into 2 groups: (1) training dataset was the 26 days data captured during February 4-29, 2016 for model training and learning process, and (2) validating dataset was the 7 days data captured during March 1-7, 2016 for verifying the model accuracy.

The testing scenarios were categorized into three cases which were (1) only the historical data of the target section were available (commonly used in the ANN model), (2) all the historical data from both the target section and neighboring sections were available, and (3) historical data from the target section were absent, but the historical data of all neighboring sections were available for constructing the prediction model.

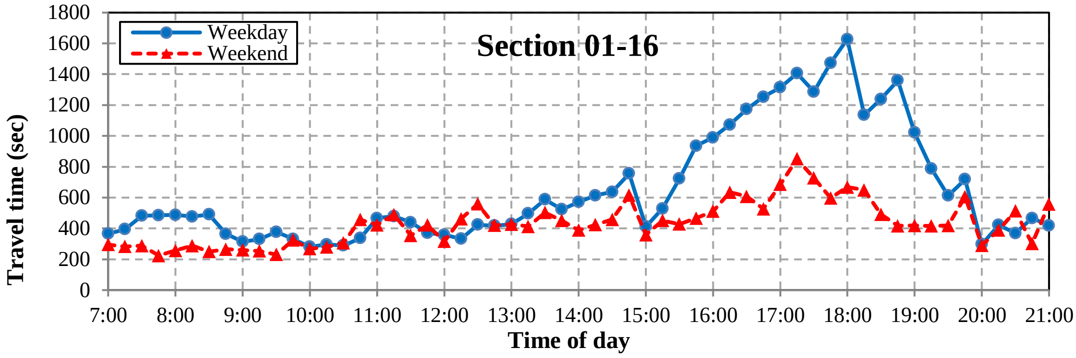
6. TRAVEL TIME PREDICTION RESULTS AND DISCUSSIONS

In order to assess the applicability of the proposed method and to achieve research objectives, numerical analyses on the travel time prediction on urban roadways were performed in this chapter, which is organized into 5 sections. First, the study sections and travel time behaviors are elaborated, and the characteristics of travel time on the study sections are presented. The correlation between (future) travel times and basic parameters (travel times) in the past on adjacent road sections are studied. Second, selection of inputs and hidden neurons for the travel time prediction model is presented. The procedures for selecting ANN model parameters, number of hidden neurons and input parameters are described. Third, the proposed travel time prediction models (ANNs) are applied under three main scenarios. The results are presented and discussed. Fourth, model performance in various situations is analyzed. The four cases of the study sections are discussed using Coefficient of Variation (CV) and Mean Absolute Percentage Error (MAPE). And, the concluding remarks of this chapter are presented in the last section.

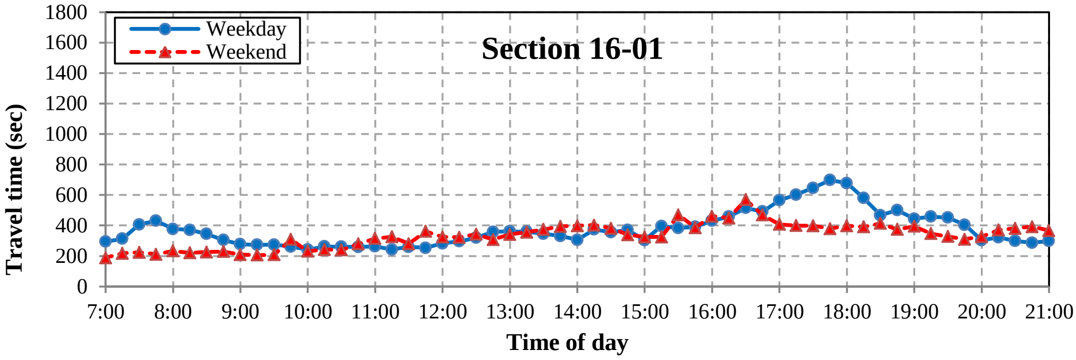
6.1 STUDY SECTIONS AND TRAVEL TIME BEHAVIORS

6.1.1 Travel times of the study sections

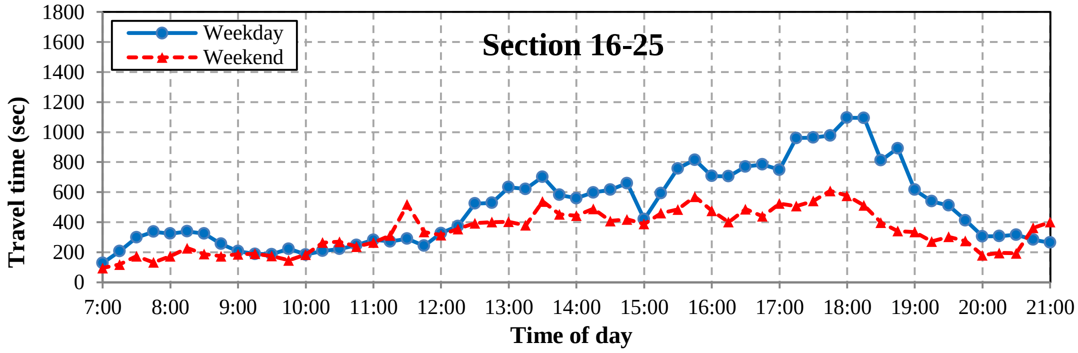
As mentioned in the previous chapter, four urban road sections (study sections) were selected as target sections for the travel time prediction study, which are section 01-16 (from Samyan to Pathumwan intersection), section 16-01 (from Pathumwan to Samyan intersection), section 16-25 (from Pathumwan to Rachathewi intersection) and section 25-16 (from Rachathewi to Pathumwan intersection). The behaviors of the travel time of each study section on weekdays and weekend are depicted in a simple time sequence diagram in Figure 6.1(a)-(d). Please note that travel time values of these sections were averaged from training dataset that were collected during February 3, 2016 to February 29, 2016.



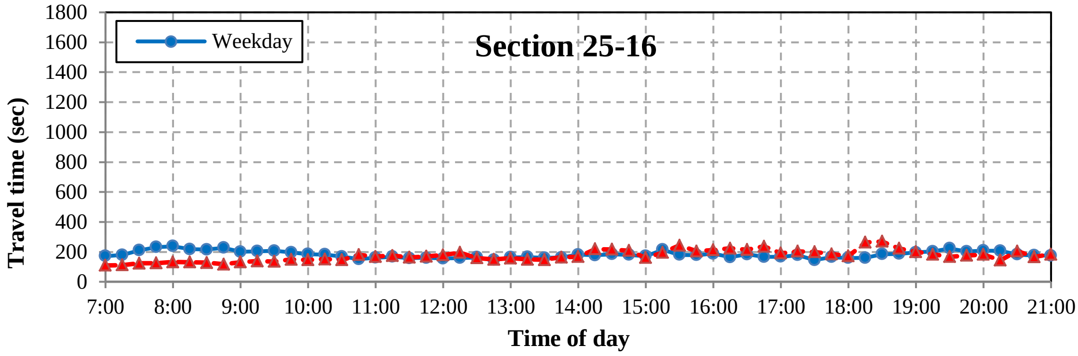
(a) Section 01-16



(b) Section 16-01



(c) Section 16-25



(d) Section 25-16

Figure 6-1 Travel times of the study sections on weekday and weekend (a) section 01-16, (b) section 16-01, (c) section 16-25, (d) section 25-16

The travel time behavior of section 01-16 is depicted in Figure 6.1(a). The travel time in uncongested traffic condition of this section is around 200 seconds which can be observed from 7:45 to 9:30 a.m. on weekend. The difference between travel times on weekday and weekend of this section can clearly be noticed. On weekday, a small morning peak of around 500 seconds (2.5 times of uncongested condition) occurs between 7:30 and 8:30 a.m. while in the evening heavier traffic congestion can be observed from the higher peak. The buildup of the evening peak starts around 15:00 (3 p.m.) and the highest value is around 1600 seconds (8 times of uncongested condition) at 18:00 (6 p.m.). Then the congestions fully dissipate at around 20:00 (8 p.m.). On weekend, the morning peak cannot clearly be observed while in the evening the moderate congestion occurs with the peak travel time of around 800 seconds (4 times of uncongested condition) at 17:15 (5:15 p.m.) and dissipates at 18:45 (6:45 p.m.).

The travel time behavior of section 16-01 is depicted in Figure 6.1(b). The travel time in uncongested traffic condition of this section is around 200 seconds which occurs from 7:00 to 9:30 a.m. on weekend. The difference between travel times on weekday and weekend of this section can slightly be noticed. On weekday, a small morning peak of around 400 seconds (2 times of uncongested condition) occurs at 7:45 a.m. while in the evening heavier traffic congestion can be observed from a higher peak. The buildup of peak starts at around 16:00 (4 p.m.) and the highest value of travel time is around 700 seconds (3.5 times of uncongested condition) at 17:45 (5:45 p.m.) then the congestion fully dissipates at around 20:00 (8 p.m.). On weekend, the morning peak cannot clearly be observed while in the evening the small congestion occurs with the peak travel time of around 600 seconds (3 times of uncongested condition) at 16:30 (4:30 p.m.).

The travel time behavior of section 16-25 is depicted in Figure 6.1(c). The travel time in uncongested traffic condition of this section is around 120 seconds which can be observed at 7:00 a.m. on weekend. The difference between travel times on weekday and weekend of this section can clearly be noticed. On weekday, a small morning peak of around 540 seconds (4.5 times of uncongested condition) occurs from 7:30 to

8:30 a.m. while in the evening heavier traffic congestion can be observed from a higher peak. The highest peak travel time is around 1100 seconds (9 times of uncongested condition) between 18:00-18:15 (6:00-6:15 p.m.). On weekend, the morning peak cannot clearly be observed while in the evening the moderate congestion occurs with the peak travel time of around 600 seconds (5 times of uncongested condition) at 17:45 (5:45 p.m.).

The travel time behavior of section 25-16 is depicted in Figure 6.1(d). The travel time in uncongested traffic condition of this section is around 100-120 seconds which can be observed from 7:00 to 10:00 a.m. on weekend. The difference between travel times on weekday and weekend of this section cannot clearly be noticed. The time spent for traveling on this section is quite constant for the entire day, the morning and evening peaks are also hard to spot.

6.1.2 Correlations between future travel times and each parameter of the study sections

Table 6.1-6.4 show the correlation of each parameter (including historical travel times of the target section, upstream sections, downstream sections, and signal sharing sections) with the future travel time in the next 15, 30, 45 and 60 minutes of section 01-16, 16-01, 16-25 and 25-16 respectively. Please note that these correlation values were calculated from Bluetooth probe data collected between February 4, 2016 and February 29, 2016, which were the training dataset for developing the travel time prediction model.

The correlation determines the level of association between the input (independent) parameter and the target (future) travel time. The parameters are treated independently. For the correlation for each pair of parameter, the greater the value, the higher correlation between the two variables. Although the value of correlation could roughly show the level of acceptability of the association, in this study only the relative degree of correlation is of interest. Therefore, the correlation values for all parameters are put in order. One can see the importance of each parameter to the resulting travel time forecast. For instance, the value of 15-min travel time on the target section (T15) could have the highest association (explanatory power) to the travel time forecast (15, 30, 45, and 60 minutes) in most cases (Table 6.1-Table 6.3), except in the case on section 25-16 (Table 6.4), in which the 15-min travel times on the target section (T15) are ranked 1-3. The rank of the correlation was used to determine the parameter(s) that would later be used as input(s) to the travel time prediction model.

