ABSTRACT

YI, TING. Travel Time Estimation from Fixed Point Detector Data. (Under the direction of Dr. Billy M. Williams).

Travel time, as a fundamental measurement for Intelligent Transportation Systems, is becoming increasingly important. Due to the wide deployment of the fixed point detectors on freeways, if travel time can be accurately estimated from point detector data, the indirect estimation method is cost-effective and widely applicable. This dissertation presents a systematic method for accurately estimating the travel time of different freeway links under various traffic conditions using fixed-point detector data.

The proposed estimation system is based on a thorough analysis and comparison of the three categories of travel time estimation methods. The applications and limitations of each model are analyzed in terms of theory, equation derivation and possible modifications. Through a simulation study of various freeway links and traffic conditions, the various models have been compared according to performance measurements. The proposed systematic method is tested using both simulation data and real traffic data. A comparison of the estimated results and measurement errors shows the accuracy of the proposed systematic method for estimating the travel times of freeway links under various traffic conditions.
Travel Time Estimation from Fixed Point Detector Data

by
Ting Yi

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APPROVED BY:

________________________________  ______________________________
Dr. Billy M. Williams                              Dr. Nagui M. Rouphail
Committee Chair

________________________________  ______________________________
Dr. Joseph E. Hummer                  Dr. Peter Bloomfield
DEDICATION

Dedicated to my family and friends
BIOGRAPHY

Ting Yi was born on June 1st 1978 in the city of Linxiang, China. She obtained her Bachelor of Science degree in Civil Engineering and Master of Science degree in Transportation Engineering from Tongji University, Shanghai, P.R.China in 2001 and in 2004. She started her Ph.D at NC State University in August 2004 and is working with Dr. Billy Williams in the area of travel time estimation. She wishes to pursue a career in traffic engineering and transportation planning after graduation.
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CHAPTER I INTRODUCTION

1.1 Background

With the dramatic growth of urban traffic congestion and the accompanying growth in the need for accurate traffic information, ITS (Intelligent Transportation System), which involves with the application of advanced electrical engineering technologies and methods, has taken on an important role in managing traffic flow and providing real-time traffic information. Travel time, as a fundamental measurement, is a basic input for Intelligent Transportation Systems. Travel time can provide information for travel routing, transportation scheduling and incident detection (Petty et al. 1998). Defined as a user service in the systems architecture of all members of the World Congress on Intelligent Transportation Systems (ITS), route guidance applies increasingly robust methods to evaluate and compare route alternatives by using travel time as the primary evaluation metric. In addition, accurate travel time estimation and prediction can supply valuable information for scheduling. Also, travel time measurements and/or estimates can provide information about congestion, which could possibly be employed to detect incidents. Link-based travel time is important for system performance evaluation and system improvements planning. Section travel time over a short distance is a basis of the long link travel time. Given the travel times of short segments, the total link travel time can be achieved according to some algorithms (Li et al 2006, Petty et al 1998, Zhang et al 1999). The more accurate of information over short distance, the more reliable of the calculated travel time of long freeway links. Therefore, accurate travel time,
especially section travel time over short distance, is critical to the development of advanced transportation information systems.

### 1.2 Motivation

This research is undertaken to develop an on-line strategy that is based on previous research and that can provide accurate travel time information.

Various methods have been developed over the past decades to acquire travel time data. Many methods sample travel time by using test vehicles, license plate matching, electronic distance measuring instruments, video imaging and probe vehicles such as Automatic Vehicle Identification (AVI) and Automatic Vehicle Location (AVL). However, these methods are not widely deployed for on-line systems due to costs and/or privacy issues (Turner 1996, Vanajakshi 2004).

Currently, the predominant detection technology used on freeways employs fixed point detectors using the inductive loop detector (ILD). Fixed point detection records continuous traffic condition data for the entire traffic stream. There are two kinds of ILD deployment systems, a single loop detector and a dual loop detector. Single loop detectors can provide traffic flow and occupancy data but cannot directly measure vehicle speed or travel time. Dual loop detectors can provide spot speed measurements in addition to traffic flow and occupancy data but likewise cannot provide direct travel time measurements. The typical distance between the consecutive ILDs are 0.5km to 2km. In order to retrieve link travel time information, methods need to be developed to estimate the short typical segments travel time.
If a method can accurately estimate link travel time between the from point measurements taken to obtain traffic flow, occupancy or spot speed data, such a method will be a cost-effective and widely applicable travel time estimation tool (Vanajakshi et al. 2008). Therefore, research into link travel time estimation using fixed point detector data is well-motivated.

1.3 Problem Statement

1.3.1 Section Travel Time Definition

Section travel time is defined as a mean travel time within the closed area and the defined time interval (Chu et al. 2005). As shown in Figure 1.1, the vehicle trajectories are outlined in time \( t \) and \( t_{n+1} \) and space (upstream \( x_u \) and downstream \( x_d \)). The space-mean speed for vehicles within the space and time interval is equal to the total travel distance divided by the total travel time of all the vehicles (Gerlough and Huber 1975). An unbiased estimate of the space-mean speed is

\[
\bar{u}_s = \frac{\sum_{n=1}^{N} \{\min(x_{n+1}^u, x_d) - \max(x_t^u, x_u)\}}{\sum_{n=1}^{N} \{\min(t+1, t_d^u) - \max(t, t_u^u)\}},
\]

Where

\[ N = \text{number of vehicles traveling through the section during the time interval;} \]

\[ x_t^n = \text{position of vehicle n at time } t; \]
\(x_{n+1}^t = \) position of vehicle \(n\) at time \(t + 1\);

\(x_u = \) position of the upstream boundary;

\(x_d = \) position of the downstream boundary;

\(t_u^n = \) time when vehicle \(n\) passes the upstream boundary; and

\(t_d^n = \) time when vehicle \(n\) passes the downstream boundary.

The average section travel time \((tt_s)\) can then be estimated from the unbiased estimate of the space-mean speed as

\[
\frac{\sum_{n=1}^{N} (t_d^n - t_u^n)}{N},
\]

(1.3)

Although the average section travel time can be considered as the true mean travel time of the temporal and spatial section, it cannot be obtained in the field study with all the vehicle trajectories because of the detector’s limitation. Actually, if the travel time of each vehicle within a section area can be measured, the travel time of the freeway link can be calculated by averaging the travel time of the vehicle passing the upstream boundary or arriving at the downstream boundary within the time interval \((t, t + I)\), as follows:
Where

\[ N = \text{number of all vehicles passing the upstream boundary or arriving at the downstream boundary during time } (t, t + 1); \]

\[ t^u_n = \text{time when vehicle } n \text{ passes the upstream boundary; and} \]

\[ t^d_n = \text{time when vehicle } n \text{ passes the downstream boundary.} \]

**Figure 1.1** A temporal and spatial illustration of section travel time (source: Chu et al. 2005, Figure 1).

### 1.3.2 Problem Definition of Travel Time Estimation from Fixed Point Detector Data

The application of the ILD, which is the most widely used detection method, to a typical freeway section is demonstrated in Figure 1.2. When vehicles enter the ILD detection zones at upstream \( x_d \) or downstream \( x_u \), the sensors are activated and remain so until the vehicles
leave the detection zone. Meanwhile, the detectors record each vehicle and its occupancy time. At each time interval \((t, t + 1)\), a set of traffic condition data is aggregated to obtain traffic flow parameters, such as flow, occupancy and speed, if a dual-loop detector is used.

\[
\{q_u(t), q_d(t), O_u(t), O_d(t), u_u(t), u_d(t), t = 1, 2, ..., t, t + 1\}
\]

the average travel time for the time interval \(\{t, t, t + 1\}\) can be estimated from the available traffic condition data.

Although each lane in the freeway link is equipped with a separate detector and the traffic data by lane are accessible, this study focuses on estimating travel time at a station, which is more practical and meaningful in real situations than travel time data for each lane. As seen in Figure 1.2, for example, the estimated travel time is the average travel time of all the vehicles travelling in the three lanes between the upstream and downstream station per time.
Previous research has provided various approaches to estimating travel time using ILD data; these approaches generally can be divided into three major categories. The most simple and fundamental method uses the spot speed taken from the dual-loop detector or other point detectors, or the relationships among speed, volume and occupancy from the single-loop detector (Athol 1965, Hall and Persaud 1989, Jacobson et al. 1990, Sisiopiku et al. 1993, Ferrier 1999, Lindveld et al. 2000, Vanajakshi 2004) to estimate the travel time. A second technique is based on the characteristics of the stochastic vehicle counting process and the principle of conservation of vehicles. Taking into account these assumptions, a cumulative flow plot can be used to calculate the total travel delay and then to estimate the average travel time (Nam and Drew 1998, Vanajakshi 2004, Vanajakshi et al. 2008). The third method considers the stochastic nature of the traffic flow and uses statistic methods (the cross-correlation method or probabilistic regression method) to estimate the average travel time (Dailey 1993, Petty 1998, Guo and Jin 2006).

The aforementioned travel time estimation algorithms can be described using three important specifications: estimation variables, time scale, and adaptability.

**Estimation variables**

An estimation algorithm can be univariate or multivariate (Guo 2005). Univariate processing requires only one traffic variable at a single station, such as spot speed at the upstream or downstream boundary. This method assumes a constant speed throughout the link;
nevertheless, this assumption is not reasonable under most traffic conditions, especially congestion. Therefore, univariate processing does not satisfy accuracy requirements and is ignored in this study. Compared to univariate processing, multivariate processing uses more traffic data and variables from the upstream and downstream detectors. Although the relationship between travel time and other traffic variables is complex, the multivariate processing seems to be the only method found in almost all the previous work that is used to estimate travel time using fixed point detector data.

**Time scale**

An estimation algorithm can be either microscopic or macroscopic according to the time scale of the provided traffic condition data. In general, the time scales used in microscopic processing are 1 second, 20 seconds, 30 seconds, or 1 minute. Microscopic processing is necessary for time-critical applications, such as incident detection (Guo 2005) or for independent variables in some estimation methods, such as the cross-correlation method or regression method (Guo and Jin 2006, Petty et al. 1998). The time scales for macroscopic processing can be 2 minutes, 5 minutes, 10 minutes or 15 minutes, as presented in the literature. Macroscopic processing relies on the aggregated traffic condition data.

For the travel time estimation, the aggregation time scale is related to the traffic state propagation and the length of the freeway link. Figure 1.3 describes a hypothetical freeway section with upstream $x_d$ and downstream $x_u$ boundaries at a distance of 0.5 mile. The traffic is dynamic, and the state on the freeway section cannot be assumed stationary under most
field traffic conditions. As shown in Figure 1.3 for the macroscopic processing, with the decrease of the time interval, the stability of the traffic state increase, the difference of the travel time between vehicles in the time interval decrease, and thus the accuracy of the estimation algorithm increase. However, for microscopic processing, the time intervals are too small and the number of vehicles employed is either limited or there are no vehicles passing the stations, so, the travel time estimation may be incorrect or meaningless. It can be concluded that the estimation accuracy is relevant to the time interval. In most previous studies, the time scales used for travel time estimation are 2 minutes, 5 minutes or 10 minutes.

![Figure 1.3: Traffic state propagation at different time intervals.](image)

**Adaptability**

Although traffic condition streams that arise from naturally dynamic traffic are dynamic, the freeway traffic conditions are always described according to three states: free-flow, transition
and congestion. The way that the estimation algorithm responds to the incoming traffic data and possibly to the changing states determines whether the estimation method is adaptive or non-adaptive. In adaptive processing, the independent variable is updated with the incoming traffic data, and the traffic condition states might change; accordingly, a model in the method can be utilized to adapt to the new traffic condition. Non-adaptive processing utilizes only the historical data and the same model; therefore, it cannot accommodate the newly updated traffic stream, and the estimation of the average travel time per time interval deviates too much from the true value and is, thus, not reliable (Guo 2005). Therefore, to improve accuracy, the estimation algorithm should use the adaptive process. The average travel time can be calculated from the most recent traffic data and an appropriate adaptive model, and, hence, the estimation accuracy is more satisfactory.

In previous studies (Petty 1998, Ferrier 1999, Lindveld et al. 2000, Vanajakshi 2004, Guo and Jin 2006), although the traffic data were updated during the time intervals, the traffic condition states could not be determined, so the model in the methods was not adjusted to adapt to the changed state. For example, speed extrapolation methods are not suitable for transition and congestion conditions because the model assumptions of the constant or linearly changing speeds are violated. The cross-correlation method does not work well under conditions with large traffic volumes or congestion due to the lack of correlation. The dynamic traffic flow methods do not work well under free-flow conditions because of the smoothing of the cumulative flow curve. Under these circumstances, none of the previous methods are totally adaptive.
1.3.3 Ideal Travel Time Estimation Methods

In the estimation framework, although there are different evaluation criteria for the different estimation algorithms, the ideal estimation methods based on fixed point detector data should include the following common characteristics: accuracy, efficiency and adaptability.

Accuracy

Accuracy is the degree to which a measurement, or an estimate based on measurements, represents the true value of the attribute that is being measured. In this study, accuracy of an estimation algorithm means that: the error between the estimated and true value is within the acceptable range; this degree of accuracy specifies the requirement; and the estimate is completely credible. In fact, accuracy serves as the basic essential requirement for any estimation algorithm. Without reasonable and adequate accuracy, the estimation algorithm is not sufficiently useful, and then cannot be considered as an ideal method.

Efficiency

The overall efficiency of an estimation algorithm includes both implementation efficiency and computation efficiency. Implementation efficiency indicates that an estimation system is easily implemented across various stations and that the method is appropriate for various freeway links comprised of different lengths and lanes. In other words, the estimation algorithm should be a plug and play method. Computation efficiency means that the models, or even the framework in the estimation system, can be coded and then the method can be
performed in a recursive form with a fast response.

Adaptability

Traffic is dynamic and not stationary; thus, traffic condition states may change with different time intervals. An estimation algorithm needs to adapt to the incoming data stream and different traffic conditions, such as free-flow, transition or congestion. Therefore, the adaptability of the ideal estimation system adopts two strategies: the update of the system structure indicated by the system parameters and/or the historical databases, and the ability to change estimation models based on the change in traffic condition states.

1.4 Objective and Scope

The main goal of this study is to develop a systematic method for accurately estimating travel time under different and changing traffic conditions for various freeway links. The scope and specifications of the proposed algorithm are described below.