Considering types of parameters (target, up-direct, up-left, up-right, down-direct, down-left, down-right, shared-direct, shared-left, shared-right), one can observe correlation ranking in a big picture from Table 6.1-6.4 that the historical travel times of the target section are the most correlated parameters to the future travel times. However, the second most correlated parameter to the future travel time of the target varies from section to section. For instance, historical travel times of the direct-downstream section are the second most correlated parameter to the future travel time of section 01-16; the historical travel times of the signal sharing section on the left hand side of the target section are the second most correlated parameter to the future travel time of section 16-01; historical travel times of the direct-downstream section are the second most correlated parameter to the future travel time of section 16-25; and historical travel times of the direct-upstream section are the second most correlated parameter to the future travel time of section 25-16. These different correlated parameters from the four study sections imply local specific behavior and consequently indicates that the appropriate model inputs at different locations should be different.

Although the values of correlation are not the main consideration here, it is worth mentioning a point on correlation values here. From the degree of correlation, one can observe that not all parameters can be good explanatory variables to the travel time forecast. Many of the low rank parameters have weak correlations. From the Tables, the correlation at each ranking varies. For instance, at Rank 5th of the four target sections, the correlations range from 0.436-0.537, 0.368-0.546, 0.392-0.587, and 0.043-0.127 on section 01-16, 16-01, 16-25, and 25-16 respectively. At Rank 10th, the correlations range from 0.330-0.375, 0.298-0.409, 0.345-0.447, and -0.024-0.103 on section 01-16, 16-01, 16-25, and 25-16 respectively. Notably, the study section 25-16 has very a low correlation. It means that the correlation is also dependent on section and traffic characteristics.

Table 6-1 Correlation between each parameter and the future travel times of section 01-16 calculated from training dataset (February 2-29, 2016).

Parameters	Prediction horizons							
	15 minutes		30 minutes		45 minutes		60 minutes	
	Correlation	Rank	Correlation	Rank	Correlation	Rank	Correlation	Rank
Target-15 (T15)	0.735	1	0.607	1	0.547	1	0.503	2
Target-30 (T30)	0.612	2	0.573	2	0.534	3	0.471	4
Target-45 (T45)	0.537	5	0.512	5	0.467	6	0.436	5
Target-60 (T60)	0.467	8	0.413	8	0.389	8	0.347	9
Up-Direct-15 (UD15)	0.316	13	0.310	12	0.326	12	0.333	10
Up-Direct-30 (UD30)	0.277	17	0.279	14	0.304	13	0.300	15
Up-Diect-45 (UD45)	0.262	19	0.261	18	0.284	19	0.292	16
Up-Direct-60 (UD60)	0.256	21	0.243	20	0.280	20	0.222	23
Up-Left-15 (UL15)	0.353	9	0.327	11	0.379	9	0.375	7
Up-Left-30 (UL30)	0.336	10	0.348	9	0.375	10	0.329	11
Up-Left-45 (UL 45)	0.333	11	0.330	10	0.329	11	0.300	14
Up-Left-60 (UL60)	0.329	12	0.288	13	0.299	14	0.267	19
Up-Rigth-15 (UR15)	0.101	31	0.078	32	0.073	31	0.082	30
Up-Right-30 (UR30)	0.078	35	0.069	34	0.060	33	0.080	31
Up-Right-45 (UR45)	0.094	32	0.069	33	0.068	32	0.065	33
Up-Right-60 (UR60)	0.088	34	0.059	35	0.038	36	0.034	35
Down-Direct-15 (DD15)	0.581	3	0.559	3	0.536	2	0.516	1
Down-Direct-30 (DD30)	0.555	4	0.517	4	0.503	4	0.493	3
Down-Direct-45 (DD45)	0.522	6	0.488	6	0.484	5	0.425	6
Down-Direct-60 (DD60)	0.478	7	0.451	7	0.406	7	0.366	8
Down-Left-15 (DL15)	0.298	15	0.278	15	0.289	17	0.308	12
Down-Left-30 (DL30)	0.300	14	0.271	17	0.295	15	0.306	13
Down-Left-45 (DL45)	0.281	16	0.251	19	0.291	16	0.278	18
Down-Left-60 (DL60)	0.250	23	0.237	21	0.263	21	0.229	22
Down-Right-15 (DR15)	[redacted]							
Down-Right-30 (DR30)								
Down-Right-45 (DR45)								
Down-Right-60 (DR60)								
Share-Direct-15 (SD15)	0.043	36	0.053	36	0.046	35	0.091	29
Share-Direct-30 (SD30)	0.090	33	0.087	31	0.101	28	0.069	32
Share-Direct-45 (SD45)	0.116	29	0.128	28	0.087	29	0.047	34
Share-Direct-60 (SD60)	0.200	25	0.149	27	0.079	30	0.003	36
Share-Left-15 (SL15)	0.117	28	0.092	30	0.058	34	0.112	28
Share-Left-30 (SL30)	0.113	30	0.094	29	0.120	27	0.138	27
Share-Left-45 (SL45)	0.119	27	0.151	26	0.146	26	0.195	26
Share-Left-60 (SL60)	0.178	26	0.190	25	0.205	25	0.204	25
Share-Right-15 (SR15)	0.256	20	0.223	24	0.223	24	0.235	21
Share-Right-30 (SR30)	0.271	18	0.231	22	0.244	23	0.285	17
Share-Right-45 (SR45)	0.253	22	0.229	23	0.288	18	0.254	20
Share-Right-60 (SR60)	0.244	24	0.272	16	0.244	22	0.213	24

Table 6-2 Correlation between each parameter and the future travel times of section 16-01 calculated from training dataset (February 2-29, 2016).

Parameters	Prediction horizons							
	15 minutes		30 minutes		45 minutes		60 minutes	
	Correlation	**Rank**	**Correlation**	**Rank**	**Correlation**	**Rank**	**Correlation**	**Rank**
Target-15 (T15)	0.846	1	0.699	1	0.557	1	0.465	1
Target-30 (T30)	0.722	2	0.575	2	0.464	4	0.368	5
Target-45 (T45)	0.593	3	0.483	6	0.368	7	0.319	7
Target-60 (T60)	0.486	8	0.383	9	0.312	11	0.273	11
Up-Direct-15 (UD15)	0.018	37	0.025	36	0.030	36	0.053	33
Up-Direct-30 (UD30)	0.023	35	0.035	33	0.045	33	0.029	38
Up-Diect-45 (UD45)	0.032	32	0.046	31	0.025	38	0.036	37
Up-Direct-60 (UD60)	0.048	30	0.042	32	0.037	35	0.041	36
Up-Left-15 (UL15)	0.149	25	0.082	29	0.070	28	0.125	20
Up-Left-30 (UL30)	0.119	27	0.085	27	0.110	23	0.115	21
Up-Left-45 (UL 45)	0.102	28	0.084	28	0.045	32	0.055	32
Up-Left-60 (UL60)	0.128	26	0.093	26	0.062	29	0.086	27
Up-Rigth-15 (UR15)	0.034	31	0.029	34	0.054	30	0.109	23
Up-Right-30 (UR30)	0.018	38	0.019	37	0.048	31	0.101	26
Up-Right-45 (UR45)	0.020	36	0.052	30	0.102	25	0.114	22
Up-Right-60 (UR60)	0.050	29	0.104	25	0.131	21	0.147	18
Down-Direct-15	0.009	39	0.005	40	0.008	39	0.053	34
Down-Direct-30	-0.005	40	0.012	39	0.042	34	0.068	31
Down-Direct-45	-0.027	34	0.015	38	0.028	37	0.006	39
Down-Direct-60	0.028	33	0.025	35	0.003	40	-0.003	40
Down-Left-15 (DL15)	0.450	9	0.383	10	0.275	13	0.211	13
Down-Left-30 (DL30)	0.409	10	0.298	14	0.201	15	0.164	15
Down-Left-45 (DL45)	0.321	18	0.225	18	0.162	19	0.102	25
Down-Left-60 (DL60)	0.259	22	0.198	22	0.103	24	0.052	35
Down-Right-15	0.404	11	0.408	8	0.390	6	0.370	4
Down-Right-30	0.396	12	0.369	11	0.337	9	0.315	8
Down-Right-45	0.368	13	0.340	12	0.316	10	0.310	9
Down-Right-60	0.340	16	0.314	13	0.307	12	0.298	10
Share-Direct-15	0.351	15	0.262	16	0.206	14	0.196	14
Share-Direct-30	0.314	19	0.245	17	0.179	16	0.125	19
Share-Direct-45	0.275	20	0.206	21	0.122	22	0.079	28
Share-Direct-60	0.242	23	0.171	24	0.083	27	0.078	29
Share-Left-15 (SL15)	0.546	5	0.534	4	0.505	2	0.444	2
Share-Left-30 (SL30)	0.581	4	0.541	3	0.483	3	0.426	3
Share-Left-45 (SL45)	0.543	6	0.490	5	0.425	5	0.359	6
Share-Left-60 (SL60)	0.502	7	0.438	7	0.365	8	0.273	12
Share-Right-15	0.367	14	0.290	15	0.169	17	0.150	17
Share-Right-30	0.321	17	0.220	19	0.164	18	0.154	16
Share-Right-45	0.260	21	0.213	20	0.149	20	0.104	24
Share-Right-60	0.227	24	0.174	23	0.096	26	0.077	30

Table 6-3 Correlation between each parameter and the future travel times of section 16-25 calculated from training dataset (February 2-29, 2016).

Parameters	Prediction horizons							
	15 minutes		30 minutes		45 minutes		60 minutes	
	Correlation	Rank	Correlation	Rank	Correlation	Rank	Correlation	Rank
Target-15 (T15)	0.822	1	0.689	1	0.638	1	0.581	1
Target-30 (T30)	0.698	2	0.636	2	0.577	2	0.496	2
Target-45 (T45)	0.645	3	0.575	3	0.489	3	0.428	4
Target-60 (T60)	0.587	5	0.489	5	0.426	6	0.392	5
Up-Direct-15 (UD15)	0.507	7	0.473	6	0.440	5	0.387	6
Up-Direct-30 (UD30)	0.479	8	0.440	8	0.384	8	0.354	8
Up-Diect-45 (UD45)	0.436	11	0.372	11	0.345	10	0.315	12
Up-Direct-60 (UD60)	0.367	12	0.329	13	0.289	16	0.242	21
Up-Left-15 (UL15)	0.094	36	0.082	36	0.072	36	0.086	36
Up-Left-30 (UL30)	0.102	35	0.093	35	0.111	35	0.100	35
Up-Left-45 (UL 45)	0.121	34	0.140	34	0.135	33	0.139	31
Up-Left-60 (UL60)	0.161	33	0.149	33	0.134	34	0.126	34
Up-Rigth-15 (UR15)	0.231	28	0.182	32	0.148	32	0.135	33
Up-Right-30 (UR30)	0.238	25	0.198	29	0.173	31	0.184	29
Up-Right-45 (UR45)	0.237	26	0.209	28	0.215	23	0.185	28
Up-Right-60 (UR60)	0.231	27	0.229	24	0.196	26	0.138	32
Down-Direct-15	0.610	4	0.512	4	0.445	4	0.434	3
Down-Direct-30	0.516	6	0.447	7	0.425	7	0.386	7
Down-Direct-45	0.453	9	0.431	9	0.378	9	0.329	9
Down-Direct-60	0.447	10	0.387	10	0.331	11	0.324	10
Down-Left-15 (DL15)	0.282	20	0.262	21	0.238	22	0.249	20
Down-Left-30 (DL30)	0.276	22	0.249	22	0.248	21	0.225	22
Down-Left-45 (DL45)	0.239	24	0.242	23	0.203	25	0.181	30
Down-Left-60 (DL60)	0.262	23	0.216	26	0.192	29	0.188	27
Down-Right-15	[redacted]							
Down-Right-30								
Down-Right-45								
Down-Right-60								
Share-Direct-15	0.225	30	0.220	25	0.192	28	0.189	26
Share-Direct-30	0.230	29	0.193	30	0.187	30	0.192	25
Share-Direct-45	0.207	32	0.191	31	0.204	24	0.197	24
Share-Direct-60	0.207	31	0.211	27	0.195	27	0.201	23
Share-Left-15 (SL15)	0.279	21	0.272	20	0.265	20	0.259	17
Share-Left-30 (SL30)	0.352	13	0.330	12	0.311	12	0.322	11
Share-Left-45 (SL45)	0.342	14	0.317	14	0.305	13	0.293	15
Share-Left-60 (SL60)	0.326	16	0.305	18	0.278	18	0.254	18
Share-Right-15	0.321	17	0.308	16	0.304	14	0.313	13
Share-Right-30	0.327	15	0.310	15	0.302	15	0.295	14
Share-Right-45	0.319	18	0.305	17	0.285	17	0.275	16
Share-Right-60	0.303	19	0.277	19	0.268	19	0.252	19

Table 6-4 Correlation between each parameter and the future travel times of section 25-16 calculated from training dataset (February 2-29, 2016).

Parameters	Prediction horizons							
	15 minutes		30 minutes		45 minutes		60 minutes	
	Correlation	Rank	Correlation	Rank	Correlation	Rank	Correlation	Rank
Target-15 (T15)	0.401	1	0.218	3	0.172	3	0.160	2
Target-30 (T30)	0.266	2	0.222	1	0.186	1	0.168	1
Target-45 (T45)	0.254	3	0.221	2	0.173	2	0.154	3
Target-60 (T60)	0.206	4	0.151	4	0.122	4	0.092	4
Up-Direct-15	0.127	5	0.059	11	0.013	28	-0.005	32
Up-Direct-30	0.100	8	0.055	14	0.021	22	-0.001	39
Up-Diect-45	0.108	6	0.066	9	0.024	19	0.009	25
Up-Direct-60	0.082	12	0.034	27	0.011	30	0.008	28
Up-Left-15 (UL15)	0.045	31	0.025	34	0.023	20	0.006	30
Up-Left-30 (UL30)	0.019	40	0.034	28	0.005	37	-0.005	33
Up-Left-45 (UL 45)	0.041	32	0.036	24	0.009	33	0.001	38
Up-Left-60 (UL60)	0.036	37	0.025	35	0.010	32	-0.005	34
Up-Rigth-15	0.069	16	0.043	18	0.007	36	0.010	24
Up-Right-30	0.069	18	0.035	25	0.033	11	0.031	8
Up-Right-45	0.045	30	0.056	13	0.044	7	0.015	19
Up-Right-60	0.072	15	0.066	8	0.028	16	-0.003	37
Down-Direct-15	0.052	24	0.035	26	0.020	23	0.012	21
Down-Direct-30	0.063	22	0.040	21	0.032	12	0.014	20
Down-Direct-45	0.066	19	0.049	16	0.027	17	0.007	29
Down-Direct-60	0.064	21	0.039	22	0.022	21	0.025	9
Down-Left-15	0.069	17	0.076	6	0.039	8	0.017	15
Down-Left-30	0.090	9	0.066	7	0.038	9	0.016	17
Down-Left-45	0.082	11	0.061	10	0.030	15	0.016	16
Down-Left-60	0.075	14	0.048	17	0.031	14	0.023	11
Down-Right-15	-0.046	28	-0.040	20	-0.036	10	-0.034	6
Down-Right-30	-0.040	33	-0.037	23	-0.031	13	-0.024	10
Down-Right-45	-0.036	38	-0.032	29	-0.019	24	-0.011	22
Down-Right-60	-0.026	39	-0.022	38	-0.013	29	-0.005	36
Share-Direct-15	0.039	34	0.027	32	0.015	26	0.010	23
Share-Direct-30	0.037	36	0.028	31	0.027	18	0.023	12
Share-Direct-45	0.046	27	0.056	12	0.046	6	0.033	7
Share-Direct-60	0.080	13	0.087	5	0.058	5	0.043	5
Share-Left-15	0.087	7	0.041	15	0.019	31	0.008	26
Share-Left-30	0.060	20	0.031	39	0.015	39	0.006	13
Share-Left-45	0.037	25	0.024	33	0.008	34	-0.001	18
Share-Left-60	0.045	26	0.024	40	0.005	40	-0.005	14
Share-Right-15	0.103	10	0.050	19	0.011	25	-0.008	27
Share-Right-30	0.066	23	0.019	30	-0.001	27	-0.022	31
Share-Right-45	0.049	35	0.026	36	-0.008	35	-0.015	40
Share-Right-60	0.048	29	0.013	37	0.000	38	0.021	35

As the prediction horizon increases, the correlation values of all parameters decrease, and this points out the difficulty of the prediction in longer time horizons. The order of parameters that are correlated to the future travel time also slightly changes when the time horizon changes, as seen from the Tables. For example, the five most correlated parameters to the future travel time in the next 15 minutes of section 01-16 are historical travel times in the past 15 minutes of the target section, the past 30 minutes of the target section, the past 15 minutes of the direct downstream section, the past 30 minutes of the direct downstream section, and the past 45 minutes of the target section, respectively. The five most correlated parameters to the future travel time in the next 45 minutes of section 01-16 are different; they are historical travel time of the past 15 minutes of the target section, the past 15 minutes of the direct downstream section, the past 30 minutes of the target section, the past 30 minutes of the direct downstream section, and the past 45 minutes of the direct downstream section, respectively. This behavior indicates different parameters should be used as the model inputs in different prediction horizons.

6.2 SELECTION OF INPUTS AND HIDDEN NEURONS FOR THE TRAVEL TIME PREDICTION MODEL

As a part of the model development process, the selection of input variables and the number of hidden neurons (or hidden nodes) is an indispensable issue for ANN modeling. The possible inputs for our prediction model consist of historical travel times (up to 4 previous horizons) of target and neighboring sections.

Having a lot of inputs does not mean the models will be more accurate than those with lesser number of inputs. On the other hand, choosing the right and optimum inputs that are able to determine the prediction results will actually make the model more accurate and reliable. The number of hidden neurons of the ANN model is in the same manner; consideration should be given to the complexity of the problem. Having too few hidden neurons cannot explain the complex problems. On the other hand, if there are too many, it can cause the overfitting problems.

Based on previous studies and literature review, it is found that each road section has different travel time behaviors, complexity, and also correlations with the other parameters. Therefore, the appropriate number of inputs and the hidden neurons for the travel time prediction model of each road section should be different.

6.2.1 Number of hidden neurons and inputs and the accuracy of travel time prediction

This section presents the investigation on the effects of number of inputs and hidden neurons on the accuracy level of the travel time prediction. Figure 6.2(a) shows the relationship between the number of inputs, the number of hidden neurons and the MAPE of travel time prediction during the training process (using training dataset for model training) of section 01-16. It could be observed that as the number of inputs and hidden neurons increase, the MAPE of prediction from training data set is not much improved, but rather the greater fluctuation in the region with higher inputs and hidden neurons can be observed.

Figure 6.2(b) demonstrates the relationship between the numbers of inputs, hidden neurons and the MAPE of the prediction based on validating dataset using the model structures (number of inputs, hidden neurons, and connecting weights) obtained from the training dataset. It could be noticed that the accuracies of travel time prediction from models with a higher number of inputs and hidden neurons are lower than the model with smaller number of inputs and hidden neurons. This manner is caused by the overfitting behaviors from the complicated model that contains more parameters than can be justified by the data. The models try to correspond to a particular set of data that may fail to reliably predict the additional dataset or future observations.

From this section, it could be concluded that the more complex models with higher number of inputs and hidden neurons do not always provide higher accurate results. On the contrary, it could lead to worse prediction results due to overfitting problems. Therefore, selecting an appropriate number of inputs and hidden neurons is a very important task in the model development process.

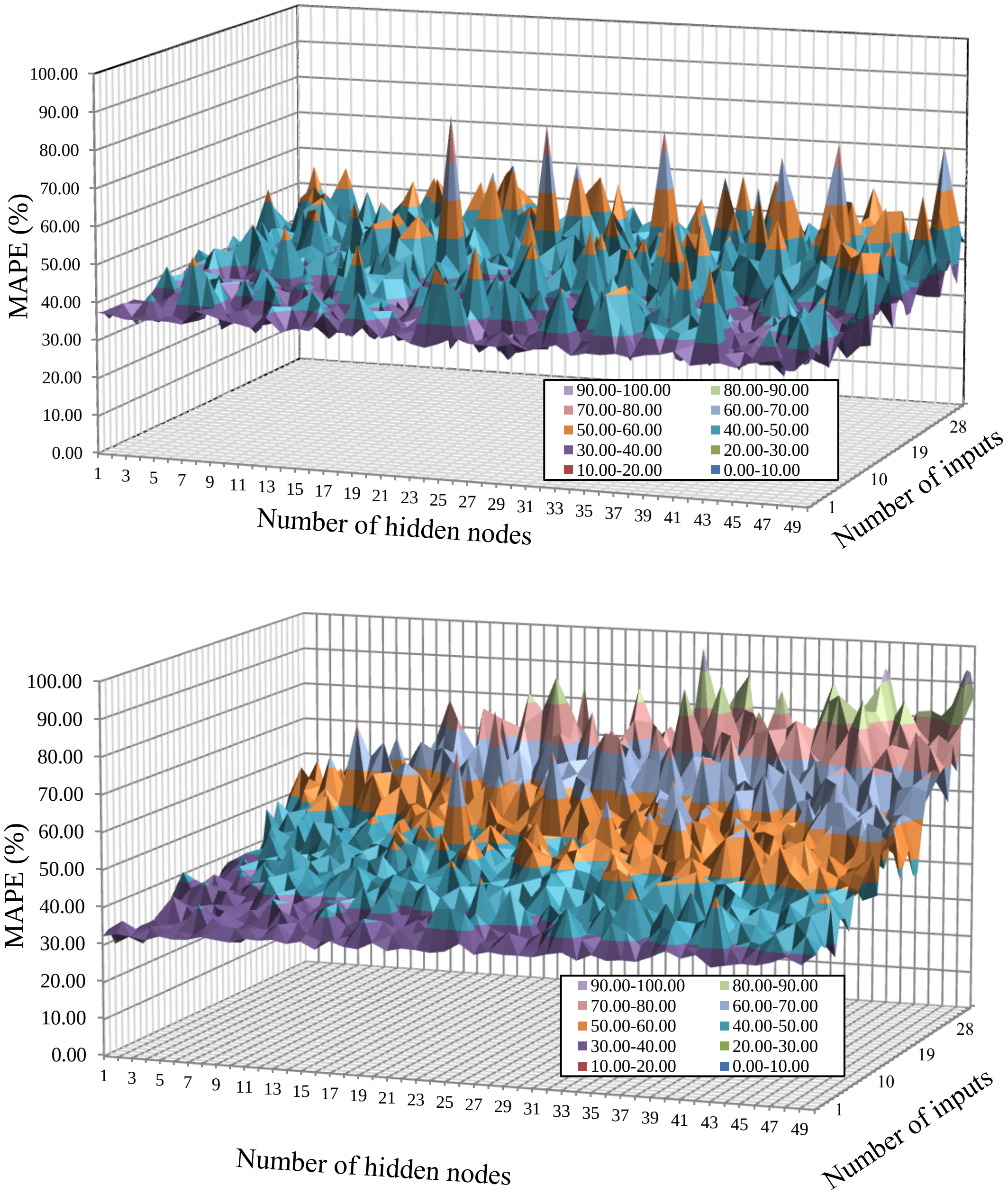


Figure 6-2 Effects of number of hidden neurons and number of inputs on the error of travel time predictions of section 01-16 (next 15 minutes) (a) MAPE of training dataset (b) MAPE of validating dataset

6.2.2 Selecting the number of hidden neurons and inputs for travel time prediction

In this study, the k-fold (5-fold) cross validation technique was used to determine the appropriate number of inputs and hidden neurons in developing ANN models for urban roadway travel time prediction.