Application in freeway links

This research is focused mainly on the freeway links between upstream and downstream detectors without an on or off ramp. To verify that this estimation strategy can be applied to various freeway links, the application of the method will be tested using simulated and real traffic data from various freeway links comprised of different lengths (264-meter, 500-meter, 647 meter, 750-meter and 1000-meter) and different lanes (1 lane, 2 lanes, 3 lanes, 5 lanes and 6 lanes).
Multivariate traffic condition data

In the proposed strategy, the dependent variable is the average travel time of the vehicles travelling through the freeway link. The independent variables used to estimate the target values are traffic condition data from both the upstream and downstream detectors, such as flow rate \((q_u, q_d)\), occupancy \((O_u, O_d)\), or spot speed \((u_u, u_d)\). In the processing, multivariate traffic variables and traffic data are applied, and the relationship between travel time and other traffic variables are studied.

Macroscopic time scale

The proposed algorithm is a systematic method in which various models are analyzed or developed, and then the appropriate models are synthesized. The time scales in the models are all macroscopic (2 minutes or more), and the estimation accuracy is relevant to the time interval. Therefore, the time scales used in the study should be macroscopic. The typical time scales of 2 minutes, 5 minutes and 10 minutes are compared to verify the best time scale for the proposed system method.

Adaptability

The proposed algorithm incorporates an updated system structure, which is indicated by the system parameters, and the ability to change estimation models based on varying traffic conditions. In other words, in the estimation system, the variables are updated using incoming traffic data, the traffic condition states are determined, and the appropriate model
for a given scenario is selected. Thus, the proposed algorithm is adaptive and can be used to estimate travel time at all time intervals and under various traffic conditions.

**Recursive processing structure**

In the study, the models of the estimation system can be coded using the analysis techniques, SAS software version 9.0 and MATLAB R2006a. Then, in the proposed method, the process is in a recursive form, and the computational burden is greatly reduced. Thus, the response is fast and the computation is efficient.

Above all, the research is intended to establish an on-line multivariate travel time estimation system. The algorithm aims to work at the macroscopic level (2 minutes, 5 minutes or 10 minutes) and is supposed to provide adaptability for various traffic conditions.

**1.5 Research Methodology**

In order to propose the aforementioned systematic travel time estimation method, first a comprehensive literature review of travel time is conducted. Specifically, the literature review examines research that focuses on the three categories of travel time estimation methods that use fixed point detector data. The results of such research are qualitatively analyzed according to each model’s theory in order to capture the limitations of each approach. The findings of this literature review will provide for the possibility of future modification and improvement in the proposed method.

Second, the simulation design and data are used to compare all the models, which include the
modified model. Various freeway links with three typical lengths (500-meter, 750-meter and 1000-meter) and lanes (1 lane, 2 lane and 3 lane) are designed, and varying traffic conditions (free-flow, transition and congestion) are simulated by changing the flow rate parameters. Through this simulation, all the traffic data, including flow, occupancy, speed and even the simulated true travel time per time interval, can be obtained. This study utilizes all the models to calculate the average travel time at 2-, 5- and 10-minute time intervals. The estimated travel time is compared with the simulated true value, and the performance measures (MAE and MAPE) are used to check the validity of the results. Therefore, the accuracy and application of all the models under varying traffic conditions and time intervals are checked. Also, by analyzing the relationships between traffic condition states and data, the appropriate parameters can be selected to determine the traffic conditions.

After the literature review and the simulation study, this dissertation proposes a systematic method that can be used in freeway links under various traffic conditions, and can also provide a more accurate estimation of the travel time per time interval. Further, the models of the framework are coded using SAS and Matlab.

For the validation of the proposed models, this systematic method is tested using both the same simulation data and the real field dataset. The estimated travel time is compared to the simulated true travel time, and the results are utilized to verify the accuracy of the proposed systematic method for travel time estimation of different freeway links under various traffic conditions.
The field data are NGSIM data that use the vehicle trajectories. After aggregation and calculation, the traffic data, including true travel time per time interval, are extracted from the original data. Also, the traffic conditions are determined according to the traffic data analysis. Under the different traffic flow conditions, the particular model in the proposed method is used to estimate the link travel time. The estimated results are compared to the true values to further validate the proposed systematic method.

1.6 Dissertation Organization

This chapter serves as an introduction to briefly outline the concepts of travel time and travel time estimation methods, as well as the goals and the contributions of this study.

Chapter 2 is a literature review of the previous research regarding travel time measurement or estimation method. The methodological highlights and the application for each method are outlined, noting the positive and negative ramifications of each. A comparison is summarized.

Chapter 3 first analyzes in detail the theory and assumption for each model in the three categories estimation methods. Then a simulation study is designed to propose the methodology for developing an on-line estimation system that includes data collection and aggregation, travel time estimations for each model, and a comparison of the results.

Chapter 4 describes the methodologies of the proposed systematic method for travel time estimation in freeway links under various traffic conditions. Then, the method is tested again using the same simulation data to estimate travel time and performance. The accuracy of the
proposed systematic method are verified by the performance measurements.

Chapter 5 first provides a description of the real traffic condition data utilized in this work for algorithm testing. The traffic condition states are determined by the field data analysis. Then, the specific models in the systematic method are utilized to estimate the travel time. Finally, the estimated results are compared to the true values to validate the systematic method.

Chapter 6 summarizes the research effort and presents the conclusions. Recommendations for future work are also presented in this chapter.
CHAPTER 2 LITERATURE REVIEW

In this Chapter 2, a literature review of the methods used to obtain freeway travel time data is presented to reveal the proposed method’s connections to and improvement over previous work. First, a summary of the classification of the various methods is presented. Then, the methodological highlights and applications of these methods are discussed. Finally, a comparison table summarizes all the methods reviewed.

2.1 Classification of Methods for Obtaining Travel Time Data

As a key element in transportation engineering, travel time data for freeway links can be obtained by direct measurement or by estimation using fixed-point detectors. Direct measurement methods are generally straightforward and provide good quality travel time data for most traffic conditions, but they also are costly due to the large amount of data that must be collected and the requirement of sensors or other necessary equipment. Estimation methods are economical for collecting sufficient data, but they are sometimes not as accurate as the direct measurement methods.

2.1.1 Direct Measurement Methods

Several data collection techniques are currently available to measure travel times directly. These collection techniques can be grouped into three general categories: test vehicle techniques, license plate matching techniques, and Intelligent Transportation System (ITS) probe vehicle techniques (FHWA 1998).
Test vehicle techniques have been used to measure travel time since the late 1920s. As the most common travel time collection method, these techniques (often referred to as *floating car* techniques) measure travel time by having an active, driven vehicle in the traffic stream as an *average car, floating car or maximum car*. Depending on the instruments used, the travel time measurements can be taken in three different ways. The first and traditional method is the manual method, the so-called *traditional floating car method*. This manual method requires a driver to operate the test vehicle and a passenger to record the travel times at upstream and downstream stations using a clipboard and stopwatch at the same time. The second method improves the manual method by integrating an electronic distance measuring instrument (DMI) into the test vehicle technique. This method determines the travel time from the speed and distance information recorded by the DMI. The third test vehicle method uses a Global Positioning System (GPS) in the test vehicle. The GPS has recently been utilized to measure travel time. In the test vehicle, a GPS is connected to a portable computer to collect the vehicle trajectory information, which can then be used to determine the travel time. Although these test vehicle techniques, such as those that use a DMI, are cost effective, their accuracy is limited due to few or even only one measurement per time interval, as well as due to the possible error from the driver’s judgment of the various traffic conditions. Furthermore, these test vehicle techniques are time-consuming, labor-intensive and expensive for collecting sufficient data (Vanajakshi 2004).

License plate matching has been used for travel time studies from the 1950s. This technique calculates the travel time from the difference in arrival times of the vehicles between the
upstream and downstream stations by matching license plate numbers. The collection and processing of license plate data can be performed in different ways, such as manual, using portable computers and video equipment with manual transcription or with character recognition. The early manual method relies on observers to record license plate numbers and arrival times on paper or into a tape recorder, then to match the license plates and calculate travel time. More recently, portable computers have been utilized in the field to record license plate numbers and automatically provide an arrival time form. Video cameras or camcorders also have been used to collect license plate numbers, which are then transcribed and matched to the manual transcriptions either by personnel or with character recognition software. These techniques can provide large sample data, but the reading and matching of license plates still involves significant labor, and the initial costs of the equipment are high. Moreover, techniques that use video cameras can elicit public disapproval due to privacy concerns.

The third data collection method, the ITS probe vehicle technique, uses instrumented vehicles in the traffic stream and remote sensing devices to collect travel time data. The ITS probe vehicles are fundamentally different than the active test vehicles used for the test vehicle techniques; the ITS vehicles can also be personal vehicles, public transit, or commercial vehicles. The ITS probe vehicle techniques are classified based on the type and capability of the electronic transponder or receiver that is used in the vehicles; these capabilities include cellular phone tracking, ground-based radio navigation, automatic vehicle identification (AVI), automatic vehicle location (AVL) and GPS. Cellular phone
tracking uses the signal sent out by the cellular phone of the motorist when he or she arrives at the upstream and downstream stations to report the vehicle location, and then generates the travel time information. Ground-based radio navigation systems relay the vehicle location and time information via radio transponders that are mounted on the vehicles; these transponders transmit a radio frequency signal to multiple antenna towers. Then, the data are relayed to the central computer system to calculate the travel times using triangulation techniques. In the AVL system, the transmitters are carried in the vehicle, which allows the vehicle’s location to be determined at frequent intervals; then, the travel times are calculated. GPS receivers in the vehicle use a network of 24 satellites to determine the vehicle position, and then information is transferred to a control center for travel time data collection. Although the probe vehicle techniques can automatically collect data, and some systems such as AVI and AVL have relatively few errors, such techniques often require new types of sensors as well as public participation and are more costly to employ. Therefore, probe vehicle techniques are not recommended for small-scale data collection, such as used for freeway links, and are not widely deployed (Turner 1996, FHWA 1998).

2.1.2 Indirect Estimation Methods

Almost all the indirect techniques are based on fixed-point detectors, such as inductive loop
detectors (ILDs) or video cameras. As discussed in Chapter 1, the detectors, especially ILDs, can provide valuable continuous traffic data, such as traffic volume, occupancy and spot speed. In general, four types of travel time estimation methods have been developed based on the measurable point detector data over recent decades: speed extrapolation methods, vehicle re-identification methods, flow-based statistical methods and dynamic traffic flow methods.

The speed extrapolation techniques simply use speeds to estimate the average travel time of the freeway link. The speeds are spot speeds measured from dual-loop detectors or other point detectors, or space-mean speeds estimated from the relationships among speed, volume and occupancy measured from single-loop detectors. These methods carry the fundamental assumption that the speeds can be applied for short distances between two measurement points (Athol 1965, Hall and Persaud 1989, Jacobson et al. 1990, Sisiopiku et al. 1993, Ferrier 1999, Lindveld et al. 2000, Oh et al. 2003, Vanajakshi 2004). So, the accuracy of the extrapolation methods is affected by several factors, such as type of facility (freeway, arterial street), distance between point detectors, traffic conditions (free-flow, transition, congestion) and accuracy of the detectors, as stated in the travel time data collection handbook (FHWA 1998). In the freeway system, although the methods can be used to estimate the average travel time under free-flow traffic conditions, they are not appropriate for the transition and congestion conditions because the assumption of the constant or linearly changing speeds is violated.

The flow-based statistical methods typically include the cross-correlation method and probabilistic regression method, which focus on the aggregate traffic flow at two consecutive
stations at small aggregation intervals (usually 1 second). The cross-correlation method determines the travel time by using cross-correlation analysis between the continuous concentration signals generated from the flow at each station. The estimated travel time equals the time delay of the maximum or significant cross-correlation coefficient between the upstream and downstream flow (Dailey 1993, Guo and Jin 2006). The probabilistic regression method assumes that the arrivals measured at the upstream point during a given time interval have the same probability density function as the average travel time over the link; then, the density is estimated by minimizing the sum of the squares of the regression residual errors. Thus, the average travel time is the fit range of times multiplied by the probability density (Petty et al. 1998). Although the statistical methods require only the traffic flow parameter for travel time estimation, they also have some drawbacks and limitations. Due to the disappearance of the correlation, the cross-correlation method does not work well under conditions with large volumes or congested traffic. Also, the effectiveness of the probabilistic regression model is highly dependent on the fit range of the probability density function of the travel time (Guo and Jin 2006).

The dynamic traffic flow methods aggregate the characteristics of the stochastic vehicle counting process and the principle of the conservation of vehicles, and then use cumulative flow plots to calculate the total travel delay and to estimate the average travel time (Nam and Drew 1998, Vanajakshi 2004, Vanajakshi et al. 2008). However, the methods are sensitive to the flow data, require the number of vehicles that initially exist on the link, and do not work well under low volume conditions because of the smoothing of the cumulative flow curve.
The vehicle re-identification methods provide a link-based travel time by capturing and matching the specific characteristics of a single vehicle or platoon of vehicles from the two consecutive fixed-point detectors; these characteristics may include vehicle detuning curves from a loop detector or vehicle lengths measured from dual-loop detectors (Kuhne et al. 1997, Coifman and Cassidy 2002, Dermer and Lall 1995). However, these characteristics are totally different between different types of vehicles, such as cars, vans, trucks, trailers. In freeway systems, most of the vehicles are standard passenger cars, which are difficult to track because of their similar signatures. Even though a vehicle or platoon is matched across the upstream and downstream, and the travel time is defined as the difference of the arrival times of the matched vehicle or platoon, the estimated travel time is not the average travel time of all the vehicles passing the upstream or downstream, but is the sample vehicle or platoon travel time estimation. To improve the accuracy, some sophisticated equipment, programs or testing algorithms are required for these re-identification techniques (Coifman 1998, Coifman and Cassidy 2002, Sun et al. 1998), which are not typically available to most traffic management centers (Vanajakshi 2004).

2.2 Methodological Highlights of Travel Time Collection Methods

This section describes the methodological highlights and applications of the different methods.

2.2.1 Traditional Floating Car Method

With the traditional floating car method, a trained driver travels as the “average” vehicle,
while a passenger uses pen and paper to record cumulative travel times along the study route. The technique requires a driver and a recorder, a stopwatch, data collection forms and a test vehicle. As the test vehicle passes the first checkpoint on the freeway segment, the recorder starts the stopwatch. When the vehicle passes the subsequent checkpoint, the recorder records the elapsed time, which is the measured travel time at one run. Several runs are usually made on the same route. After the test vehicle return to the starting point, the stop watch is reset, a new field data collection sheet is prepared, and the above procedure is repeated until the end of the study time period (FHWA 1998).