The concept of 5-fold cross validation is illustrated in Figure 6.3. From this concept, the training dataset (which was captured on February 4-29, 2016) was grouped into 5 equal sizes of subsamples. From these 5 subsamples, a single subsample was selected as the validation dataset for testing the model accuracy, and the remaining 5-1 subsamples were used as dataset for model training. The cross-validation process was then repeated for 5 times, with each subsample exactly used once as the validation dataset. The supervised training with error back-propagation as described in chapter 5 was used to find the appropriate connection weights within networks.

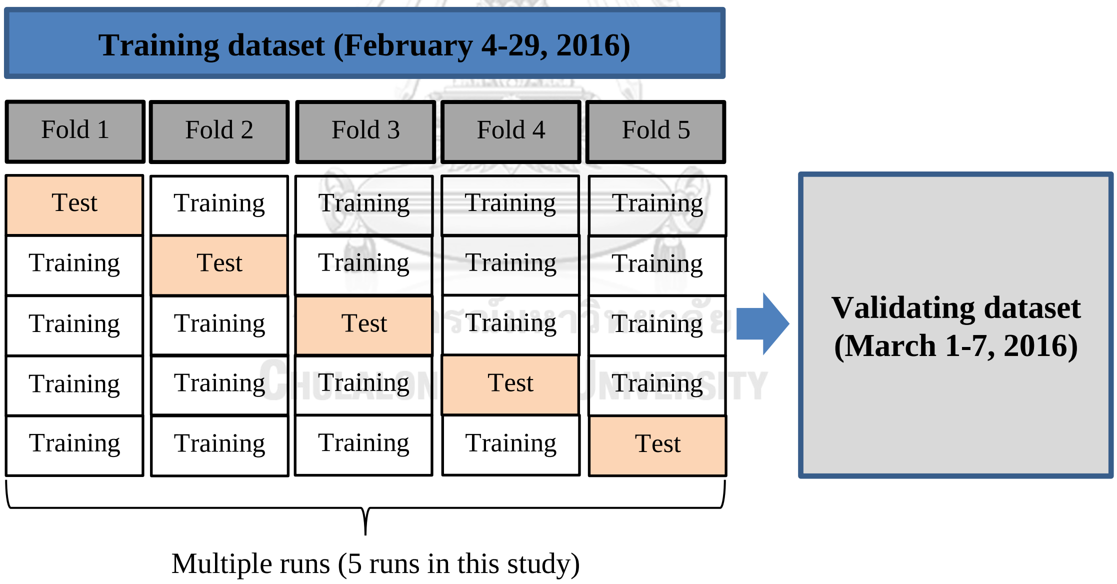


Figure 6-3 Five-fold cross validation in selecting number of inputs and hidden neurons for ANN models.

Based on the 5-fold cross validation test with the training dataset, the appropriate number of inputs and hidden neurons for each case could be determined by the optimal model that provided the most accurate result. Since the appropriate structure of the model such as the number of inputs, hidden nodes, and the connecting weight was determined, the capability of models in travel time prediction could be found by testing the resulting model with the validating dataset.

6.2.3 Structures of appropriate ANN models obtained from training dataset

Table 6.5-6.8 show the summary of the appropriate model structures of section 01-16, 16-01, 16-25 and 25-16, which were determined from 5-fold cross validation with training dataset. The predicted horizons in the Tables were divided into 4 horizons; 15, 30, 45 and 60 minutes in advance. The test scenarios were separated into three scenarios: Scenario 1: only the historical data of the target section were available for developing the ANN model, Scenario 2: data of the target and all neighboring sections were obtainable, and Scenario 3: historical data from the target section were absent, but the data of neighboring sections were available.

From Table 6.5 and 6.8, one could observe different model structures among the three scenarios. For example, in scenario 1 of section 01-16 (Table 6.5), the appropriate prediction model for the next 15 minutes comprises 1 input (historical travel time of the study section from the previous 15 minutes) and 1 hidden neuron with MAPE of 31.07% during the training process. In scenario 2, the appropriate prediction model for the next 15 minutes comprises 4 inputs (historical travel time of the study section from previous 15 and 30 minutes and historical travel time of the direct-downstream section from the previous 15 and 30 minutes) and 1 hidden neuron with MAPE of 30.07%. In scenario 3, the appropriate prediction model for the next 15 minutes comprises 7 inputs (historical travel time of the downstream-direct section form the previous 15, 30, 45 and 60 minutes and historical travel time of the upstream-left section from the previous 15 and 30 minutes) and one hidden node with MAPE of 32.73% from training dataset.

However, in Table 6.6 and 6.7, the same model structure from different scenarios could be observed in some cases. For example, in scenario 1 and 2 of section 16-01 (Table 6.6), the appropriate prediction model for the next 15 minutes comprises 3 inputs (historical travel times of the target section from the previous 15, 30, and 45 minutes) and 3 hidden neurons with the same MAPE of 21.49% during the training process. This behavior indicates the strong influence of historical travel times of target section over the future travel times.

From Table 6.5 to 6.8, in different prediction horizons of the same scenario, dissimilar model structures can be observed. For example, the appropriate model structures of section 01-16 for travel time prediction in the next 15 minutes and for the prediction in the next 30 minutes in scenario 2 (considering the historical travel time from both the target and neighboring sections) have the same 4 inputs (historical travel time of the study section from the previous 15 and 30 minutes and historical travel time of the direct-downstream section from the previous 15 and 30 minutes) and 1 hidden node. While, in travel time prediction for the next 45 minutes horizons, the appropriate model structure comprises only 3 inputs (historical travel time of the study section form the previous 15 and 30 minutes and historical travel time of direct-downstream section from previous 15 minutes) and 1 hidden neuron.

Table 6-5 Selected inputs and hidden neurons for travel time predictions on section 01-16 determined from 5-fold cross validation with training dataset.

Scenario 1 Only target sections			**Scenario 2 All sections available**			**Scenario 3 Missing target section**		
Inputs	**Hidden nodes**	**MAPE (training dataset)**	**Inputs**	**Hidden nodes**	**MAPE (training dataset)**	**Inputs**	**Hidden nodes**	**MAPE (training dataset)**
Next 15 Minutes								
T15	1	31.07	T15 T30 DD15 DD30	1	30.58	DD15 DD30 DD45 DD60 UL15 UL30 UL45	1	32.73
Next 30 Minutes								
T15	1	37.73	T15 T30 DD15 DD30	1	36.39	DD15 DD30	1	33.89
Next 45 Minutes								
T15 T30 T45 T60	1	38.45	T15 T30 DD15	1	36.35	DD15	4	34.59
Next 60 Minutes								
T15 T30	2	34.97	T15 T30 T45 DD15 DD30 DD45 UL15	1	34.49	DD15 DD30 DD45 DD60 UL15 UL30 UD15 DL15	1	34.88

Table 6-6 Selected inputs and hidden neurons for travel time predictions on section 16-01 determined from 5-fold cross validation with training dataset.

Scenario 1 Only target sections			Scenario 2 All sections available			Scenario 3 Missing target section		
Inputs	**Hidden nodes**	**MAPE (training dataset)**	**Inputs**	**Hidden nodes**	**MAPE (training dataset)**	**Inputs**	**Hidden nodes**	**MAPE (training dataset)**
Next 15 Minutes								
T15 T30 T45	3	21.49	T15 T30 T45	3	21.49	SL15 SL30 SL45 SL60 DL15 DL30 DR15 DR30 DR45 DR60 SD15 SR15	7	30.20
30 Minutes								
T15 T30	7	25.57	T15 T30	7	25.57	SL15 SL30 SL45	2	30.98
45 Minutes								
T15	4	28.12	T15	4	28.12	SL15 SL30 SL45 DR15	4	31.03
60 Minutes								
T15	2	28.66	T15	2	28.66	SL15	2	31.10

Table 6-7 Selected inputs and hidden neurons for travel time predictions on section 16-25 determined from 5-fold cross validation with training dataset.

Scenario 1 Only target sections			Scenario 2 All sections available			Scenario 3 Missing target section		
Inputs	**Hidden nodes**	**MAPE (training dataset)**	**Inputs**	**Hidden nodes**	**MAPE (training dataset)**	**Inputs**	**Hidden nodes**	**MAPE (training dataset)**
Next 15 Minutes								
T15	1	31.21	T15	1	31.21	DD15 DD30 DD45 DD60 UD15 UD30 UD45	3	51.34
30 Minutes								
T15	1	34.35	T15	1	34.35	DD15 DD30 UD15	9	70.17
45 Minutes								
T15	1	38.49	T15	1	38.49	DD15	4	55.80
60 Minutes								
T15 T30 T45 T60	5	64.56	T15 T30 T45 DD15	1	65.54	DD15	5	66.11

Table 6-8 Selected inputs and hidden neurons for travel time predictions on section 25-16 determined from 5-fold cross validation with training dataset.

Scenario 1 Only target sections			**Scenario 2 All sections available**			**Scenario 3 Missing target section**		
Inputs	**Hidden nodes**	**MAPE (training dataset)**	**Inputs**	**Hidden nodes**	**MAPE (training dataset)**	**Inputs**	**Hidden nodes**	**MAPE (training dataset)**
Next 15 Minutes								
T15 T30 T45 T60	3	33.25	T15 T30 T45 T60 UD15 UD30 SL15	3	34.86	UD15 UD30 UD45 UD60 DL30 DL45 SD60 SL15 SR15	2	35.50
30 Minutes								
T15 T30 T45 T60	1	33.36	T15 T30 T45 T60 DL15 DL30 SD60 UR60	1	32.97	UD15 UD30 UD45 UR45 UR60 DL15 DL30 DL45 SD45 SD60	3	34.71
45 Minutes								
T15 T30 T45	3	34.99	T15 T30 T45 T60 UR30 UR45 DD30 DL15 DL30 DL60 DR15 DR30 SD45 SD60	2	34.04	UD45 UL15 UR30 UR45 UR60 DD30 DD45 DD60 DL15 DL30 DL45 DL60 DR15 DR30 SD30 SD45 SD60	1	35.81
60 Minutes								
T15 T30 T45	7	32.19	T15 T30 T45 T60 UR30 DD60 DL60 DR15 DR30 SD30 SD45 SD60 SL30	6	33.66	UR30 DD60 DL15 DL45 DL60 DR15 DR30 SD30 SD45 SD60 SL30 SL60	5	35.07

6.3 TRAVEL TIME PREDICTION RESULTS

This section presents the results of the proposed technique in addressing the short-term travel time prediction problems on urban roadways. All analyses described here came from the results of travel time forecast using validating dataset conducted from the urban roadway sections in Bangkok Metropolis during March 1-7, 2016 as previously described in section 6.1.