In the manual test vehicle method, there is no need of specific equipment and hardware training, and the equipment costs are minimal. However, the technique is labor-intensive and time-consuming, and thus the collected sample size is usually limited. Also, due to the greater potential for human error and data entry errors, the accuracy of the collected travel time data maybe not very good.

The traditional floating car technique has been used for collecting travel time data since 1920s. In 1962, to conduct a study of travel time estimation from a central point to various locations in a metropolitan area, the Automobile Club of Southern California utilized their employees to record the locations and times on their trip home from the downtown office (May 1990). In the study of an evaluation of high-occupancy vehicle lanes in Texas by the Texas Transportation Institute (Henk et al, 1995), the tradition test vehicle method was originally used due to its simplicity and flexibility (FHWA 1998). Travel times were recorded in the field by using a stopwatch, pen and paper. A few years later, an audio recorder was
used to reduce the staff required to collect the travel time data. Besides travel time information, traffic flow information was collected by the floating car technique, which was originally developed in England in the early 1950s (Wardrop and Charlesworth 1954) and applied in Illinois in the mid-1950s (Mortimer 1957).

2.2.2 Distance Measuring Instrument (DMI)

A DMI is a hardware unit that can interpret information from a sensor and then convert it to distance and speed. The DMI test vehicle data collection technique consists of a test vehicle with a sensor, a DMI and an output data receiving and analyzing tool. When the test vehicle is moving, the consecutive pulses based on the vehicle’s speed are sent from the sensor to the on-board DMI; then the DMI converts the pulses to units of measure and calculates the distance and speed. Then, the travel time can be estimated from the distance and speed information.

In the early 1970s, the manual DMI used an adding machine tape or circular graphs to record the distance; these were difficult to read and required large amounts of data entry. The sensor in the manual DMI was a magnetic wheel sensor, which sometimes did not read properly and unbalanced the wheel (FHWA 1998). The electronic DMI has been developed to solve these problems by using an on-board portable computer and specialized software to record and analyze the distance and speed information, and using an improved transmission sensor. To improve the accuracy of the technique for average travel time estimation, the equipment should be calibrated and multiple travel time runs should be conducted.
Compared to the traditional floating car technique, the DMI is more cost-effective and safer to use when collecting travel time data. Also, the electronic DMI technique can automatically record detailed information used for congestion analysis. However, the technique remains labor-intensive, and the collected data for the time intervals are usually limited.

The DMI technique for travel time data collection has been utilized in many state departments of transportation (DOTs) and metropolitan planning organizations (MPOs). The California DOT used the electronic DMI technique to monitor congestion and analyze delays on California’s freeway system (Epps et al. 1994). The data for a minimum of four travel time runs were collected for each segment every year. The Texas Transportation Institute used electronic DMIs to collect travel times along freeway and high-occupancy vehicle (HOV) corridors in Houston to monitor lane performance (Turner 1996). The Utah DOT used electronic DMIs to collect travel time data for analyzing and investigating the congestion measurement technique that was developed by Thurgood in 1994 and was based on detailed travel speed information measured also with electronic DMI equipment.

2.2.3 Global Positioning System (GPS)

The GPS utilizes signals from a constellation of at least 24 earth-orbiting satellites to determine location, direction, speed and time. The system was developed by the United States Department of Defense for military tracking and many other applications, such as maritime shipping, air traffic management and vehicle navigation (FHWA 1998). The GPS test vehicle technique includes a test vehicle, an in-vehicle GPS unit (antenna and receiver)
and output data receiving and storage computers. When the test vehicle travels along the freeway, the signals based on the earth-orbiting satellites are sent from the GPS antenna to the GPS receiver, and then converted into information about distance, speed and time. In order to improve the accuracy of the data, some differential correction data from the differential correction receiver are also transferred to the GPS receiver. Finally, the corrected information is output to an in-vehicle computer and later stored in the central computer to automatically calculate the travel time.

The GPS can also be used in an ITS probe vehicle to collect personal travel survey data. The GPS probe vehicle technique for travel time data collection differs from the typical GPS test vehicle technique, because the motorists are not trained and do not drive on specified corridors, and the information must be returned to a control center. However, the equipment, data collection and analysis for the two techniques are almost the same.

The GPS can always provide more portable and accurate travel time measurements than the other techniques. However, sometimes signals from the satellites can be lost due to large buildings, trees, tunnels, or parking decks, which can degrade the accuracy of the technique. Also, the system needs more advanced software, such as GIS, and the initial installation cost is relatively high. In the ITS probe vehicle technique, although the GPS is becoming increasingly available as a consumer product, the sample data are also limited because of privacy concerns.

Previous studies have used the GPS technique for travel time data collection. In 1996,
Louisiana State University (LSU) developed a methodology to use a GPS for travel time data collection in congestion management systems, which include 330-mile urban highways in the three metropolitan areas in Louisiana: Baton Rouge, Shreveport, and New Orleans. The study concluded that the GPS could accurately provide the location and speed of a vehicle and was efficient in measuring travel time (Bullock et al. 1996). In Boston, GPS technology was used by the Central Transportation Planning Staff to provide detailed data, such as travel time, queue lengths, delay and speed, for a performance analysis of its congestion management system (Gallagher 1996). The Texas DOT (TXDOT 1998) utilized GPS technology to collect a large amount of travel time data to serve as an historical database for about 150 miles of freeway and arterial roadways in San Antonio. The Federal Highway Administration (FHWA) sponsored TransCore for research into GPS travel time data collection in Northern Virginia (Roden 1996). The GPS probe vehicle technique has also been used by the Lexington, Kentucky Area MPO for personal travel surveys (Gallagher 1996).

2.2.4 License Plate Matching

License plate matching is a technique by which license plate numbers are recorded and later matched at various checkpoints. This process records vehicle license plate numbers and arrival times at the upstream and downstream stations, matches the license plates between the two stations, and then calculates the travel time from the difference in arrival times.

In the manual approach of license plate matching, observers record license plate numbers and arrival times in the field, transcribe the license plate numbers and stamp the times in the
office, and then match the numbers and times to calculate the average travel time at the time intervals. However, it is difficult to collect large samples, so manually matching is labor-intensive. In the portable computer-based method, the license plate numbers are entered in the computer in the field with an automatic time stamp produced by the computer program, and the license plate matching is executed in the office. In the video-based license plate matching method, the license plates and a time stamp can be provided by the video cameras or camcorders, and the transcription and matching can be processed by the computerized image reading and matching algorithm. Although the video technique can capture high-speed traffic and provide a permanent record of license plates and traffic conditions, the cost is higher than the other two techniques, and the accuracy is poor in low-light conditions.

In 1988, Schaefer addressed practical issues and statistical considerations for manual license plate matching surveys. Research was conducted to compare the floating car technique to the portable computer-based license plate matching technique for travel time data collection in Seattle, Washington (Richman et al. 1990). The Chicago Area Transportation Study (CATS) used the computer-based license plate matching method to measure travel time on Chicago’s 245-mile arterial system (Bailey and Rawling 1991). In the “Quantifying Congestion” study of the National Cooperative Highway Research Program (NCHRP), the computer-based technique was used for travel time data collection of freeway lanes (Lomax et al. 1995). In 1993, a study conducted by Volpe compared various travel time collection techniques, including computer-based and video-based license plate matching, based on the travel time surveys conducted in Seattle, Lexington, and Boston (Liu and Haines, 1996). In 1996, the
Florida Urban Transportation Research Center utilized video and character recognition-based techniques for traffic data collection in its congestion management system. The Washington DOT (1995) used an automated video-based technique to measure travel times for two HOV corridors in Seattle (Woodson et al. 1995). Research into the use of automated license plate recognition systems to collect travel time and origin-destination (OD) data was conducted by West Virginia University and the West Virginia DOT (French et al. 1998).

2.2.5 Cellular Phone Tracking

Cellular phone tracking is the method by which vehicles are tracked from a volunteer motorist’s cellular phone or by the cellular geolocation technique. The cellular phone tracking technique for travel time data collection consists of a probe vehicle with cellular phone, cellular phone tower/network and traffic information center. When the vehicle passes the upstream and downstream stations, the call from the cellular phone is identified, the location and time are determined by the driver’s report or the cellular tower/network, and then the information is transferred to the traffic control center for travel time calculation. In this reporting technique, the volunteer drivers must be careful to place the call at the stations. However, they often call too early or too late, or even miss making the call all together. Thus, human error can sometimes lead to inaccurate freeway travel time observations. The cellular geolocation technique can automatically detect the cellular phone call and locate the probe vehicle, but it is often impaired by topography and line-of-sight barriers. Moreover, this technique risks public disapproval due to concern that phone calls may be monitored and vehicles may be tracked.
In 1993, the Texas DOT conducted a test on the cellular phone tracking technique. In the test, about 200 participating motorists were required to report their locations, and then the information was transferred to a communications center to calculate the travel times. These travel times were then posted on the message signs along the freeway (Levine, 1993). In the CAPITAL operation test in the Washington, D.C. area, the cellular phone geolocation tracking technique was used to automatically locate vehicles with cellular phones used in the traffic stream (Robinson et al. 1993). Compared to the differential GPS data, the error in the cellular geolocation data is large due to the topographic interference and line-of-sight problems (FHWA 1998). A study at the University of Technology in Sydney, Australia was conducted to evaluate the Mobile Telephone Positioning System and compare the system with the GPS for vehicle position application (Drane, 1996).

2.2.6 Automatic Vehicle Identification (AVI)

An AVI system for travel time data collection consists of probe vehicles with electronic transponders, two roadside reading units (antenna and reader) at the upstream and downstream stations, and a control center. When the probe vehicle passes the consecutive two stations, the vehicle number is sent to the roadside readers with the different time stamps, and then the data are transmitted to the control center to calculate the probe vehicle’s travel time, which is the difference between the time stamps.

Compared to cellular phone tracking, the AVI technique reduces the human error and can collect large amounts of data automatically and accurately. However, the technology requires
new and expensive infrastructure (e.g., AVI transponders and reader units). Also, it requires probe vehicles with tags, which allow the vehicles to be tracked. Again, the tracking capability could lead to public disapproval due to privacy concerns.

The Texas DOT developed an AVI system along the 300 miles of freeway and 100 miles of HOV lanes in Houston to monitor traffic conditions, to detect incidents and to collect travel time data (Levine and McCasland 1994, Turner 1996). In 1992, the Washington State Transportation Center (TRAC) conducted a study in the Seattle region to investigate the use of AVIs using commercial probe vehicles for travel time measurements (Hallenbeck et al. 1992). In 1994, an AVI system using buses was tested for travel time data collection (Liu 1994). In 2000, a study of the San Antonio AVI system was conducted to compare AVI and GPS probe vehicle techniques for travel time calculations (Zhu 2000). Most often, AVI systems are used for electronic toll collection; in the United States, many toll collection agencies use an AVI system to collect tolls electronically.

**2.2.7 Automatic Vehicle Location (AVL)**

The AVL system automatically tracks the location of a probe vehicle by the transmitter unit carried in the probe vehicle. The AVL system includes a vehicle transmitter unit and tower/communication network. There are different technologies in the AVL system that can be classified as signpost-based AVL, ground-based AVL and GPS-based radio AVL (see the previous section regarding GPS). The different AVL systems for travel time data collection consist of a probe vehicle with a transmitter unit (sensor and radio transmitter),
In the signpost-based AVL system, electronic signposts at the upstream and downstream stations emit a unique identification code, which is received by the vehicle sensor with the assigned time stamp and vehicle identification. Then, the information is transferred from the transmitter to the control center to track the vehicle and calculate the travel time, which is the difference of the arrival times at the consecutive stations. Although the technology is relatively simple, it is used by only some transit agencies, and it has almost been replaced by the GPS-based AVL due to its poor accuracy and outdated approach (FHWA 1998).

In the ground-based radio AVL system, the vehicle identification number and the transmission time are transmitted via a radio frequency signal from the probe vehicle to multiple antenna towers. Simultaneously, the location is determined by the transmissions between the probe vehicle and towers. Then, the information is transferred to the control center to compute the travel time. This system requires a ground-based radio navigation service, which is mostly operated by private companies and cannot be used widely. Also, the accuracy of this system is poorer than the GPS-based AVL due to less precision in the ground-based radio navigation system compared to the GPS.

The VIA metropolitan transit system in San Antonio, Texas operated a signpost-based AVL system for real-time bus fleet tracking (Pekingson 1994). The system cost $3.7 million and covers a 1200 square mile area with 437 buses. However, the collected data were never used in other applications, only for the fleet management (VIA 1996). In 1993, the New Jersey
Transit agency began to utilize signpost-based AVL technology to provide accurate real-time information for its bus fleet management. In 1994, the Center for Urban Transportation Research (CUTR) at the University of South Florida conducted a study in Miami to test the ground-based radio AVL for travel time data collection and the difference using the manual test vehicle technique. A study by the Texas Transportation Institute (TTI) in Houston evaluated the accuracy of the ground-based AVL system based on the triangulation location technique and the DGPS measurements in the high-density urban area (Vaidya 1996).

2.2.8 Speed Extrapolation

The speed extrapolation method estimates the average travel time of a freeway link from the spot speeds at the upstream and downstream stations. The method assumes that the change between the spot speeds at the two detector stations is constant between the measurement points. The travel time is calculated as the distance between the two detectors divided by the speed (Athol 1965, Hall and Persaud 1989, Jacobson et al. 1990, Sisiopiku et al. 1993, Ferrier 1999, Lindveld et al. 2000, Oh et al. 2003, Vanajakshi 2004).

The spot speeds can be measured directly from dual-loop detectors or other point detectors, i.e.,

\[ v_u = \frac{D}{T_u}, \quad v_d = \frac{D}{T_d}, \]

where \( D \) is the fixed space of the dual-loop detector, \( T_u, T_d \) are the traversal times of the upstream and downstream via the fixed distance between the inductive loops, and \( v_u, v_d \) are the measured spot speeds of the upstream and downstream. However, some point detectors, such as the single-loop detector, cannot provide spot speed
measurements, but collect vehicle counts and occupancy data. The spot speeds can be estimated from the relationships among speed, flow, and occupancy, i.e.,
\[ v_u = \frac{q_u}{O_u * g_u}, v_d = \frac{q_d}{O_d * g_d}, \]
where \( q_u, q_d \) are the upstream and downstream flows, \( O_u, O_d \) are the occupancy times of the consecutive stations’ loop detectors, and \( g_u, g_d \) are the speed correction factors based on the effective car lengths.