6.3.1 Testing scenarios and baseline methods

To understand the capability and advantage of using data on neighboring sections in short-term travel time prediction, this research investigates travel time prediction from the ANN model using various input data, not only in the common situation (only target section data) but also in the case of rich data from neighboring sections and in the case of an absence of Bluetooth probe data on the target section. Therefore, the ANN models from the proposed technique were tested with three different testing scenarios as previously described in Chapter 5:

Scenario 1: Only the historical data of the target section were available for developing the ANN model, or ANN(Target).

Scenario 2: Historical data of target and all neighboring sections were obtainable, or ANN(All).

Scenario 3: Historical data from the target section were absent but the data of all neighboring sections were available, or ANN(Miss).

In addition to the above scenarios, the use of average travel time from the database (e.g. average travel time on Monday at 8:00-8:15 A.M. is calculated by averaging all travel time records obtained on Monday 8:00-8:15 A.M. from training dataset), the use of current travel time data for representing future travel time and the simple moving average method, which are commonly used in travel time prediction, were tested and compared with the proposed techniques.

Simple moving average is a mean of previous *N* data points that can be calculated by

$$SMA_t(N) = \frac{(T_t + T_{t-1} + \cdots + T_{t-N+1})}{N} \tag{6-1}$$

Where SMA is the travel time average by the moving average method, T_t is travel time (average) on the corresponding section during time period *t*.

The prediction for the future at any predicted horizons ($\hat{T}_{T+\tau}$) is the same as the latest estimated value. The prediction equation using the moving average technique is stated in Equation (6-2)

$$\hat{T}_{T+\tau} = SMA_t \qquad for\ \tau = 1, 2, \ldots \tag{6-2}$$

6.3.2 Travel time prediction results

The accuracy of the proposed method for travel time prediction can be determined by testing the models structured described in Table 6.5-6.8 and their connection weights obtained during training processes with a new dataset. Therefore, all models were tested with the validating dataset for multiple times (5 times in this study). The average MAPE of travel time prediction from the proposed and baseline methods (including the case of using travel time from the database (database)), using current travel time (Current TT), and the case of the moving average methods with *N* =2 to 4 or MA(2), MA(3), MA(4), respectively) are presented in Table 6.9.

For section 01-16 with highly fluctuated travel time behavior as described in section 6.1, the prediction model that provided best prediction results in 15, 45, and 60 minutes rolling horizons was the ANN(All) models that used historical data from both the target and neighboring sections as the model inputs, with the MAPE of 29.27%, 40.92% and 53.37%, respectively. While the model that provided best prediction results in 30 minutes rolling horizons was the ANN(Miss) model that used only historical data from neighboring sections as the model inputs, with the MAPE of 33.20%. The baseline models including; using current travel time, and the moving average from 2, 3 and 4 previous horizons to represent future travel time performed significantly worse than ANNs. Furthermore, in the case that historical data from the target section were absent, the ANN model developed by using only historical data from the neighboring sections, ANN(Miss), could provide superior prediction results than all the baseline models in all prediction horizons (even compared to the baseline models that used historical data of the target section as inputs).

Table 6-9 MAPE of proposed and baseline methods in urban travel time prediction (tested with validating dataset obtained during March 1-7, 2016).

Models	Prediction horizon			
	15 Minutes	30 Minutes	45 Minutes	60 Minutes
Section 01-16				
Database	55.64	57.47	61.66	60.85
Current TT	37.69	52.89	56.01	59.52
MA(2)	42.95	52.00	55.11	60.12
MA(3)	44.70	51.82	55.99	61.31
MA(4)	46.51	52.22	56.76	60.99
ANN (Target)	32.77	37.16	50.05	60.01
ANN (All)	29.27	35.58	40.92	53.37
ANN (Miss)	33.59	33.20	49.97	54.03
Section 16-01				
Database	39.74	39.71	40.13	41.79
Current TT	19.90	24.30	26.97	30.06
MA(2)	19.14	22.65	25.32	28.64
MA(3)	19.12	22.20	24.67	27.21
MA(4)	19.42	21.90	24.37	26.58
ANN (Target)	18.82	20.98	22.82	25.27
ANN (All)	18.82	20.98	22.82	25.27
ANN (Miss)	25.97	30.57	32.91	31.84
Section 16-25				
Database	48.01	48.03	49.43	48.98
Current TT	33.63	47.81	59.02	64.86
MA(2)	37.27	49.55	59.81	63.74
MA(3)	41.18	51.72	60.09	64.16
MA(4)	44.09	53.07	60.90	64.52
ANN (Target)	31.84	43.88	51.03	61.62
ANN (All)	31.84	43.88	51.03	59.15
ANN (Miss)	47.89	48.09	49.74	59.44
Section 25-16				
Database	22.73	23.72	23.94	24.25
Current TT	23.28	27.39	29.29	29.26
MA(2)	23.24	26.44	27.25	25.99
MA(3)	23.41	26.06	25.34	24.93
MA(4)	23.16	25.59	25.09	25.74
ANN (Target)	29.20	30.07	32.02	48.35
ANN (All)	29.01	29.76	32.20	47.64
ANN (Miss)	29.66	32.27	47.64	47.78

For section 16-01 with slightly fluctuated travel time behavior as described in section 6.1, the prediction model that provided best prediction results in 15, 30, 45, and 60 minutes rolling horizons was the ANN(Target) models that used only historical data from the target section as the model inputs, with the MAPE of 18.82%, 20.98%, 22.82% and 25.27%, respectively. The baseline models including using current travel time, and moving average from 2, 3 and 4 previous horizons performed slightly poorer than ANN(Target) and ANN(All). In the case that historical data from the target section were absent, the ANN(Miss) model that used only historical data from neighboring sections could provide tolerable prediction results with MAPE of 25.97%, 30.57%, 32.91% and 31.84% in 15, 30, 45, and 60 minutes prediction horizon, respectively.

For section 16-25 with moderately fluctuated travel time behavior as described in section 6.1, the prediction model that provided best prediction results in 15 and 30 minutes rolling horizons was the ANN(Target) models that used only historical data from the target section as the model inputs, with the MAPE of 31.84% and 43.88%, respectively. While the model that provided best prediction results in 45 and 60 minutes rolling horizons was the travel time from the database with the MAPE of 49.43% and 49.98%, respectively. The baseline models including; using current travel time, and moving average from 2, 3 and 4 previous horizons preformed slightly worse than ANN(Target) and ANN(All). In the case that historical data from the target section were absent, the ANN(Miss) could provide comparable prediction results to the baseline models (even compared to the baseline models that used historical data of the target section as inputs).

For section 25-16 with almost constant travel time behavior as described in section 6.1, the prediction model that provided best prediction results in 15, 30, and 45 minutes rolling horizons was the travel time from the database with the MAPE of 22.73%, 23.72%, and 23.94% respectively followed by MA(4) models that average the historical data from the previous 4 horizons for representing future travel times, with the MAPE of 23.16%, 25.59%, and 25.09% respectively. While the model that provided best prediction results in 60 minutes rolling horizons was the travel time from the database with the MAPE of 24.25% followed by MA(3) models that average the historical data from the previous 3 horizons for representing future travel times, with the MAPE of 24.93%. All the ANN models performed slightly worse than the baseline methods.

6.4 ANALYSIS OF MODEL PERFORMANCE IN VARIOUS SITUATIONS

This section provides the analysis of model performance in different travel time behaviors. Therefore, data captured in each day was divided into three time periods which were morning-peak (07:00-10:00), off-peak (10:00-16:00), and evening-peak period (16:00-21:00). The summaries of travel time behaviors of the 4 target sections in different periods of day are illustrated in Table 6.10. Please note that data in Table 6.10 were determined from validating dataset obtained during March 1-7, 2016.

The coefficient of variation (CV) in Table 6.10 is the ratio of the standard deviation to the mean as shown in Eq.(6-3). The higher CV, the higher dispersion level around the mean. This value allows to unbiasedly compare distributions of data in different measurement scales.

$$CV = \frac{Standard\ diviation\ (Stdev)}{Mean} \tag{6-3}$$

Table 6-10 Summary of travel time behaviors of 4 target sections in different periods of day.

Section	07:00-10:00			10:00-16:00			16:00-21:00		
	Mean TT (sec)	Stdev (sec)	CV	Mean TT (sec)	Stdev (sec)	CV	Mean TT (sec)	Stdev (sec)	CV
01-16	355.94	195.42	**0.55**	461.96	264.66	**0.57**	741.49	627.30	**0.85**
16-01	276.76	100.85	**0.36**	332.75	125.61	**0.38**	409.47	212.40	**0.52**
16-25	237.40	192.60	**0.81**	463.67	280.41	**0.60**	584.94	394.25	**0.67**
25-16	172.60	47.25	**0.27**	172.85	58.90	**0.34**	178.79	82.46	**0.46**

Small travel time fluctuation: $CV \leq 0.4$
Moderate travel time fluctuation: $0.40 < CV \leq 0.60$
High travel time fluctuation: $CV > 0.60$

It can be inspected from Table 6.10 that in section 01-16, 16-01, and 16-25 travel times in the morning-peak period are the lowest compared to those of the off-peak and evening-peak periods, indicating the relatively small congestion (or uncongested) in this period. While in the evening-peak period the congested traffic could be noticed through the highest value travel time compared to the other periods of day. In section 25-16, the small and quite constant travel time could be observed, indicating the uncongested traffic condition for the entire day on this section. The variations of travel time (or travel time fluctuation) which can be represented by CV value are different from section to section and from time to time.

For section 01-16, the overall travel time fluctuation was the 2nd highest among the 4 target sections. In the morning-peak and off-peak periods, moderate travel time fluctuations with the CV of 0.55 and 0.57 could be observed. Meanwhile, higher travel time fluctuation with CV of 0.85 occurred in the evening-peak period.

For section 16-01, the overall travel time fluctuation was the 3rd highest among the 4 target sections. In the morning-peak and off-peak periods, small travel time fluctuations with the CV of 0.36 and 0.38 could be observed. Meanwhile, moderate travel time fluctuation with CV of 0.52 occurred in the evening-peak period.

For section 16-25, the overall travel time fluctuation was the highest among 4 target sections. In the morning-peak, very high travel time fluctuation with CV of 0.81 could be observed. Meanwhile, in the off-peak and evening-peak periods, travel time fluctuated in a moderate fashion with the CV of 0.60 and 0.67.

For section 25-16, the overall travel time fluctuation was the lowest among 4 target sections. In the morning-peak and off-peak periods, small travel time fluctuations with the CV of 0.27 and 0.34 could be observed. While, moderate travel time fluctuation with CV of 0.46 occurred in the evening-peak period.

Table 6.11 provides the MAPE of predictions from proposed and baseline methods clustered by time period of day and prediction horizon. It could be noticed that the best prediction models vary from case to case. For instance, on section 01-16, ANN(All) provided the best prediction results for all cases in 15 minutes prediction horizon and for the off-peak period for 45 minutes prediction horizon. ANN(Miss) provided the best results for off-peak and evening peak periods in the 30 minutes prediction horizon, etc. The travel time from the database provided the best prediction results in the morning-peak periods for 30, 45, and 60 minutes prediction horizons. Considering only the data from the Table 6.11, it may not be possible to make a clear conclusion about the suitability of a specific model for each situation.

Table 6-11 MAPE of prediction from various models in different time periods and prediction horizons.

Models	Prediction horizon											
	15 Minutes			30 Minutes			45 Minutes			60 Minutes		
	7-10	10-16	16-21	7-10	10-16	16-21	7-10	10-16	16-21	7-10	10-16	16-21
Section 01-16												
Database	27.01	60.44	91.19	26.41	61.30	99.00	29.35	65.57	105.03	34.84	64.02	95.70
Current TT	31.98	37.32	44.58	43.21	54.52	61.41	48.42	54.06	67.24	45.17	51.97	86.81
MA(2)	34.11	43.57	52.10	42.61	51.14	64.09	45.98	47.17	77.13	44.62	46.64	97.74
MA(3)	36.50	43.21	56.21	41.66	46.03	72.07	44.79	42.37	88.77	43.17	43.95	107.62
MA(4)	36.87	42.45	63.50	39.45	43.19	80.25	42.20	41.21	96.18	39.64	42.12	112.73
ANN(All)	26.26	31.53	34.21	30.76	35.64	42.97	36.07	37.13	51.36	49.09	47.88	64.46
ANN(Target)	30.92	34.29	38.51	34.35	37.96	38.52	47.80	40.49	68.86	59.35	53.72	73.04
ANN(Miss)	26.57	34.43	40.46	28.21	33.42	38.44	35.66	39.71	44.11	49.40	49.95	61.97
Section 16-01												
Database	26.79	30.03	62.30	27.52	29.88	60.07	25.12	34.32	58.96	25.76	39.61	57.14
Current TT	17.55	20.37	20.94	21.40	24.87	25.59	22.95	25.78	30.91	25.18	28.29	35.20
MA(2)	16.24	19.94	20.19	20.62	22.50	24.15	20.77	23.73	30.04	23.39	25.80	35.17
MA(3)	16.29	19.49	20.57	19.29	21.98	24.36	20.58	22.60	29.59	23.19	24.04	33.27
MA(4)	15.73	19.76	21.49	18.58	20.94	25.13	20.48	22.11	29.39	22.51	23.21	32.92
ANN(All)	18.38	19.23	19.26	19.65	21.13	21.90	21.13	23.02	24.20	22.85	26.24	26.65
ANN(Target)	18.38	19.23	19.26	19.65	21.13	21.90	21.13	23.02	24.20	22.85	26.24	26.65
ANN(Miss)	18.87	24.23	33.04	32.78	27.84	32.60	34.17	29.20	36.85	32.29	29.26	35.01
Section 16-25												
Database	62.50	44.51	38.34	65.05	43.92	37.57	68.58	42.59	41.70	64.33	41.44	46.33
Current TT	37.12	32.32	28.10	57.01	45.69	38.47	77.03	49.17	52.02	85.45	48.41	63.98
MA(2)	43.11	37.01	29.66	59.21	46.66	41.26	81.02	46.29	55.53	83.98	44.32	68.82
MA(3)	46.39	40.64	34.53	62.78	45.94	46.68	81.69	43.76	60.56	82.63	42.07	75.34
MA(4)	51.03	40.84	39.75	67.21	43.70	51.14	80.83	42.16	66.93	81.45	39.24	82.12
ANN(All)	39.12	29.77	28.94	60.34	39.45	37.01	74.65	41.55	45.44	87.53	45.84	55.07
ANN(Target)	39.12	29.77	28.94	60.34	39.45	37.01	74.65	41.55	45.44	94.24	48.42	54.05
ANN(Miss)	71.16	42.76	36.62	64.27	43.12	42.18	63.32	45.42	45.00	88.18	50.93	48.49
Section 25-16												
Database	23.36	20.16	27.07	25.00	20.17	29.08	25.82	20.77	27.70	25.62	22.27	26.35
Current TT	18.70	23.74	27.95	20.23	30.05	31.37	25.30	28.24	35.83	26.52	27.55	35.47
MA(2)	17.43	22.85	30.80	20.55	26.06	34.11	23.65	24.78	35.78	25.43	23.09	31.65
MA(3)	19.02	21.46	31.98	20.81	24.19	35.54	23.66	22.32	32.51	25.46	22.53	28.41
MA(4)	19.30	20.28	32.70	21.68	22.68	35.22	24.16	22.06	31.39	25.54	22.91	30.85
ANN(All)	31.42	28.46	27.10	32.32	30.16	26.04	33.84	33.17	28.88	46.69	48.57	47.17
ANN(Target)	30.93	29.46	26.72	32.46	30.36	26.75	33.83	32.70	29.39	46.74	48.98	49.24
ANN(Miss)	32.03	28.88	28.19	32.63	29.81	26.76	33.87	32.57	28.85	47.16	47.93	48.27

To test the ability of the models in various situations, the relationship between MAPE of predictions in Table 6.11 and variations of travel time indicated by coefficient of variation (CV) in Table 6.10 were plotted and illustrated in Figure 6.4-6.7.

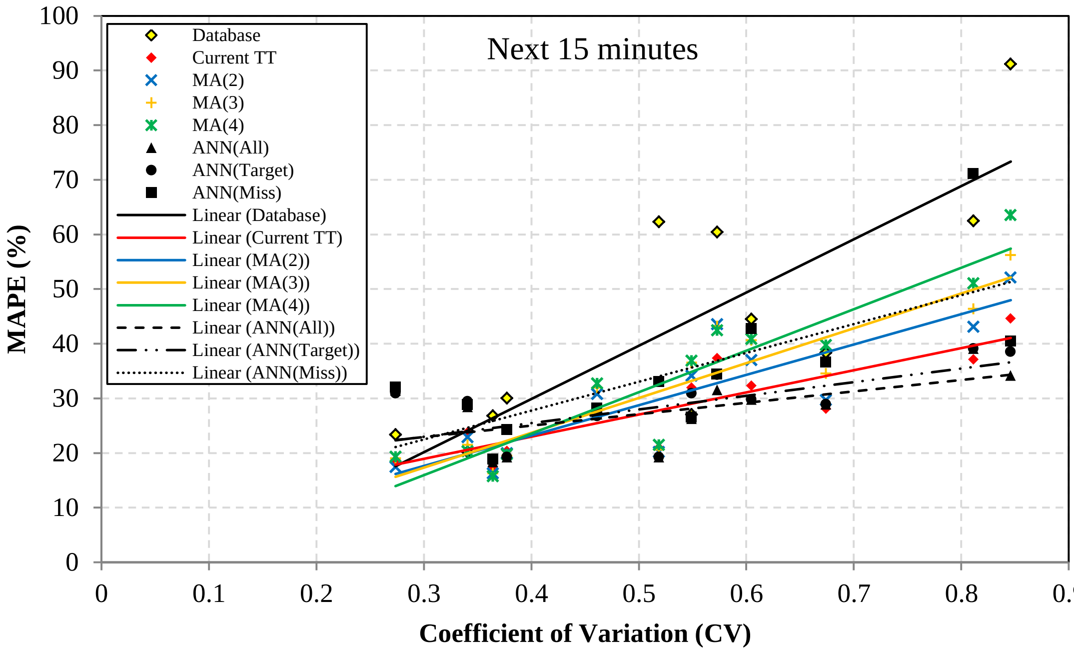


Figure 6-4 Relationship between MAPE of predictions and coefficient of variation (CV) for 15 minutes prediction.

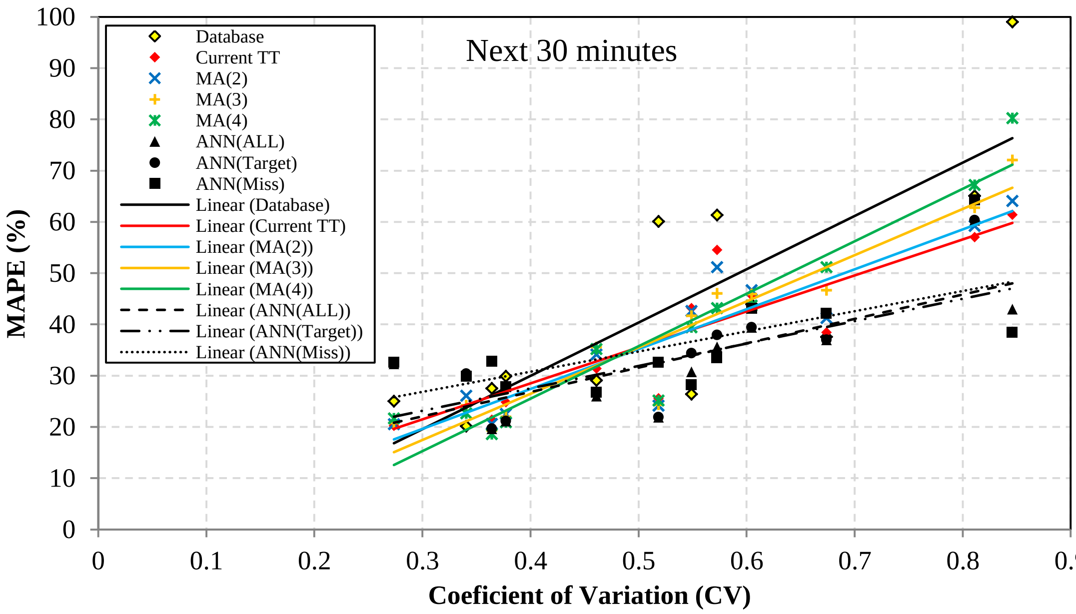


Figure 6-5 Relationship between MAPE of predictions and coefficient of variation (CV) for 30 minutes prediction.

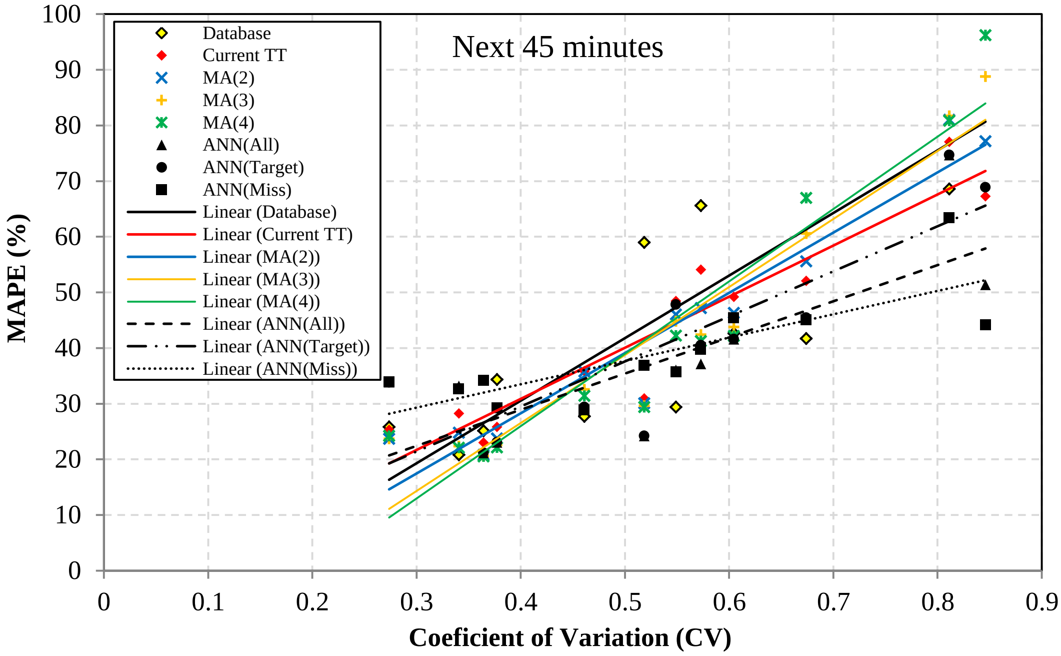


Figure 6-6 Relationship between MAPE of predictions and coefficient of variation (CV) for 45 minutes prediction.