There are several assumptions about the change in spot speed at the two stations along the freeway links. The change between the speeds could be assumed to be constant versus time along the freeway link, i.e.,
\[ \bar{v} = \frac{v_u + v_d}{2}, t_t = \frac{x_d - x_u}{\bar{v}} = \frac{\Delta x}{(v_u + v_d)/2}, \]
where \( \Delta x \) is the distance between the two detector stations, \( \bar{v} \) is the average speed, and \( t_t \) is the average travel time of the freeway link. Or, the change between the speeds could be assumed to be constant versus distance along the freeway link (Vanajakshi et al. 2008), i.e.,
\[ tt = \Delta x \frac{Ln(v_d) - Ln(v_u)}{v_d - v_u}. \]

The speeds at the upstream or downstream stations could be assumed to be applicable to half the distance on both sides (Vanajakshi 2004), i.e.,
\[ tt = \frac{1}{2} \left( \frac{\Delta x}{v_d} + \frac{\Delta x}{v_u} \right). \]
Or, the average speed along the freeway link could be assumed to be the minimum speed of the two spot speeds at the two stations (Vanajakshi 2004), i.e.,
\[ tt = \frac{\Delta x}{\min(v_d, v_u)}. \]

The speed extrapolation method is based on the assumption that the speed is constant or linearly changes between the two stations, so the method is applicable only when the
variation in the traffic condition is minimal, such as under the free-flow condition. Under transition or congestion conditions, the stop-and-go traffic and shock waves can significantly affect vehicle speeds, which cannot be constant or change linearly, so the discrepancy inherent of the travel time estimation is significant (FHWA 1998, Ferrier 1999, Lindveld et al. 2000, Vanajakshi 2004). Also, the errors of the spot speeds due to device inaccuracy, the fixed space D of the dual-loop detector, or the effective car length estimation (car length error) can also affect the accuracy of the method (Hall and Persaud 1989, Woods 1994, FHWA 1998, Guo and Jin 2006). The spot speeds at the upstream and downstream stations may be the time-mean speed or space-mean speed, which are different in both definition and calculation, but nonetheless related to each other (Wardrop 1952, Dailey 1999, Rakha and Zhang 2005), and thus can lead to different results for travel time estimation. A detailed description of the models with regard to theory, equation, deviation, comparison and validation is presented in Chapter 3.

2.2.9 Probabilistic Regression

Petty et al. (1998) presented a probabilistic regression model for travel time estimation from the flow data obtained from single-loop detectors; these data are the aggregate traffic flows of the upstream and downstream points at some aggregation interval $\Delta$ (usually 1 second). The model is based on the assumption that during a given time interval $(b_1, b_2)$ the vehicles arriving at the upstream station have the same probability distribution of the travel times over the freeway link, i.e., $y(t) = \sum_{i=n_{1}/\Delta}^{n_{1}/\Delta-1} [x(t-i)f_i], t \in (b_1 / \Delta, b_2 / \Delta)$, where $x(t)$, $y(t)$ are the vehicles
that arrive at the upstream and downstream points at time $t$, $f_i$ is the probability density function of travel time $i$, and $[a_1, a_2]$ is the fit range of the probability density function (range of travel time). The probabilistic density $f_i$ can be estimated from the least sum of the squares of the regression residual errors in the model, i.e.

$$\text{Minimizing} : \sum_{t=(b_1+a_2)/\Delta}^{(b_2+a_1)/\Delta-1} \left(y(t) - \sum_{i=a_1/\Delta}^{a_2/\Delta-1} x(t-i)f_i \right)^2 \quad f_i \geq 0, \sum_{i=a_1}^{a_2} f_i = 1.$$  

Then, the average travel time can be calculated by the travel times in the fit range multiplied by the estimated probability densities, i.e., $tt = \Delta \sum_{i=a_1}^{a_2} f_i \Delta$. Petty et al. utilized the model to estimate the average travel time based on I-80 data, which were then compared with the probe vehicle measurements and dual-loop travel time estimates to validate the accuracy of the method.

In this model, the assumption of a constant travel time distribution can be applicable under either free-flow or congestion conditions. Under free-flow conditions, the speeds are close to the free-flow speeds, and the travel times do not change much. Under the congestion flow condition, the density changes are small, so the traffic could be considered as statistically stationary. However, under transition conditions, the traffic varies between free-flow and congestion and is not stationary, so the error of the travel time estimation using the model increases. Moreover, the accuracy of the model relies on the determination of the travel time fit range. If the fit range is too wide, there will be too many density parameters to be estimated, and the solution in the optimization solver is unstable. If the fit range is too narrow, the resolution and accuracy may be too poor to obtain an appropriate probability density
(Guo and Jin 2006). Petty recommends that the fit range can be determined from the spot speed estimates of the flow-speed relationship, i.e. \( v = \frac{q}{O \ast g} \). The model modifications with five kinds of fit ranges and extended data are presented in Chapter 3.

### 2.2.10 Cross-Correlation

Cross correlation is a standard method of estimating the degree to which two series are correlated. In 1993, Dailey used the cross-correlation model to estimate the average travel time of a freeway link from flow data obtained from single-loop detectors. The method is based on aggregating the traffic flow of the upstream and downstream stations \( x(t) \) and \( y(t) \) during some sampling interval \( \Delta \), which Dailey suggests to be five seconds. The model assumes that the travel time of the vehicles from the upstream to the downstream is the same as during the time interval \((b_1, b_2)\). That is, the traffic flow at the upstream point would arrive at the downstream after some time delay \( k \). In other words, for the cross-correlation model, the degree of correlation between the upstream flow \( x(t) \) and downstream flow \( y(t) \) is at its maximum at the time delay \( K \). Hence, the estimated travel time at the time interval \((b_1, b_2)\) using the maximum cross-correlation method is equal to the time delay of the maximum cross-correlation coefficient between the upstream and downstream flow:

\[
\rho_{yx}(k) = \frac{\sum_{t=b_1+k}^{b_2} (x(t-k) - \bar{x})(y(t) - \bar{y}) \sum_{t=b_1}^{b_2} x(t) \sum_{t=b_1}^{b_2} y(t)}{\sqrt{\sum_{t=b_1}^{b_2} (x(t) - \bar{x})^2 \sum_{t=b_1}^{b_2} (y(t) - \bar{y})^2}}, \quad \bar{x} = \frac{\sum_{t=b_1}^{b_2} x(t)}{b_2 - b_1 + 1}, \quad \bar{y} = \frac{\sum_{t=b_1}^{b_2} y(t)}{b_2 - b_1 + 1},
\]

\( tt = \Delta \ast K = \Delta \ast \max^{-1} \{ \rho_{yx}(k) \} \), where \( \rho_{yx}(k) \) is the cross-correlation coefficient at delay \( k \),
and $\bar{x}, \bar{y}$ are the mean traffic flows at the upstream and downstream during time interval $(b_1, b_2)$.

The maximum cross-correlation method does not consider the variability in average travel times among the different vehicles. Guo and Jin 2006 modified the model by integrating the cross-correlation analysis with the probabilistic regression model, wherein the travel times of the vehicles at the upstream are considered as random variables and have the same probability distribution over the freeway link, i.e.,

$$f_k = \rho_{xy}(k) \frac{\sum_{t=b_1+k}^{b_2} (y(t) - \bar{y})^2}{\left(\sum_{t=b_1}^{b_2} (x(t) - \bar{x})^2 \right)} \cdot$$

The probability density function of travel time $f_k$ can be determined by the cross-correlation coefficients $\rho_{xy}(k)$, which follow a normal distribution with mean zero and standard deviation $\sigma_\rho$. The modified model uses the statistical t-test to determine the significant cross-correlation coefficients, and the calculated $f_k$ is the estimated probability density corresponding to the travel time $\Delta t * k$. The average travel time can be calculated as $\bar{t} = \Delta \frac{\sum_{k=c_1}^{c_m} (\rho_{xy}(k) * k)}{\sum_{k=c_1}^{c_m} \rho_{xy}(k)}$, where $(c_1, c_m)$ is the range of the delay $k$ corresponding to the significant cross-correlation coefficients.

Although the two models based on the cross correlation are used to estimate travel time from only traffic flow parameters, the correlation of the traffic flows at the consecutive stations disappears under the congestion condition or when there are multiple lanes with a large flows. The travel time cannot be estimated in the absence of cross correlation, and therefore, the
applications of the models are limited (Petty 1998, Guo and Jin 2006). Cross-correlation models can be used to estimate travel times under low or normal traffic conditions, however. Chapter 3 provides a detailed description and discussion of the models.

2.2.11 Dynamic Traffic Flow Approach

Nam and Drew (1998) developed a dynamic traffic flow model for estimating freeway travel time from flow measurements taken at upstream and downstream stations. The model is based on the characteristics of a stochastic vehicle counting process and the principle of the conservation of vehicles. The stochastic process for a freeway link without on- or off-ramps is that vehicles entering or leaving the link by time \( t_n \) are considered as random variables \( Q(x_a, t_n) \) and \( Q(x_b, t_n) \); this phenomenon is also referred to as cumulative flow at the upstream or downstream stations, and the variables are non-negative, non-decreasing and \( Q(x_a, t_n) \geq Q(x_n, t_n) \). The conservation of vehicles is that the difference between the number of vehicles entering and exiting the link during time interval \( \Delta t \) equals the change in the number of vehicles traveling on the link during the same interval, i.e.,

\[
q(x_a, t_n + \Delta t) \Delta t - q(x_b, t_n + \Delta t) \Delta t = k(t_n + \Delta t) \Delta x - k(t_n) \Delta x,
\]

where \( q(x_a, t_n + \Delta t) \) and \( q(x_b, t_n + \Delta t) \) are the upstream and downstream flow rates at the time \( t_n + \Delta t \), \( k(t_n + \Delta t) \) is the freeway link density at time \( t_n + \Delta t \), \( k(t_n) \) is the freeway link density at time \( t_n \), and \( \Delta x \) is the freeway link length.

The overall model by Nam and Drew consists of two separate models, one for free-flow and
the other for congestion. If any vehicle that enters the link at a given time interval \((t_{n-1}, t_n)\) can exit it during the same interval, this is considered the free-flow condition, and these vehicles that can enter and exit the link are used to estimate the average travel time, i.e.,

\[
\frac{\Delta t}{2} = \frac{q(x_a, t_n)k(t_{n-1}) + q(x_b, t_n)k(t_n)}{q(x_a, t_n)q(x_b, t_n)}.
\]

Under the congestion condition, in which none of the vehicles can exit the link during the same interval, the average travel time is represented by all the vehicles that can enter the link and is estimated as \(\frac{\Delta t}{2} = \frac{k(t_{n-1}) + k(t_n)}{q(x_b, t_n)}\). The model for the free-flow condition, which ignores a portion of the vehicles that enter the link at the time interval but do not exit, was modified by Vanajakshi (2004, 2008). The improved model considers all the entering vehicles during the time interval and calculates the travel time for both free-flow and congestion, i.e., \(\frac{\Delta t}{2} = \frac{k(t_{n-1}) + k(t_n)}{q(x_b, t_n)}\).

In some previous studies (Quiroga 2000, Dhulipala 2002, Corter et al. 2002), it has been pointed out that the accuracy of the determined flow rates and calculated densities will affect the model. To decrease the sensitivity of the density and flow parameters, Vanajakshi et al. (2008) suggest using occupancy values to estimate density. Also, this model requires the number of vehicles that initially exist on the link. Moreover, the model uses an inductive approach along with geometric interpretations of cumulative arrival-departure flow diagrams (Ferrier 1999), so it is not appropriate for low volume conditions due to the smoothing of the cumulative flow curve. The model also assumes constant downstream flow rates during consecutive time intervals, which is not applicable in the field. The modification of the model
with the detailed equation derivation is presented in Chapter 3.

2.2.12 Vehicle Signature Matching

In 1997, Kühne et al. presented a travel time estimation method based on inductive loop detectors by matching vehicle signatures of frequency detuning curves, which have different characteristics among the different types of vehicles. When vehicles pass the detectors, some unique features of the vehicle curve at the upstream are captured and then compared to signatures at the downstream station. If a large number of feature correlations within vehicle signatures appear at the downstream, the vehicle is matched, and the difference between the arrival times is the travel time. In this technique, because the characteristics of the vehicle curves are different within various types of car, truck or trailer, only some percentage of vehicles can be matched due to the small ratio for trailers or trucks, and therefore, the travel time is the average travel time of only a portion of the vehicles.

Coifman (1998, 2002) developed a vehicle length sequence matching method to estimate travel time. In this method, the lengths of vehicles are measured by dual-loop detectors, i.e.,

\[ l = \frac{D}{T_{\text{on}}} T_{\text{on}}, \]

where \( l \) is the vehicle length, \( D \) is the distance between the two loops, \( T_{\text{on}} \) is the total on-time at the first or second loop, and \( T_{\text{f}} \) is the difference between the times that the front tire arrives at the two loops or that the back tire exits the two loops. This method assumes that: the vehicles do not change lanes; they retain positions within some platoon; the specific sequence of vehicle lengths captured at an upstream detector can be re-identified at the downstream detector; the vehicle whose length was identified is matched in the platoon;
and the difference between its arrival times is the travel time. Although this method is based
on the vehicle length sequence from loop detectors, the difference in vehicle lengths is small,
and with the large percentage of cars in the freeway, its accuracy is not as good as the actual
vehicle matching methods (AVI, AVL, license plate matching), and the errors of the
estimation results obtained from the individual or sample matching vehicle are more
significant.

Other matching techniques based on individual or platoon vehicle signatures use some
complicated re-identification algorithms; these techniques include the lexicographic
optimization method and testing algorithms with sophisticated equipments or programs (Sun
et al. 1998, 2003, May et al. 2003). These techniques are not typically available to most traffic
management centers (Vanajakshi 2004).

2.3 Summary

The methods of obtaining travel time data are reviewed in Table 2.1. An ideal method should
be accurate, effective and applicable for freeway links under all traffic conditions.

In the direct methods, the average travel time is calculated from the collected travel time data
for the vehicles. Although some techniques can collect accurate travel time data for the
sample vehicles, the errors of the average travel time per interval should be tested due to
small sample sizes. In order to collect enough data, the techniques may be time-consuming,
labor-intensive and expensive, or may risk public disapproval because of privacy concerns
due to tracking and monitoring devices used in data collection. In this dissertation, these
direct measurement methods are not considered as candidates for travel time data collection methods and, therefore, are not discussed in the remainder of the dissertation.