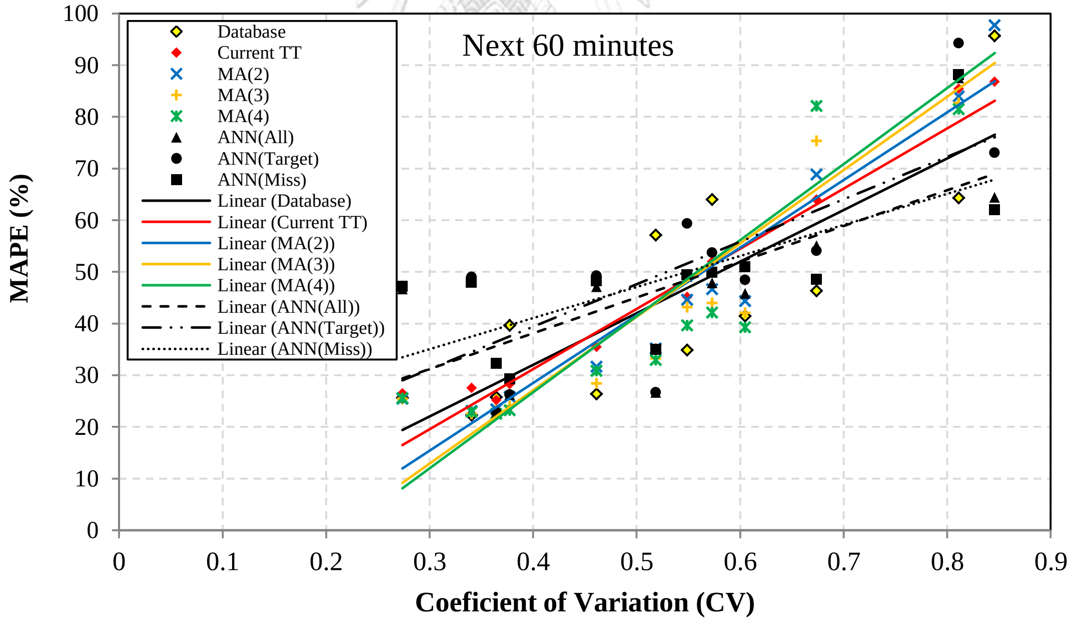


Figure 6-7 Relationship between MAPE of predictions and coefficient of variation (CV) for 60 minutes prediction.

From Figure 6.4-6.7 it could be observed that, in the small travel time fluctuation situations with CV≤0.40, the baseline models which predict travel time from the database (database), current travel time (current TT), MA(2), MA(3), and MA(4) perform slightly better than all the ANN models. The model that provides the best prediction results is the MA(4). The moving average model, which mainly considers historical data of the target section, provides better estimation when the time series of travel time data on the section is nearly constant. For moderate travel time fluctuation with 0.4<CV≤0.6, the ANNs and the baseline models yield comparable prediction accuracy. However, considering the results in detail, the ANN models provide slightly better results in the next 15, 30 and 45 minutes predictions. While the baseline models give somewhat healthier result in 60 minutes prediction. In the case that travel time is highly fluctuated (CV>0.60), the ANN models perform significantly better than the baseline models.

As could be seen from the results in this section that the ANN models have potential in application to predict travel time on the urban roadways, where travel time behaviors naturally fluctuate due to various reasons; for example, from traffic friction along road sections, roadside entry/exit, on-street parking, from pedestrian crossing, or traffic signal, etc. Four road sections show different travel time behaviors as seen from various CVs. Generally speaking, the baseline models fail to effectively forecast travel time when the fluctuation is high. Although the baseline models can perform slightly better in less fluctuated traffic conditions (roughly speaking, off-peak or less congested section), the ANN models outperform the baseline models in fluctuated traffic conditions (high CV).

One interesting point that should be addressed here is the potential of the ANN(Miss) model in travel time prediction. Unlike other models discussed in this chapter, the ANN(Miss) model does not require historical data from the target section. Therefore, in the case that historical data of the target road are missing, ANN(Miss) could be a good solution for use as a travel time prediction model with acceptable results.

6.5 SECTION TRAVEL TIME AND ROUTE TRAVEL TIME

In order to illustrate the difference between travel time prediction errors on the trip made on a single road section and the trip with a combination of multiple sections (route), the travel time prediction results using validating dataset considering only the interval whose data were available in all target sections (for the purpose of combining each section together) are presented in Table 6.12.

Table 6-12 MAPE of travel time prediction of the trip with different number of road sections.

Section (s)	Length (km)	Database	Current TT	MA(2)	MA(3)	MA(4)	ANN (All)	ANN (Target)	ANN (Miss)
15 Minutes Prediction									
01-16	1.491	70.69	22.75	27.30	26.19	26.40	15.36	25.28	30.79
16-01	1.491	54.74	14.29	14.52	13.94	14.59	11.71	11.71	23.04
16-25	0.794	30.48	16.89	19.28	18.95	21.18	21.48	27.02	56.25
25-16	0.794	24.39	38.71	34.35	37.21	30.97	33.62	33.90	36.71
01-16,16-25	2.285	25.22	12.33	15.10	16.18	19.00	12.62	20.24	22.20
25-16,16-01	2.285	31.45	17.52	12.60	12.84	13.94	17.00	16.81	21.74
25-16,16-01, 01-16,16-25	4.570	18.54	11.42	11.76	11.36	12.44	10.09	14.14	10.38
30 Minutes Prediction									
01-16	1.491	84.20	29.38	29.36	27.72	33.05	28.08	27.43	33.67
16-01	1.491	42.27	20.23	16.50	17.64	17.35	16.76	16.76	17.67
16-25	0.794	30.14	27.07	26.26	27.27	27.53	44.80	44.80	53.92
25-16	0.794	29.39	37.96	39.12	36.80	31.83	33.31	34.02	36.29
01-16,16-25	2.285	27.59	19.23	20.52	22.44	24.97	25.12	30.78	26.39
25-16,16-01	2.285	26.36	16.66	14.78	14.58	14.59	24.48	24.69	14.16
25-16,16-01, 01-16,16-25	4.570	19.58	15.01	14.42	14.67	15.33	17.80	21.25	16.78
45 Minutes Prediction									
01-16	1.491	72.91	24.40	27.12	32.11	37.56	31.32	40.57	28.25
16-01	1.491	32.14	21.64	21.51	19.84	19.82	21.42	21.42	22.20
16-25	0.794	27.09	40.69	41.42	39.74	37.48	41.56	41.56	58.15
25-16	0.794	24.87	36.77	33.94	34.34	28.46	32.86	31.88	33.24
01-16,16-25	2.285	32.05	20.04	23.61	25.92	27.20	25.61	36.48	34.08
25-16,16-01	2.285	26.05	18.47	16.63	18.35	17.97	22.57	22.39	14.71
25-16,16-01, 01-16,16-25	4.570	21.12	14.38	15.87	17.11	17.34	16.83	21.03	19.48
60 Minutes Prediction									
01-16	1.491	72.90	28.50	34.53	37.72	38.37	33.79	49.84	39.08
16-01	1.491	22.39	21.89	19.32	21.29	19.54	20.62	20.62	22.67
16-25	0.794	29.26	55.23	52.15	47.55	41.82	40.37	45.04	59.18
25-16	0.794	24.44	37.38	38.96	37.66	32.00	42.66	41.68	45.39
01-16,16-25	2.285	45.12	25.85	28.68	29.15	27.38	29.67	42.68	37.39
25-16,16-01	2.285	23.22	19.21	22.31	22.06	19.91	23.61	23.76	18.35
25-16,16-01, 01-16,16-25	4.570	24.16	15.05	15.92	15.65	13.70	13.35	22.76	19.34

It could be observed that the errors of predictions from the trip through a single road section tend to be higher than the trip through a combination of two road sections (route). Also, the prediction errors from the trip through two road sections tend to be higher than the trip through four road sections. For instance, the next 15 minutes prediction error of ANN(All) models from the trip through section 01-16 was 15.36%, and the trip through section 16-25 was 21.48%, while the prediction error of the trip that traversed both section 01-16&16-25 was 12.62% and the prediction error of the trip through 4 road sections (25-16&16-01&01-16&16-25) was only 10.09%.

The above behavior is caused by the self-offsetting or balance out of error between different road sections on each trip. Therefore, from the results, it could be concluded that the error of travel time prediction on the trip consisting of multiple road sections is often less than the prediction error of an individual section.

It should be noted that this section aims to show the effects of the number of sub-road sections for each trip on the travel time prediction accuracy. It could not be used to indicate which prediction method is more accurate because of the effect of the self-offset of error as discussed above. The analysis of performance of each method in short-term travel time prediction is illustrated in section 6.3 and 6.4

6.6 CONCLUDING REMARKS

This chapter provided the results and analysis of travel time prediction on urban roadways, starting with the study sections and their travel time behaviors, then the selection of inputs and hidden neurons for ANN models, followed by travel time prediction results, and finally the analysis on the performance of the model in various situations.

In this study, four target sections were selected as the target sections for testing the travel time prediction models from proposed and baseline techniques. The target sections had different travel time behaviors. For instance, some sections had highly fluctuated travel time, and some sections had almost constant travel time for the entire day. The analyses on the correlation between future travel times of target sections and historical travel times of target and neighboring sections also indicated the differences in behaviors among the target sections. On all 4 target sections, the parameter that was most correlated to their future travel time was their historical travel times. However, the second most correlated parameter to future travel time varied, from historical travel time of down-direct, share-left, and up-direct sections, depending on the test sections and prediction horizons.

In selection of inputs and hidden neurons for ANN models, the preliminary analyses pointed out that the more complex models with a greater number of inputs and hidden neurons did not always provide more accurate results. In fact, it could lead to worse prediction results due to overfitting problems. Therefore, the 5-fold cross validations technique was employed for selecting appropriate inputs and hidden neurons using training dataset (obtained during February 4-29, 2016). The results prediction models from the analyses differed from section to section, from prediction horizon to prediction horizon, and from scenario to scenario (three scenarios: only the historical data of the target section were available for developing the ANN model, historical data of the target and all neighboring sections were obtainable, historical data from target section were absent but the data of all neighboring sections were available).

The result of short-term travel time prediction on urban roadways was tested by the new dataset (validating dataset) conducted during March 1-7, 2016 with the model structures obtained from training dataset. From 3 out of 4 target sections, the ANN models performed better than the baseline models (including; using current travel time, MA(2), MA(3) and (MA4)) in short-term travel time prediction. However, there was 1 target section that the baseline models outperformed ANNs. Therefore, the in-depth analysis was performed in order to find out the performance of each model in different situations.

The in-depth analysis indicated that in the small travel time fluctuation regions (CV $\leq$ 0.4), the baseline models provided slightly better prediction results than ANN models. The model that provided the best prediction result in this region was MA(4). This was because in the moving average model, in which historical data were mainly considered, provided better estimation when a time series was nearly constant. For moderate travel time fluctuation regions with 0.4<CV≤0.6, the ANNs and baseline models yielded comparable results (or ANNs were slightly better). In the case that travel time highly fluctuated (0.60<CV), the ANN models performed significantly better than the baseline models.

Unlike other models, the ANN(Miss) model did not require historical data from the target section. Therefore, in the case that historical data of the target road are missing, the ANN(Miss) could be a good solution for use as a travel time prediction model with acceptable results.

Furthermore, the analysis on the effects of the number of sub-road sections on each trip (route) pointed out that the error of travel time prediction on the trip consisting of multiple road sections is often less than the prediction error of individual section due to the self-offsetting or balance out of error between different road sections on each trip.

7. CONCLUSIONS AND FUTURE RESEARCH

As the core of advanced traveler information system (ATIS) and advanced traffic management system (ATMS), travel time is increasingly on attention of researchers and professional in the area of transportation. Travel time could be considered as the simplest indicator for representing traffic conditions. It is also easy to understand and well accepted from all stakeholders. However, the development of accurate travel time information is not an easy task, particularly on urban roadways with the complicated behavior and disturbances from surroundings.

The main objective of this dissertation is to develop the methodology for travel time estimation and short-term travel time prediction on urban roadway networks. At first, the research investigated the applicability of two data collection methods for travel time estimation -- GPS probe-based and Bluetooth-based. These two data collection methods have high potentials for cost-effective and rich data gathering for further travel time estimation and prediction. Then, the methodology for short-term travel time prediction using ANNs in relation to travel time on neighboring sections was proposed and verified with the real Bluetooth probe data captured from the BMS system installed on urban roadways in Bangkok CBD.

This dissertation will conclude with a summary of the primary research findings and a list of recommended future works to extend the science and knowledge on travel time estimation and prediction topics.

7.1 CONCLUSIONS

In this dissertation, we have proposed techniques for developing travel time information from GPS probe data and Bluetooth probe data. Moreover, the travel time prediction models using ANNs with information from target and neighboring sections were also proposed and compared with traditional techniques. The contributions of this dissertation are listed as follows:

Travel time estimation from high-resolution GPS probe data

We have proposed a modified algorithm for calculating travel time and travel speed on urban roadways from probe data called the "Running Speed and Stopped Delay (RSSD) method". This technique was modified from the average speed method using the advantage of movable sensors in which the location and speed of the tracked vehicle could be automatically detected. Consequently, the running speed and stopped delay time of a probe vehicle during its trip on any road segment could be extracted from recorded data. Moreover, for illustrating the applicability range of the RSSD technique, we also provided some discussions on the limits of error in speed associated with each GPS device to maintain the advantage of the proposed technique in travel speed estimation.

Results from the analysis indicated the advantages of RSSD over the average speed approach in addressing travel time and speed estimation which could be demonstrated by the higher allowable limiting error in speed associated with each GPS device to maintain the same accuracy level with the benchmark method and also pointed out the higher accuracy level when the RSSD approach was employed as the travel time and speed estimation technique, particularly in the highly congested traffic conditions.

Travel time estimation from low-resolution GPS probe data

For the real world application, we have proposed the new analytical algorithm for allocating travel time into individual road sections by integrating instantaneous speed together with tracked locations and time stamp. From traffic state information represented by instantaneous speed data, the proposed model applied the speed-time-distance relationship for model tuning and then allocated travel time into each section. The performance of the proposed model in travel time allocation was tested and compared with the widely used technique at both complete section and local levels using high resolution (ground truth) field data.

It was found that the proposed technique provided a significant improvement in travel time allocation at both complete section and intersection levels compared to the benchmark technique. Moreover, from the in-depth analysis at the local level, the stopping (traffic) behavior within the intersection region affected the level of accuracy on both models. Accuracy from both techniques was lower at the intersections with stopping behavior due to its complicated movement behavior. Still, the proposed technique outperformed the baseline approach in both intersections with low and high stopped delays. The average speed of vehicles within the intersection region, which represented the local traffic state, also influenced the model accuracy. Intersections with the higher average speed could achieve the higher accuracy level of travel time estimation by both methods. Furthermore, an analysis on the effects of speed fluctuation at the local level pointed out the outstanding performance of the proposed model in addressing the complicated movement behavior compared to the baseline approach.

Travel time estimation from Bluetooth probe data

We have presented the development of the traffic data collection system from the Bluetooth MAC Scanner (BMS) system starting from the basic components of BMS, the possible installation locations for collecting traffic data on urban roadways, details of captured data, and also suggested a framework for constructing travel time information from Bluetooth probe data.

Results from the field study with 40 BMSs installed on urban roadways in Bangkok CBD indicated the potential of BMS in traffic data collection by showing the sufficiency of raw data for constructing travel time information. The analysis on data spreading along the day pointed out that during 00:00-05:00 the amount of captured data was considerably lower than the data during daytime that could create the missing data problem in some road sections. However, the amount of captured data was higher and approximately sufficient for developing reliable traffic information during daytime which was a period that highly requires traffic information for disseminating to road users.

Form the suggested framework, data filtering by Hampel identifier could successfully remove outliers that greatly deviated from the group median resulting in the more reasonable travel time estimation results and proved consistency with real traffic behavior. The in-depth analysis also pointed out that only a small amount of data were considered as outliers and were taken out in the filtering process, but this could significantly improve the estimation results.

Travel time prediction from Bluetooth-probe data

We have proposed the travel time prediction model using ANNs with the information from both target section and neighboring sections as the candidates for model inputs.

In the model development, the multilayer feedforward neural network model with one hidden layer was selected as the main structure for the travel time prediction model. The candidate inputs for the travel time prediction model were historical travel times of the target section and its neighboring sections including; upstream, downstream and signal sharing sections. The input selection for the prediction model was based on the order of the correlation coefficients between desired output and each input parameter. The appropriate number of hidden neurons for each model was tested by the cross validation technique from the number of hidden neurons ranging from 1 to 50.

The study corridor was on urban roadways in Bangkok Metropolitan comprising 4 target sections. From the 33 days of Bluetooth probe dataset collected during 06:00 to 21:00, the full dataset was then divided into 2 groups: (1) training dataset had 26 days of data for model training and learning process, and (2) validating dataset had 7 days of data for verifying the model accuracy.

From 4 target sections, each target section had different travel time behaviors from highly fluctuated to almost constant travel time for the entire day. The analysis on the correlation between future travel times of target sections and historical travel times of target and neighboring sections also indicated the difference in behaviors among target sections. In all 4 target section, the parameter that most correlated to their (target sections) future travel time was their (target sections) historical travel times. However, the second most correlated ones varied.

In the selection of inputs and hidden neurons for the ANN model, the preliminary analyses pointed out that the more complex models with a greater number of inputs and hidden neurons did not always provide more accurate results. In fact, it could lead to worse prediction results due to overfitting problems. Therefore, the 5-fold cross validations technique was employed for selecting appropriate inputs and hidden neurons using training dataset. The results prediction models from the analyses differed from section to section, from prediction horizon to prediction horizon, and from scenario to scenario (three scenarios: only the historical data of target section were available for developing the ANN model, historical data of the target and all neighboring sections were obtainable, historical data from the target section were absent but the data of all neighboring sections were available).

The result of short-term travel time prediction was tested by the new dataset (validating dataset) with the model structures obtained from the training dataset. From 3 out of 4 target sections, the ANN models performed better than the baseline models (including using travel time from database, current travel time, MA(2), MA(3) and (MA4)) in short-term travel time prediction. However, there was 1 target section that the baseline models outperformed ANNs. Therefore, the in-depth analysis was performed in order to find out the performance of each model in different situations.

The in-depth analysis indicated that in the small travel time fluctuation regions ($CV \leq 0.4$), the baseline models provided slightly better prediction results than the ANN models. The model that provided the best prediction result in this region was MA(4). This was because, in the moving average model in which historical data were mainly considered, the model provided better estimation when a time series was nearly constant. For moderate travel time fluctuation regions with $0.4<CV\leq0.6$, the ANNs and the baseline models yielded comparable results (or ANNs were slightly better). In

the case that travel time highly fluctuated (0.60<CV), the ANN models performed significantly better than the baseline models.

Unlike other models, the ANN(Miss) model did not require historical data from the target section. Therefore, in the case that historical data of the target road were missing, ANN(Miss) could be a good solution for use as a travel time prediction model with acceptable results.

Furthermore, the analysis on the effects of number of sub-road sections on each trip (route) pointed out that the error of travel time prediction on the trip consisting of multiple road sections is often less than the prediction error of individual section due to the self-offsetting or balance out of error between different road sections on each trip.

7.2 FUTURE RESEARCH

Based on the findings and limitation of this work, the following topics are recommended for future research. These topics improve and complement the study in this dissertation:

In this dissertation, GPS probe and Bluetooth probe data were used to perform travel time estimation separately. A possible extension to our work is the combining of data coming from various sources by data fusion techniques, not only the data mentioned in this work but also from more sources such as RFID tags, video cameras, and inductive loop detectors, etc. A system with more data sources is expected to deliver more accurate and robust estimated travel time than a system with one individual set of data.

Missing data is one of the main limitations in developing a robust travel time prediction model. In this study, we did not address the issue of missing data problem. However, during the preliminary analysis, the missing data occurred on every BMS station from several reasons, such as running out of electricity for the Bluetooth scanner, obstacles from the environment or no Bluetooth devices entered to the communication zone. Therefore, the missing data issue should be considered in the future research in order to develop and provide sufficient candidate inputs for travel time prediction models.

Based on travel time prediction results, none of the models yielded the best prediction outcomes in all traffic conditions. Each model provided decent results in some traffic conditions. Since traffic conditions change, the accuracy levels change and there were other suitable prediction models. Therefore, the use of hybrid structures of NN for tackling traffic prediction problems is one of the interesting topics that should be further concentrated on.

Once the long-term historical travel time is available, the future study should address the long term travel time prediction problem that is necessary for traffic operators in operating an advanced traffic management system, and for logistic business in long-term scheduling, etc. The environmental and seasonal effects such as effect of raining that could disturb the travel time behaviors can also be carried out.

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APPENDIX

VITA

Porntep Puangprakhon was born on April 9, 1978 in Burirum province, Northeastern territory of Thailand. He finished his undergraduate study in Civil Engineering from Suranaree University of Technology, Nakornratchasima, Thailand in 1999.

In 2000, he continued his graduate study at Mahanakorn University of Technology and received Master degree in Civil Engineering majoring in Structural Engineering in 2003. After graduation, he worked as a Lecturer in Civil Engineering Department at Mahanakorn University of Technology, Thailand.

In 2005, he continued his second graduate degree at Faculty of Business Administration, Ramkhamheang University and received Master degree in Business Administration majoring in General Management in 2007.

In 2010, he received scholarship from Mahanakorn University of Technology to study in Doctor of Philosophy program in Civil Engineering majoring in Transportation Engineering, Chulalongkorn Unversity. During his PhD study, he received ERASMUS mundus scholarship to pursue his research in the Institute for Transport Studies (ITS), the University of Leeds, UK. After graduation from Chulalongkorn University, he continued his working at Mahanakorn University of Technology.