In the indirect methods, the average travel time is estimated from fixed-point detector data, i.e., flow, occupancy and speed. Although the vehicle signature matching methods are also based on these simple data, some complicated algorithms, equipment or programs may be required for matching or re-identifying the vehicles, and are not available in most management systems. Therefore, the vehicle signature matching methods are not included for study in this dissertation.

With regard to the three categories of methods shown in Table 2.1, although they have some drawbacks and cannot be adapted to all traffic conditions, they are nonetheless competitive. In fact, a hybrid of two or more of these methods will likely yield better performance than any one of the methods operating independently. The proposed work aims to provide a systematic method for accurate and effective travel time estimation under all traffic conditions for freeway links. To accomplish this contribution to the literature, these competitive three methods are compared through quality and quantity analyses. In Chapter 3, the theory, equation derivation, and modification of each model are described. Then, a simulation study is designed to compare the revised models, and finally, the proposed systematic method is presented.
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<th>Application</th>
<th>Drawbacks</th>
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<tr>
<td><strong>Indirect Estimation Methods</strong></td>
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<td></td>
<td>Flow-based Statistical Method</td>
<td>Use maximum cross-correlation coefficient to determine travel time; Assume constant vehicle speed</td>
<td></td>
<td>Not for transition and congestion</td>
</tr>
<tr>
<td></td>
<td>Maximum Cross-Correlation</td>
<td>Integrate the cross-correlation analysis with probabilistic model; Use t-test to determine the significant coefficients</td>
<td></td>
<td>Not for transition and congestion, or multiple lanes</td>
</tr>
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Table 2.1 Continued

<table>
<thead>
<tr>
<th>Method</th>
<th>Model</th>
<th>Description</th>
<th>Accuracy</th>
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<tr>
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<td>Probabilistic Regression Model</td>
<td>Assume the same travel time distributions over the link; Density function from least sum squares of regression residual errors</td>
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<tr>
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<td></td>
<td>Adapt to free-flow, and congestion</td>
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</tr>
<tr>
<td>Dynamic Traffic Flow Models</td>
<td>Dynamic Traffic Flow Models</td>
<td>Based on stochastic vehicle process and vehicle conservation principle; Assume smooth cumulative flow curve, and <strong>constant flow rate at the consecutive time interval</strong></td>
<td>Adapt to transition and congestion</td>
</tr>
<tr>
<td>Vehicle Signature Matching</td>
<td>Re-identification Methods</td>
<td>Based on vehicle/platoon or the characteristic of vehicle/platoon: curves, color and length; matching algorithm</td>
<td>Complicate algorithms/ programs/ equipment</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Not for free-flow; Sensitive to flow/density; Initial flow conditions</td>
<td></td>
</tr>
</tbody>
</table>
CHAPTER 3 TRAVEL TIME ESTIMATION MODELS AND SIMULATION STUDY

As discussed in Chapter 1, the proposed travel time estimation method should utilize fixed-point detector data (flow, spot speed or occupancy) to accurately estimate the travel time of various freeway links that are comprised of different lengths and number of lanes and under various traffic conditions (free-flow, transition and congestion). In Chapter 2, among a variety of methods for achieving travel time, the three estimation methods that are based on fixed-point data are deemed the most competitive methods under certain traffic conditions.

In order to develop a systematic method that is adaptable to all traffic conditions for various freeway links, first of all, each of the three methods is analyzed in detail with regard to the model’s theory, equation derivation, and possible modification (Section 3.1). Then, a simulation study of the various freeway links and traffic conditions and their corresponding data is used to compare all the models (Section 3.2).

3.1 Description and Modification of the Three Travel Time Estimation Models

The three categories of models for travel time estimation using fixed-point detector data are: speed extrapolation models, flow-based statistical models and dynamic traffic flow models. In this Section 3.1, each of these models is described in terms of the model’s theory, then the equations are derived, the applications and limitations are analyzed, and finally, the possible modifications are presented.
3.1.1 Speed Extrapolation Models

Speed extrapolation models utilize the measured or estimated spot speeds at upstream and downstream points to calculate the mean speeds for each station. With the average speed over the link derived from the assumption that the two mean speeds linearly change between the two stations, the travel time is computed as the distance between the two detectors divided by the average speed. The procedure can be summarized as

Two fixed-point detectors are located at upstream location \( x_u \) and downstream location \( x_d \), respectively. During time interval \([t_{n-1}, t_n]\), the measured or estimated spot speeds at the two stations are \( v_{u,i}, v_{d,j} \quad i = 1, 2, \ldots, m \quad j = 1, 2, \ldots, n \), where \( m \) is the number of vehicles measured at the upstream and \( n \) is the number of vehicles measured at the downstream.

The mean speeds at two locations \( v_u, v_d \) are time-mean speeds or space-mean speeds of the spot speeds and are described as \( v_u = \text{mean}(v_{u,1}, v_{u,2}, \ldots, v_{u,m}) \), \( v_d = \text{mean}(v_{d,1}, v_{d,2}, \ldots, v_{d,n}) \).

Assume that \( v_u, v_d \) changes linearly between the two points; then, the average speed of the
freeway link $\bar{v}$ can be derived as the function of the two mean speeds, $v_u, v_d$, i.e.,

$$\bar{v} = f(v_u, v_d).$$

So, for the time interval $[t_{n-1}, t_n]$, the travel time $tt(t_n)$ is calculated as

$$tt(t_n) = \frac{x_d - x_u}{\bar{v}}.$$

(1) **Spot speeds estimation or measurement** $v_{u,j}$ $v_{d,j}$

- Spot speeds estimated from the single-loop detector

The single-loop detector, plotted in Figure 3.1, is not capable of directly measuring spot speed and vehicle lengths data. Spots speeds must be estimated from the occupancy data and the assumed vehicle lengths.

![Figure 3.1: One vehicle passing over a single-loop detector.](image)

Figure 3.1 is a time-space diagram wherein a vehicle passes over a single-loop detector.
When the vehicle enters the detection zone with width $L_d$, the sensor is activated from time $t_{on}$ and remains so until the vehicle leaves the detection zone at time $t_{off}$.

The vehicle occupancy time $t_{occ}$, also referred to as the “on” time that it takes for a vehicle to pass through the detection zone, is calculated as $t_{occ} = t_{off} - t_{on}$.

From Figure 3.1, it can be seen that during the “on” time the vehicle travels a distance equal to its length plus the detection zone width, i.e., $L = L_i + L_d$, where $L_i$ is the length of the vehicle and $L_d$ is the width of the detection zone.

Then, the spot speed of the vehicle is calculated as the transversal distance divided by the occupancy time, i.e., $v_j = \frac{L}{t_{occ}} = \frac{L_i + L_d}{t_{off} - t_{on}}$.

However, vehicle length $L_i$ is an unknown parameter, because different types of vehicles have different lengths. To estimate the spot speed, the vehicle length is assumed to be a constant, effective vehicle length $L_v$. Therefore, the estimated spot speed $v_j$ is derived as $v_j = \frac{L_v + L_d}{t_{off} - t_{on}}$.

Given the constant vehicle length $L_v$, during the time interval $[t_{n-1}, t_n]$, the estimated spot speeds of the upstream and downstream can be determined as
\[ v_{u,i} = \frac{L_v + L_d}{(t_{\text{occ}})_i} = \frac{L_v + L_d}{(t_{\text{off}})_i - (t_{\text{on}})_i} \quad i = 1, 2, \ldots, m \]  

\[ v_{d,j} = \frac{L_v + L_d}{(t_{\text{occ}})_j} = \frac{L_v + L_d}{(t_{\text{off}})_j - (t_{\text{on}})_j} \quad j = 1, 2, \ldots, n \]  

where

- \( v_{u,i} \): the estimated spot speed of vehicle \( i \) passing the upstream location
- \( v_{d,j} \): the estimated spot speed of vehicle \( j \) passing the downstream location
- \( m \): the number of vehicles passing the upstream station during the time interval
- \( n \): the number of vehicles passing the downstream station during the time interval
- \( (t_{\text{occ}})_i \): the occupancy time of vehicle \( i \) at the upstream loop detector
- \( (t_{\text{occ}})_j \): the occupancy time of vehicle \( j \) at the downstream loop detector

• Spot speed measurements obtained from the dual-loop detector

For the dual-loop detector, instead of assuming the vehicle length, the spot speed data can be directly measured, as seen in Figure 3.2.
Figure 3.2: One vehicle passing over a dual-loop detector.

Figure 3.2 is a time-space diagram wherein a vehicle passes over a dual-loop detector. The dual-loop detector is the same as two single loops with a known distance between the two detectors. As the vehicle enters the first loop $A$ detection zone, the vehicle is detected at time $t_{on,A}$. When the vehicle passes the second loop $B$ detector, the sensor is activated at time $t_{on,B}$. Between time $t_{on,A}$ and time $t_{on,B}$, the vehicle travels from the front edge of detection zone $A$ to the front edge of detection zone $B$, which is a known distance defined as $L_D$. Then, the spot speed of the vehicle is calculated as the transversal distance $L_D$ divided by the difference in the time that it takes the vehicle to pass the front edge of the two detectors, i.e.,

$$v_t = \frac{L_D}{t_{on,B} - t_{on,A}}.$$ 

Therefore, during the time interval $[t_{n-1}, t_n]$, the measured spot speeds of the upstream and downstream can be determined as
\[ v_{u,i} = \frac{L_D}{(t_{on,B})_i - (t_{on,A})_i} \quad i = 1, 2, ..., m \]  

(3.3)

\[ v_{d,j} = \frac{L_D}{(t_{on,B})_j - (t_{on,A})_j} \quad j = 1, 2, ..., n \]  

(3.4)

where

- \( L_D \): the distance between the front edges of the two loops in the dual-loop detector
- \( v_{u,i} \): the measured spot speed of vehicle \( i \) at the upstream location
- \( v_{d,j} \): the measured spot speed of vehicle \( j \) at the downstream location
- \( m \): the traffic volume at the upstream station during the time interval
- \( n \): the traffic volume at the downstream station during the time interval
- \( (t_{on,A})_i \): the time that vehicle \( i \) is detected at the first loop \( A \) in the upstream detector
- \( (t_{on,B})_i \): the time that vehicle \( i \) is detected at the second loop \( B \) in the upstream detector
- \( (t_{on,A})_j \): the time that vehicle \( j \) is detected at the first loop \( A \) in the downstream detector
- \( (t_{on,B})_j \): the time that vehicle \( j \) is detected at the second loop \( B \) in the downstream detector
(2) Mean speeds of the upstream and downstream $v_u, v_d$

The mean speeds of the traffic streams include the time-mean speed and the space-mean speed. Time-mean speed is the average speed of a traffic stream passing a specific stationary point during an interval of time $\Delta t$, i.e.,

$$v_i = \frac{1}{N} \sum_{i=1}^{N} \left( \frac{v_i \cdot \Delta t}{\Delta t} \right) = \frac{1}{N} \sum_{i=1}^{N} v_i,$$

where $v_i$ is the time-mean speed; $N$ is the observation; and $v_i$ is the spot speed of vehicle $i$, so that the time-mean speed is the arithmetic mean of the observed vehicle spot speeds.

The space-mean speed reflects the average speed over a spatial section $D$, i.e.,

$$v_s = \frac{D}{\frac{1}{N} \sum_{i=1}^{N} t_i} = \frac{D}{\frac{1}{N} \sum_{i=1}^{N} \frac{D}{v_i}} = \frac{1}{\frac{1}{N} \sum_{i=1}^{N} \frac{1}{v_i}},$$

where $t_i$ is the time it takes for vehicle $i$ to cross distance $D$ and $t_i = \frac{D}{v_i}$; thus, the space-mean speed is the harmonic mean of the spot speeds of the vehicles.

The time-mean speed is greater than or equal to the space-mean speed. The relationship between the time-mean speed and space-mean speed is derived as

$$v_i = v_s \left[ 1 + \frac{\sigma^2}{v_i^2} \right],$$

(Rakha and Zhang 2005). According to the definition of travel time provided in Chapter 1, the average travel time over a freeway link can be estimated from the unbiased estimate of the space-mean speed as

$$tt = \frac{X_d - X_u}{v_s}.$$
speeds of the upstream and downstream should be the space-mean speeds.

- Space-mean speeds at two stations obtained from a single-loop detector

Incorporating Equations 3.1 and 3.2 into the space-mean speed equation, during the time interval $[t_{n-1}, t_n]$, the space-mean speeds at the upstream and downstream obtained from the single-loop detector can be computed as

$$v_u = \frac{1}{\frac{1}{m} \sum_{i=1}^{m} \frac{1}{v_{u,i}}} = \frac{1}{\frac{1}{m} \sum_{i=1}^{m} \frac{1}{L_v + L_d}} = \frac{L_v + L_d}{\sum_{i=1}^{m} \frac{1}{t_{occ,i}}} \quad i = 1, 2, ..., m$$  \hspace{1cm} (3.5)

$$v_d = \frac{1}{\frac{1}{n} \sum_{j=1}^{n} \frac{1}{v_{d,j}}} = \frac{1}{\frac{1}{n} \sum_{j=1}^{n} \frac{1}{L_v + L_d}} = \frac{L_v + L_d}{\sum_{j=1}^{n} \frac{1}{t_{occ,j}}} \quad j = 1, 2, ..., n$$  \hspace{1cm} (3.6)

As the occupancy for the time interval $T = t_n - t_{n-1}$ is calculated as $O = \frac{\sum_{i=1}^{N} (t_{occ,i})}{T}$, then Equations 3.5 and 3.6 can be derived as

$$v_u = \frac{L_v + L_d}{T} \cdot \frac{m}{O_u}$$  \hspace{1cm} (3.7)

$$v_d = \frac{L_v + L_d}{T} \cdot \frac{n}{O_d}$$  \hspace{1cm} (3.8)
where

\[ O_u = \text{the upstream detector occupancy during the time interval } T = t_n - t_{n-1} \]

\[ O_d = \text{the downstream detector occupancy during the time interval } T = t_n - t_{n-1} \]

For the single-loop detector, the estimation of the space-mean speeds at the two stations is based on the assumption of a constant effective vehicle length. However, studies (Hellinga 2002, Guo and Jin 2006) have shown that these speed estimates are inaccurate, and the effect of the vehicle length error on the estimated average travel time is clearly evident. Thus, this estimation method will not be used in this research.

- Space-mean speeds at two stations obtained from a dual-loop detector

As for the dual-loop detector, the spot speeds can be directly calculated according to Equations 3.3 and 3.4. Therefore, during the time interval \([t_{n-1}, t_n]\), and given the measured spot speeds at consecutive locations \(v_{u,i}, v_{d,j}\), the space-mean speeds at the two stations can be described as

\[
v_u = \frac{1}{1 \sum_{i=1}^{m} \frac{1}{v_{u,i}}} \quad i = 1, 2, \ldots, m
\]

(3.9)

\[
v_d = \frac{1}{1 \sum_{j=1}^{n} \frac{1}{v_{d,j}}} \quad j = 1, 2, \ldots, n
\]

(3.10)
(3) Speed extrapolation models based on $v_u,v_d$ assumptions and travel time $tt(t_n)$

There are various assumptions that describe the way the space-mean speeds at the two stations change along the freeway link. Among these assumptions are three speed extrapolation models that estimate travel time. These models are discussed in the following.

- Speed Extrapolation Model 1

This speed extrapolation model assumes that acceleration $a$ between the speeds $v_u,v_d$ is constant versus time $t$ across the freeway link. Based on this assumption, parameters such as acceleration, speed and distance can be stated as the following equations, respectively.

Acceleration rate: $a = \frac{v_d - v_u}{tt(t_n)}$ (3.11)

Speed at time $t$ during the link: $v = v_u + at$ (3.12)

Distance that the vehicle traveled at time $t$: $s = \frac{[v + v_u]t}{2}$ (3.13)

Given the condition that $v = v_d$, $t = tt(t_n)$ and $s = x_d - x_u$, the average link travel time $tt(t_n)$ during the time interval $[t_{n-1}, t_n]$ can be derived as

$$tt(t_n) = \frac{2(x_d - x_u)}{v_d + v_u}$$ (3.14)
• Speed Extrapolation Model 2

In the second speed extrapolation model, it is assumed that acceleration \( a \) between the speeds \( v_u, v_d \) is constant versus distance \( s \) traveled along the link.

Acceleration rate: \[ a = \frac{v_d - v_u}{x_d - x_u} \] (3.15)

The speed along the link can be defined as

\[ v = v_u + as \] (3.16)

\[ \Rightarrow \frac{ds}{dt} = v_u + as \quad \Rightarrow \frac{ds}{v_u + as} = dt \]

\[ \Rightarrow \int_0^t \frac{ds}{v_u + as} = \int_0^t dt = \frac{1}{a} \ln(v_u + as) + c = t \]

\( t = 0, s = 0 \)

\[ \Rightarrow c = -\frac{1}{a} \ln v_u \]

\[ \Rightarrow \frac{1}{a} \ln(v_u + as) - \frac{1}{a} \ln v_u = t \] (3.17)

When \( s = x_d - x_u \), \( t = tt(t_n) \), then the average link travel time \( tt(t_n) \) during the time interval \([t_{n-1}, t_n]\) can be derived as

\[ tt(t_n) = \frac{1}{a} \ln(v_u + \frac{v_d - v_u}{x_d - x_u} * (x_d - x_u)) - \frac{1}{a} \ln v_d = \frac{1}{a} \left( \ln v_d - \ln v_u \right) \]
This third speed extrapolation model assumes that the change in pace $1/v$ is constant versus distance $s$ traveled along the link.

Average change rate:

$$c = \frac{1/v_d - 1/v_u}{x_d - x_u}$$  \hspace{1cm} (3.19)

The change in pace versus distance can be defined as

$$\frac{1}{v} = \frac{1}{v_u} + cs$$  \hspace{1cm} (3.20)

$$\Rightarrow \frac{1}{ds/\,dt} = \frac{1}{v_u} + cs$$

$$\Rightarrow dt = \left(\frac{1}{v_u} + cs\right)ds$$

$$\Rightarrow \int_0^t dt = \int_0^s \left(\frac{1}{v_u} + cs\right)ds$$

$$\Rightarrow t = \frac{s}{v_u} + \frac{cs^2}{2}$$  \hspace{1cm} (3.21)
When \( s = x_d - x_u \), \( t = t(t_n) \), then the average link travel time \( t(t_n) \) during the time interval \([t_{n-1}, t_n]\) can be calculated as

\[
\frac{x_d - x_u}{v_u} + \frac{(x_d - x_u)^2}{2} \left[ \frac{1}{v_d} - \frac{1}{v_u} \right] = \frac{\Delta x}{2} \left[ \frac{1}{v_u} + \frac{1}{v_d} \right] = \frac{\Delta x + \Delta x}{2}
\]

(3.22)

(4) Relationship of travel times based on the three speed extrapolation models

To derive the relationships among the estimated travel times obtained from the three different speed extrapolation models, the equations in the models need to be combined into a uniform equilibrium based on the following procedures.

Model 1, from Equation 3.12:

\[
v = v_u + at = v_u + \frac{v_d - v_u}{t(t_n)}
\]

\[
v_u + (v_d - v_u) \frac{v_d + v_u}{v + v_u} \frac{s}{x_d - x_u}
\]

\[
v_u + d_1s \quad \quad \quad \quad d_1 = \frac{v_d - v_u}{x_d - x_u} \frac{v_d + v_u}{v + v_u}
\]

Model 2, from Equations 3.15 and 3.16:
Model 3, from Equations 3.19 and 3.20:

\[
v = v_u + as = v_u + \frac{v_d - v_u}{x_d - x_u} s
\]

\[
= v_u + d_2 s \quad \quad \quad \quad \quad \quad d_2 = \frac{v_d - v_u}{x_d - x_u}
\]

\[
\frac{1}{v} = \frac{1}{v_u} + as = \frac{1}{v_u} + \frac{1}{v_d} \frac{v_d - v_u}{x_d - x_u} s
\]

\[
\Rightarrow v = v_u + \frac{(v_d - v_u)}{x_d - x_u} \frac{v}{v_d} s
\]

\[
= v_u + d_3 s \quad \quad \quad \quad \quad \quad d_3 = \frac{v_d - v_u}{x_d - x_u} \frac{v}{v_d}
\]

Then, the three models can be summarized as

\[
v = v_u + ds
\]

\[
d_1 = \frac{(v_d - v_u)}{x_d - x_u} \frac{v_d + v_u}{v + v_u}
\]

\[
d_2 = \frac{v_d - v}{x_d - x_u}
\]

\[
d_3 = \frac{v_d - v}{x_d - x_u} \frac{v}{v_d}
\]

\[
\Rightarrow \quad d_1 > d_2 > d_3 \quad \text{if} \quad v_d > v_u
\]

\[
d_1 = d_2 = d_3 \quad \text{if} \quad v_d = v_u
\]

\[
|d_1| < |d_2| < |d_3| \quad \text{if} \quad v_d < v_u
\]
The figures below describe the relationships between distance $s$ and speed $v$ in these three models under different traffic conditions.

\[ \frac{ds}{dt} = \frac{v}{v} \]

From the figures, for the same $ds$, the speeds of the three models can be shown as

\begin{align*}
\text{if } v_d &\neq v_u \\
\text{Model 1 } &v_1 > \text{Model 2 } v_2 > \text{Model 3 } v_3 \\
\Rightarrow &\text{ Model 1 } dt < \text{Model 2 } dt < \text{Model 3 } dt \\
\therefore &tt(t_n) = \int dt \\
\Rightarrow &\text{ Model 1 } tt(t_n) < \text{Model 2 } tt(t_n) < \text{Model 3 } tt(t_n)
\end{align*}

\begin{align*}
\text{if } v_d &= v_u \\
\text{Model 1 } &v_1 = \text{Model 2 } v_2 = \text{Model 3 } v_3 \\
\Rightarrow &\text{ Model 1 } dt = \text{Model 2 } dt = \text{Model 3 } dt \\
\therefore &tt(t_n) = \int dt \\
\Rightarrow &\text{ Model 1 } tt(t_n) = \text{Model 2 } tt(t_n) = \text{Model 3 } tt(t_n)
\end{align*}
From the previous figures, it can be seen that under traffic conditions that have a $V_d$ different than $V_u$, the travel speed extrapolated from Model 1 is always greater than that from Model 2, which is in turn greater than the speed from Model 3. When $V_d$ equals $V_u$, the estimated travel speeds from the three models maintain the same $V_d$ or $V_u$. Therefore, given the same travel distance $s$, if the space-mean speeds of vehicles passing the two detectors are different, then the travel time for distance $s$ from Model 1 is the shortest, whereas the travel time estimated from Model 3 is the longest, and the estimated travel time estimated from Model 2 is between Model 1 and Model 3. If the space-mean speeds are equal in both the upstream and downstream of the link, then the estimated travel times from the three models are the same.

### 3.1.2 Flow-based Statistic Models

The probabilistic regression model and the cross-correlation model are two types of statistical models that can be applied to estimate travel times from traffic flow data at upstream and downstream locations. Next, these two models are described in detail.

**1) Probabilistic Regression Model**

The probabilistic regression model presented by Petty et al (1998) is based on the assumption that the arrivals measured at the upstream point during a given time interval have the same probability density function as the average travel time over the link. With the relationship between the upstream traffic flow and downstream flow stated in the assumption, the travel time density function can be estimated from the cumulative flow measured at the
two stations by minimizing the sum of the squares of the regression residual errors. Therefore, the average travel time is equal to the fit range of times multiplied by probability density.

Two fixed-point detectors are located at the upstream location and downstream location. During time interval \([b_1, b_2]\), the number of vehicles that reach the two stations at time \(t\) are \(x(t)\) and \(y(t)\), \(t \in [b_1, b_2]\). Let \(f_i\) denote the density of travel time \(i\). In the field, the range of the travel times over the freeway link is defined as \([a_1, a_2]\).

![Diagram of travel times](image)

Under this assumption, the density \(f_i\) of travel time \(i\) does not change with time \(t\). That is, for each upstream arrival \(x(t)\) \(t \in [b_1, b_2]\), the density of travel time \(i\) is \(f_i\). Also, the downstream arrival \(y(t)\) at time \(t\) comes from the upstream flow \(x(t-i)\) \(i \in [a_1, a_2]\). Thus, the arrivals at the downstream point can be modeled as
The density function $f_i$, $i \in [a_1, a_2]$ can be estimated by minimizing the sum of the square errors from Equation 3.23, as follows:

$$y(t) = \sum_{i=a_1}^{a_2} [x(t - i) f_i]$$  \quad (3.23)

subject to \quad \left\{ f : f_i \geq 0, \sum_{i=a_1}^{a_2} f_i = 1 \right\} \quad (3.25)

Then, the estimated travel time during the time interval $[b_1, b_2]$ is

$$tt = \sum_{i=a_1}^{a_2} f_i i$$  \quad (3.26)

In practice, in order to use Equations 3.23 and 3.24, the arrivals at the upstream and downstream $x(t), y(t)$ should be aggregated in a discrete time length $\Delta$, and $b_1, b_2, a_1, a_2$ are assumed to be multiples of $\Delta$. Then, Equation 3.23 can be converted to

$$y(t) = \sum_{i=a_1/\Delta}^{a_2/\Delta - 1} [x(t - i) f_i]$$  \quad (3.27)

And Equation 3.24 can be converted as
\[
\sum_{i=(b_1 + a_1)/\Delta}^{(b_2 + a_2)/\Delta} \left( y(t) - \sum_{i=a_1/\Delta}^{a_2/\Delta} [x(t-i)f_i] \right)^2
\]

Subject to: \( f : f_i \geq 0, \sum_{i=a_1}^{a_2} f_i = 1 \) \hfil (3.28)

The estimated travel time during the time interval \([b_1, b_2]\) is

\[
 tt = \Delta \sum_{i=a_1}^{a_2} f_i i
\]

Several parameters can affect the accuracy of the model and are discussed in the following.

- Aggregation time length \( \Delta \)

According to Equation 3.27, and given \( a_1, a_2 \), the number of parameters \( f_i \) is \( \frac{a_2 - a_1}{\Delta} - 1 \). If \( \Delta \) is too small, there are too many parameters \( f_i \) to be estimated, which would lead to unreliable results due to the resultant instability. If \( \Delta \) is too large, some necessary parameters could be lost, thus leading to a biased result (Petty 1998). Petty (1998) found that \( \Delta = 1 \) sec seems to be an appropriate aggregation time length; this aggregation time length is used in this dissertation.

- Time interval \([b_1, b_2]\)

The probabilistic regression model is based on the assumption that the travel time
distribution is constant within the time interval \([b_1, b_2]\). However, if the range of the time interval is too wide, the conditions experienced during the time interval may not be stable, and the traffic may vary between free-flow, transition and congestion. Thus, the requirement of a consistent travel time distribution cannot be satisfied. If the value \(b_2 - b_1\) is too small or even less than the travel time, not enough parameters are available to estimate the travel time if there are no traffic data for the future time intervals. So, Equation 3.28 is modified as

\[
\sum_{t=(b_1+a_1)/\Delta}^{b_2/\Delta-1} \left( y(t) - \sum_{i=a_1/\Delta}^{a_2/\Delta-1} \left[ x(t-i) f_i \right] \right)^2
\]

(3.30)

In this study, different time scales -2 minutes, 5 minutes and 10 minutes- are used to estimate the travel times, and the results are compared to verify the effect of time scale on the model.

- Fit range of travel time \([a_1, a_2]\)

As explained in the discussion of the aggregation time length \(\Delta\), and given \(\Delta = 1\text{sec}\), the density parameter \(f_i\) has a positive correlation with \(a_2 - a_1\). If the fit range is too wide, the estimated parameters are too numerous, and the solution in the optimization solver is unstable. If the fit range is too narrow, the resolution and accuracy may be too poor to obtain an appropriate density (Guo and Jin 2006). Petty (1998) offered some suggestions about determining the fit range. The central value can be calculated from the spot speed estimates obtained from the flow-speed relationship, i.e., \(v = \frac{q}{O* g}\), and the fit range could be 20
seconds. The speed extrapolation model using the single-loop detector has been discussed in Section 3.1.1, but it is not used in this study due to the clearly evident effect of the vehicle length error on the travel time estimation. In this dissertation, the central value of the fit range is determined from five models: 1) the true value during the current time interval or the most recent time interval, 2) the upstream space-mean speed measurements, 3) speed extrapolation Model 1, 4) the dynamic traffic flow model, or 5) the modified traffic flow model. Then, the estimated travel times are compared to verify the appropriate fit range of the regression model.

(2) Cross-Correlation Model

Cross correlation is a standard statistical method to estimate the degree of correlation between two series. For the purposes here, the cross-correlation model is applied to analyze the correlation of the aggregation flow at the upstream and downstream by calculating the correlation coefficients at various delays. Then, the travel time is estimated from the time delay which generates the maximum cross correlation or the significant correlation, thus resulting in two different models: the maximum cross-correlation model (Dailey 1993) and the significant cross-correlation model (Guo and Jin 2006).

- Maximum Cross-Correlation Model

A fixed-point detector is located at both the upstream location and downstream location. During time interval $[b_1, b_2]$, the number of vehicles arriving at the two stations at time $t$ are
\(x(t)\) and \(y(t)\), \(t \in [b_1, b_2]\). The cross-correlation coefficient of \(x(t)\) and \(y(t)\) at delay \(k\) is defined as

\[
\rho_{xy}(k) = \frac{\sum_{t=b_1+k}^{b_2} (x(t-k) - \bar{x})(y(t) - \bar{y})}{\sqrt{\sum_{t=b_1+k}^{b_2} (x(t-k) - \bar{x})^2 \left[\sum_{t=b_1+k}^{b_2} (y(t) - \bar{y})^2\right]}}
\]  

(3.31)

where \(\bar{x}\) and \(\bar{y}\) are the means of the traffic flow at the upstream and downstream series,

\[
\bar{x} = \frac{\sum_{t=b_1}^{b_2} x(t)}{b_2 - b_1 + 1}
\]

(3.32)

\[
\bar{y} = \frac{\sum_{t=b_1}^{b_2} y(t)}{b_2 - b_1 + 1}
\]

The maximum cross-correlation model assumes that the average travel time of vehicles passing over the link is the constant (Dailey 1993). If the fixed travel time is defined as \(k\), then under the assumption, the downstream arrivals \(y(t)\) at time \(t\) come from the upstream flow \(x(t-k)\), which is shown as the following figure. Thus, the arrivals at the downstream point can be modeled as

\[
y(t) = x(t-k) \quad t \in [b_1 + k, b_2]
\]

(3.33)
Inserting Equation 3.33 into Equation 3.31 approximates the ideal cross-correlation coefficient $\rho_{xy}(k)$ to be close to 1. Therefore, the fixed travel time $tt$ is equal to the time delay $k$ where the cross-correlation coefficient is closest to 1, i.e. $tt = f^{-1}(\rho_{xy}(k) \approx 1)$.

However, in practice, due to errors of the difference of $\bar{x} - \bar{y}$ and the various travel times among the different vehicles, the cross-correlation coefficients are far away from 1. Then, the maximum cross-correlation model assumes that the average travel time is the time delay of the maximum correlation degree (i.e., the maximum cross-correlation coefficient) between the upstream and downstream flows.

$$tt = \max^{-1}(\rho_{xy}(k)) \quad \text{(3.34)}$$

Also, to calculate the cross-correlation coefficients $\rho_{xy}(k)$, the arrivals at the upstream and
downstream $x(t), y(t)$ should be aggregated in a discrete time length $\Delta$, and $b_1, b_2, k$ are assumed to be multiples of $\Delta$. Then, the cross-correlation coefficient $\rho_{yx}(k)$ is modified as

$$\rho_{yx}(k) = \frac{\sum_{t=(b_1+k)/\Delta}^{b_2/\Delta} (x(t-k) - \bar{x})(y(t) - \bar{y})}{\sqrt{\sum_{t=(b_1+k)/\Delta}^{b_2/\Delta} (x(t-k) - \bar{x})^2 \sum_{t=(b_1+k)/\Delta}^{b_2/\Delta} (y(t) - \bar{y})^2}}$$

(3.35)

Then, the average travel time during the time interval $[b_1, b_2]$ is

$$tt = \Delta \ast \text{max}^{-1}\left(\rho_{yx}(k)\right)$$

(3.36)

- **Significant Cross-Correlation Model**

The significant cross-correlation model integrates the cross-correlation analysis with the probabilistic regression model in which the travel times of vehicles passing the upstream detection are considered as random variables and have the same probability density over the link (Guo and Jin 2006).

Following the assumption of the probabilistic model, during the time interval $[b_1, b_2]$, the upstream arrival $x(t)$ has the constant density function $f_i$ of travel time $i \in [a_1, a_2]$, and the downstream arrivals $y(t)$ at time $t$ come from the upstream flow $x(t-i)$ $i \in [a_1, a_2]$, which is modeled as
\[ y(t) = \sum_{i=d_1}^{a_2} [x(t-i)f_i] \quad (3.23) \]

And then \[ \overline{y} = \sum_{i=d_1}^{a_2} [\overline{x}f_i] \quad (3.37) \]

According to the cross-correlation analysis, the cross-correlation coefficient of \( x(t) \) and \( y(t) \) at delay \( k \) is defined as

\[
\rho_{yx}(k) = \frac{\sum_{t=a_1+k}^{b_2} (x(t-k) - \overline{x})(y(t) - \overline{y})}{\sqrt{\sum_{t=a_1+k}^{b_2} (x(t-k) - \overline{x})^2 \left[ \sum_{t=a_1+k}^{b_2} (y(t) - \overline{y})^2 \right]}}
\quad (3.31)
\]

After inserting Equations 3.23 and 3.37, Equation 3.31 becomes

\[
\rho_{yx}(k) = \frac{\sum_{t=a_1+k}^{b_2} (x(t-k) - \overline{x}) \left( \sum_{i=d_1}^{a_2} x(t-i)f_i - \sum_{i=d_1}^{a_2} \overline{x}f_i \right)}{\sqrt{\sum_{t=a_1+k}^{b_2} (x(t-k) - \overline{x})^2 \left[ \sum_{t=a_1+k}^{b_2} (y(t) - \overline{y})^2 \right]}}
\]

\[
= \frac{\sum_{i=d_1}^{a_2} f_i \left( \sum_{t=a_1+k}^{b_2} (x(t-k) - \overline{x})(x(t-i) - \overline{x}) \right)}{\sqrt{\sum_{t=a_1+k}^{b_2} (x(t) - \overline{x})^2 \left[ \sum_{t=a_1+k}^{b_2} (y(t) - \overline{y})^2 \right]}}
\]
\[
\sqrt{\frac{\sum_{t=h}^{b_h-k} (x(t) - \bar{x})}{\sum_{t=h+k}^{b_k} (y(t) - \bar{y})}} \sum_{i=a_k} f_i \frac{\sum_{j=h+k}^{b_h-k} (x(t-k) - \bar{x})(x(t-i) - \bar{x})}{\sqrt{\sum_{t=h}^{b_h} (x(t) - \bar{x})^2 \sum_{t=h}^{b_h} (x(t) - \bar{x})^2}}
\]

\[
= \sqrt{\frac{\sum_{t=h}^{b_h-k} (x(t) - \bar{x})^2}{\sum_{t=h+k}^{b_k} (y(t) - \bar{y})^2}} \sum_{i=a_k} f_i \rho_{xx}(i-k)
\]

(3.38)

Assume the upstream flow \( x(t) \) to be independent samples,

\[
\rho_{xx}(i-k) = \begin{cases} 
1 & i = k \\
0 & \text{others}
\end{cases}
\]

(3.39)

Then, Equation 3.38 can be converted to

\[
\rho_{yx}(k) = \sqrt{\frac{\sum_{t=h}^{b_h-k} (x(t) - \bar{x})^2}{\sum_{t=h+k}^{b_k} (y(t) - \bar{y})^2}} f_k
\]

\[
\Rightarrow f_k = \sqrt{\frac{\sum_{t=h+k}^{b_k} (y(t) - \bar{y})^2}{\sum_{t=h}^{b_h} (x(t) - \bar{x})^2}} \rho_{yx}(k)
\]

(3.40)

Equation 3.40 shows that the probability density function \( f_k \) can be determined by all the
nonzero cross-correlation coefficients \( \rho_{xy}(k) \). However, due to the unknown true value of \( \rho_{xy}(k) \), the sample cross-correlation function \( \hat{\rho}_{xy}(k) \) is used in practice. To calculate the \( \hat{\rho}_{xy}(k) \), the arrivals at the upstream and downstream \( x(t), y(t) \) should be aggregated in a discrete time length \( \Delta \), and \( b_1, b_2, k \) are assumed to be multiples of \( \Delta \). Then, the cross-correlation coefficient \( \hat{\rho}_{xy}(k) \) is modified as the following:

\[
\hat{\rho}_{xy}(k) = \frac{\sum_{t=(b_1+k)/\Delta}^{b_2/\Delta} (x(t-k) - \bar{x})(y(t) - \bar{y})}{\sqrt{\sum_{t=(b_1+k)/\Delta}^{b_2/\Delta} (x(t) - \bar{x})^2 \sum_{t=(b_1+k)/\Delta}^{b_2/\Delta} (y(t) - \bar{y})^2}}
\]  

(3.41)

\[
\bar{x} = \frac{\sum_{t=b_1/\Delta}^{b_2/\Delta} x(t)}{b_2/\Delta - b_1/\Delta + 1} \quad \bar{y} = \frac{\sum_{t=b_1/\Delta}^{b_2/\Delta} y(t)}{b_2/\Delta - b_1/\Delta + 1}
\]

Whether the cross-correlation coefficient \( \hat{\rho}_{xy}(k) \) is zero or not can be determined by applying the statistical hypothesis t-test, as follows:

\[
H_0 : \rho_{xy}(k) = 0
\]

\[
H_1 : \rho_{xy}(k) \neq 0
\]  

(3.42)

If there are sufficient data at the time interval \([b_1, b_2] \), then \( \hat{\rho}_{xy}(k) \) under \( H_0 \) follows a normal distribution with mean zero and the standard deviation \( \sigma_{\hat{\rho}} \), i.e., \( \sigma_{\hat{\rho}} = \frac{1}{\sqrt{n}} \), where \( n \) is
the number of data points and \( n = \frac{b_2 - b_1 - k}{\Delta} + 1 \).

\[
\hat{\rho}_{xy}(k) \sim N(0, \frac{1}{\sqrt{1 + \frac{(b_2 - b_1 - k)}{\Delta}}})
\]

Given a confidence level \( \alpha \) value, the t-test that is used to check if \( \hat{\rho}_{xy}(k) \) is equal to zero transfers to:

The t-test statistic: 
\[
t_{\rho,k} = \frac{\hat{\rho}_{xy}(k) - 0}{\sigma_{\rho}}
\]  
(3.43)

If \( t_{\rho,k} > t_{1-\alpha/2,n} \), \( H_0 \) is rejected and the cross-correlation coefficient \( \hat{\rho}_{xy}(k) \) is significant.

Then, the probabilistic density \( f_k \), which corresponds to the average travel time \( \Delta^* k \), can be estimated according to Equation 3.40.

During the time interval \([b_1, b_2]\), if the number of the density \( f_{c_i} \), estimated from all the significant coefficients \( \hat{\rho}_{xy}(c_i) \), is \( m \), and the corresponding average travel time is \( \Delta^* c_i \), then the estimated travel time over the link is the mean estimate of the average travel time \( \Delta^* c_i \), which is obtained as

\[
tt = \Delta \frac{i=1}{m} f_{c_i} c_i = \Delta \frac{\sum_{i=1}^{i=m} (f_{c_i} * c_i)}{\sum_{i=1}^{i=m} f_{c_i}} = \Delta \frac{\sum_{i=1}^{i=m} (\hat{\rho}_{xy}(c_i) * c_i)}{\sum_{i=1}^{i=m} \hat{\rho}_{xy}(c_i)}
\]  
(3.44)
Overall, the two cross-correlation models are based on the cross correlation of the aggregated upstream and downstream flow per time interval. The traffic flow, time interval $[b_1, b_2]$, aggregation time length $\Delta$ and time delay $k$, which together determine the correlation coefficients, can affect the model’s accuracy and application. These factors are discussed in the following paragraphs.

- Traffic flow of the two stations

If under the congestion condition, the transition condition or the free-flow condition with multiple lanes, the traffic flow $x(t), y(t)$ of all the lanes at each station is large and close to average flows $\bar{x}, \bar{y}$, then all the cross-correlation coefficients $\rho_{yx}(k)$ calculated from Equation 3.31 are equal to zero and are not significant using the statistical hypothesis of Equations 3.42 and 3.43. In other words, there is no cross correlation between the two station flows under such conditions, and thus the travel time cannot be estimated.

- Time interval $[b_1, b_2]$

According to the previous analysis, if the traffic condition is considered to be transition or congestion, the travel time cannot be calculated due to the lack of cross correlation. Thus, the time interval $[b_1, b_2]$, in which the traffic may vary between free-flow, transition and congestion, cannot be too long. Moreover, during the time interval $[b_1, b_2]$, if the traffic is only under the free-flow condition, the length of the time interval can affect the accuracy of the travel time estimation.
The assumption of the maximum cross-correlation model is that the travel time during the time interval is constant. The significant cross-correlation model assumes that the travel time distribution is constant within the time interval. With the lengthening of the time interval, there are more upstream vehicles with different travel times and also more data to satisfy the normal distribution of $\hat{\rho}_{yx}(k)$ under $H_0$. Thus, the significant model may exhibit better performance than the maximum model. In the later quantity analysis, the time intervals 2 minutes, 5 minutes and 10 minutes are used to estimate the travel time. The results are compared to verify the effect of time scale in the two models.

- Aggregation time length $\Delta$

Equations 3.35 and 3.41 show that, given $b_1, b_2, k$, the number of flow parameters needed to estimate the coefficients and to verify the normal distribution equals $\frac{b_2 - b_1 - k}{\Delta} + 1$. If $\Delta$ is too large, there are not enough data to obtain the significant coefficients, and the assumption of the normal distribution of $\hat{\rho}_{yx}(k)$ under $H_0$ cannot be satisfied; thus, the travel time cannot be estimated from these two models. Guo and Jin (1998) used $\Delta = 1\text{sec}$ to estimate the travel time, which satisfies the results. In this dissertation, the aggregation time length selected is 1 second.

- Time delay $k$

The number of the estimated cross coefficients $\hat{\rho}_{yx}(k)$ is $k$. If the range of the time delay $k$
is too wide, then the estimated coefficients are numerous, and the significant $\hat{\rho}_s(k)$ may be
not in practice. If the range is too narrow, then some appropriate time delays are not included,
and the estimated travel time is biased. In the Guo and Jin study (2006), the range of time
delay $k$ is $[0, 35]$, with an average travel time 22 seconds. To improve the accuracy of the
models, the time delay $k$ should be in a true value range; this will be discussed in the later
analysis.

3.1.3 Dynamic Traffic Flow Models

The dynamic traffic flow model first presented by Nam and Drew (1998) is based on the
stochastic process in traffic flow theory and the concept of the conservation of vehicles. The
model uses the cumulative traffic flow of upstream and downstream to estimate the travel
time over the freeway link. In the model, the initial traffic on the link is required, the density
is calculated from the cumulative flow measurements, cumulative arrival-departure flow
diagrams are used to estimate travel time, and the vehicles considered as targets for the travel
time estimation are different for both the free-flow and congestion conditions, which
provides two separate models with different diagrams in different traffic situations.
Vanajakshi (2004, 2008) modified the model by: combining the two separate models into one
using the same targeted vehicles; using the speed extrapolation model for low traffic flow
conditions; suggesting an estimation of density from occupancy; and providing an
optimization to verify the initial traffic flow. This dissertation also proposes some
modifications to the model using the cumulative flow diagrams.
(1) Dynamic Traffic Flow Model (Nam and Drew Model)

The theoretical concept of the dynamic traffic flow model, also called the Nam and Drew model, is based on the stochastic process and conservation of vehicles. As such, the equation of the model can be derived from the flow-density-speed relationship and the diagram of the cumulative flows of the two stations, as the following procedures indicate.

- **Stochastic Process**

In the stochastic process, the two stations’ cumulative flows $Q(x_u, t_n) , Q(x_d, t_n)$ by time $t_n$ ($n \in [1, n]$), defined as the number of vehicles passing the fixed stations located at the upstream location $x_u$ and downstream location $x_d$ of the freeway link without on/off ramps, are treated as random variables because they have non-negative and non-decreasing characteristics.

Accordingly, the number of vehicles on the freeway link at time $t_n$ is $Q(x_u, t_n) − Q(x_d, t_n)$ and $Q(x_u, t_n) − Q(x_d, t_n) \geq 0$. And, the vehicles passing the upstream and downstream stations during the time interval $(t_{n-1}, t_n]$ are $Q(x_u, t_n) − Q(x_u, t_{n-1})$ and $Q(x_d, t_n) − Q(x_d, t_{n-1})$.
• Conservation of vehicles

Naming $q(x_u, t_n)$ and $q(x_d, t_n)$ as the flow rates at the upstream and downstream at the time interval $(t_{n-1}, t_n]$, $k(t_n)$ as the density over the freeway link at the time interval $(t_{n-1}, t_n]$, $\Delta t$ is the time interval fixed length, i.e., $\Delta t = t_n - t_{n-1}, n \in [1, n]$, and $\Delta x$ is the length of the freeway link, i.e., $\Delta x = x_d - x_u$.

Then, during the time interval $(t_{n-1}, t_n]$, the vehicles passing the upstream and downstream locations are

$$q(x_u, t_n) \Delta t$$
$$q(x_d, t_n) \Delta t$$

The vehicles traveling over the freeway link at time $t_n$ are

$$k(t_n) \Delta x$$

According to the stochastic analysis in the above section, the equations can be derived as

$$Q(x_u, t_n) - Q(x_u, t_{n-1}) = q(x_u, t_n) \Delta t$$

(3.45)

$$Q(x_d, t_n) - Q(x_d, t_{n-1}) = q(x_d, t_n) \Delta t$$

(3.46)

$$Q(x_u, t_n) - Q(x_d, t_n) = k(t_n) \Delta x$$

(3.47)

Subtracting Equation 3.46 from Equation 3.45 gives
\[
\left[ Q(x_u, t_n) - Q(x_u, t_{n-1}) \right] - \left[ Q(x_d, t_n) - Q(x_d, t_{n-1}) \right] = q(x_u, t_n) \Delta t - q(x_d, t_n) \Delta t
\]

\[
\Rightarrow q(x_u, t_n) \Delta t - q(x_d, t_n) \Delta t = \left[ Q(x_u, t_n) - Q(x_u, t_{n-1}) \right] - \left[ Q(x_d, t_n) - Q(x_d, t_{n-1}) \right]
\]

(3.48)

Inserting Equation 3.47 into Equation 3.48 gives

\[
q(x_u, t_n) \Delta t - q(x_d, t_n) \Delta t = k(t_n) \Delta x - k(t_{n-1}) \Delta x
\]

(3.49)

where

\[
q(x_u, t_n) \Delta t - q(x_d, t_n) \Delta t \text{ is the difference between the number of vehicles entering the link flow and the number departing it during the time interval } (t_{n-1}, t_n).
\]

\[
k(t_n) \Delta x - k(t_{n-1}) \Delta x \text{ represents the change in the number of vehicles traveling on the freeway link during the same time interval.}
\]

Therefore, according to Equation 3.49, it can be verified that the difference between the number of vehicles entering the link flow and the number departing it during the time interval corresponds to the change in the number of vehicles traveling on the freeway link during the same time interval, which is the principle of the conservation of vehicles.

- Flow-density-speed relationship

From Equations 3.45 and 3.46, the relationship between cumulative flow and flow rate is expressed as
\[ Q(x_u, t_n) - Q(x_u, t_{n-1}) = q(x_u, t_n) \Delta t \]
\[ Q(x_d, t_n) - Q(x_d, t_{n-1}) = q(x_d, t_n) \Delta t \]

\[ \Rightarrow Q(x_u, t_n) = q(x_u, t_n) \Delta t + Q(x_u, t_{n-1}) \]
\[ = q(x_u, t_n) \Delta t + q(x_u, t_{n-1}) \Delta t + Q(x_u, t_{n-2}) \]
\[ = q(x_u, t_n) \Delta t + q(x_u, t_{n-1}) \Delta t + \ldots + q(x_u, t_1) \Delta t \quad (3.50) \]
\[ = \Delta t \sum_{i=1}^{n} q(x_u, t_i) \]

\[ \Rightarrow Q(x_d, t_n) = \Delta t \sum_{j=1}^{n} q(x_d, t_j) \quad (3.51) \]

From Equation 3.47, the relationship between density and cumulative flow is presented as

\[ k(t_n) = \frac{Q(x_u, t_n) - Q(x_d, t_n)}{\Delta x} \quad (3.53) \]

The initial conditions are

\[ Q(x_u, t_0) = 0, Q(x_d, t_0) = -n(t_0), k(t_0) = \frac{n(t_0)}{\Delta x} \quad (3.52) \]

where \( n(t_0) \) is the number of vehicles traveling on the freeway link at time \( t_0 \).

Let \( n(t_n) \) be the number of vehicles traveling on the freeway link at time \( t_n \):

\[ n(t_n) = Q(x_u, t_n) - Q(x_d, t_n) \quad (3.53) \]

Let \( m(t_n) \) be the number of vehicles entering and leaving the link during the time interval
\((t_{n-1}, t_n]\), which can be derived as

\[
m(t_n) = Q(x_d, t_n) - Q(x_d, t_{n-1}) - n(t_{n-1})
= Q(x_d, t_n) - Q(x_d, t_{n-1}) - [Q(x_u, t_{n-1}) - Q(x_d, t_{n-1})]

= Q(x_d, t_n) - Q(x_u, t_{n-1}) \tag{3.54}
\]

Let \(u_f\) be the free-flow speed of the vehicles over the link. Under some appropriate

\[\Delta t, \Delta t > \frac{\Delta x}{u_f}\]

, the model assumes that \(m(t_n)\) is the performance measurement necessary to
determine the traffic flow conditions:

Normal flow: \(m(t_n) > 0\)

Congestion flow: \(m(t_n) \leq 0\)

And, under the different traffic conditions, two separate equations from the cumulative flow diagrams are used to estimate travel time; these equations are described in the next section.

- Cumulative flow diagram and travel time in normal-flow condition

Figure 3.3 shows a diagram of the cumulative flows at the upstream and downstream under
normal-flow conditions, \(m(t_n) > 0, Q(x_d, t_n) > Q(x_u, t_{n-1})\).

It can be seen that the diagram assumes that the initial condition is known, the cumulative
flow curve per time interval is smooth, and the flows \(q(x_u, t_n), q(x_d, t_n)\) are constant during
the time interval \((t_{n-1}, t_n]\). The total travel time for the vehicles \(m(t_n)\) that enter and leave the
link during the time interval \((t_{n-1}, t_n]\) is indicated schematically in Figure 3.3 as the shaded area.

![Figure 3.3: Schematic representation of the total travel time during the interval \((t_{n-1}, t_n]\) under normal-flow conditions. (Source: Nam and Drew, 1999, Figure 2)](image)

Thus, the total travel time is

\[
T(t_n) = \frac{1}{2} \left[ (t_1' - t_{n-1}) + (t_n - t_1') \right] m(t_n) \tag{3.55}
\]

where

\(t_1'\): expected departure time from the link of the first vehicle that enters the link at the time interval \((t_{n-1}, t_n] \)
\( t' \): arrival time into the link of the last vehicle that departs the link during interval \((t_{n-1}, t_n)\)

From Figure 3.3, it can be seen that

\[
\begin{align*}
t' - t_{n-1} &= \frac{Q(x_u, t_{n-1}) - Q(x_d, t_{n-1})}{q(x_d, t_n)} = \frac{k(t_{n-1})\Delta x}{q(x_d, t_n)} \quad (3.56) \\
t_n - t' &= \frac{Q(x_u, t_n) - Q(x_d, t_n)}{q(x_u, t_n)} = \frac{k(t_n)\Delta x}{q(x_u, t_n)} \quad (3.57)
\end{align*}
\]

Incorporating Equations 3.56 and 3.57 with Equation 3.55 derives the total travel time as

\[
T(t_n) = \frac{1}{2} \left[ \frac{k(t_{n-1})\Delta x}{q(x_d, t_n)} + \frac{k(t_n)\Delta x}{q(x_u, t_n)} \right] m(t_n) = \frac{\Delta x}{2} \left( \frac{k(t_{n-1})}{q(x_d, t_n)} + \frac{k(t_n)}{q(x_u, t_n)} \right) m(t_n) \quad (3.58)
\]

The average travel time \( \bar{t}(t_n) \) is the total travel time \( T(t_n) \) divided by \( m(t_n) \):

\[
\bar{t}(t_n) = \frac{T(t_n)}{m(t_n)} = \frac{\Delta x}{2} \left( \frac{k(t_{n-1})}{q(x_d, t_n)} + \frac{k(t_n)}{q(x_u, t_n)} \right) \quad (3.59)
\]

- Cumulative flow diagram and travel time under the congested flow condition

Figure 3.4 shows a diagram of the cumulative flow at the upstream and downstream under congestion-flow conditions, \( m(t_n) \leq 0 \), \( Q(x_d, t_n) \leq Q(x_u, t_{n-1}) \).
The assumptions in the diagram include: the known initial condition, the smooth cumulative flow curves per time interval, and the downstream flow rate of the interval that is the same as that of the next time interval \((q(x_d, t_n) = q(x_d, t_{n+1}))\).

Due to \(m(t_n) \leq 0\), no vehicles enter the link during the time interval and exit the link during the same interval; thus, the travel time is based on all the vehicles \(n(t_n)\) that enter the link during the time interval \([t_{n-1}, t_n]\). The total travel time \(T(t_n)\) for the vehicles \(n(t_n)\) is shown in Figure 3.4 as the shaded area.

Thus, the total travel time is

\[
T(t_n) = \frac{1}{2} \left[ (t' - t_{n-1}) + (t'' - t_n) \right] n(t_n) \tag{3.60}
\]

where
\( t^* \): expected departure time from the link of the first vehicle that enters the link at the time interval \( (t_{n-1}, t_n) \)

\( t^- \): expected departure time from the link of the last vehicle that enters the link at the time interval \( (t_{n-1}, t_n) \)

From Figure 3.4, it can be seen that

\[
t^* - t_{n-1} = \frac{Q(x_n, t_{n-1}) - Q(x_d, t_{n-1})}{q(x_d, t_n)} = \frac{k(t_{n-1})\Delta x}{q(x_d, t_n)}
\]  \( (3.61) \)

\[
t^- - t_n = \frac{Q(x_n, t_n) - Q(x_d, t_n)}{q(x_d, t_{n+1})} = \frac{k(t_n)\Delta x}{q(x_d, t_{n+1})}
\]  \( (3.62) \)

By inserting Equations 3.61 and 3.62 into Equation 3.60, and also assuming that \( q(x_d, t_n) = q(x_d, t_{n+1}) \), the total travel time is

\[
T(t_n) = \frac{1}{2} \left[ \frac{k(t_{n-1})\Delta x}{q(x_d, t_n)} + \frac{k(t_n)\Delta x}{q(x_d, t_{n+1})} \right] n(t_n) = \frac{1}{2} \left[ \frac{k(t_{n-1})\Delta x}{q(x_d, t_n)} + \frac{k(t_n)\Delta x}{q(x_d, t_{n+1})} \right] n(t_n)
\]

\[
= \frac{\Delta x}{2} \frac{k(t_{n-1}) + k(t_n)}{q(x_d, t_n)} n(t_n)
\]  \( (3.63) \)

The average travel time \( tt(t_n) \) is the total travel time \( T(t_n) \) divided by \( n(t_n) \):

\[
T(t_n) = \frac{\Delta x}{2} \frac{k(t_{n-1}) + k(t_n)}{q(x_d, t_n)}
\]  \( (3.64) \)
In the Nam and Drew model, the distinction between normal and congested flow is based on whether a vehicle enters the link during the time interval and leaves during the same interval. If no vehicles depart during the interval, the condition is considered congested flow, and so the travel time is averaged for all the vehicles that enter during the time interval. Under normal-flow conditions, the model considers only the vehicles that enter and exit the link during the same interval, and so, a portion of the vehicles are not used for travel time estimation. However, under the transition condition, only a small portion of the vehicles exit at the interval and could be used for travel time estimation in the normal-flow model, but this model thereby ignores the majority of the vehicles and thus is inappropriate for travel time estimation. Also, as mentioned in Chapter 1, the travel time is the average travel time of the vehicles passing the upstream station or arriving at the downstream station at the time interval; thus, the estimated travel time derived from only some of the vehicles leads to significant error. The normal-flow model was modified by Vanajakshi in 2004 and 2008 such that the travel time can be estimated from all the vehicles that enter the link during the time interval. This modified model is discussed in the next section.

(2) Modified Dynamic Traffic Flow Model by Vanajakshi et al

The Nam and Drew model was modified by Vanajakshi et al in 2004 and 2008. Under normal-flow conditions \( m(t_n) > 0 \), if all the vehicles \( n(t_n) \) that enter the link during the interval are considered for travel time estimation, then the diagram shown in Figure 3.3 can be modified to show the cumulative flows at the two stations, as shown in Figure 3.5.
Figure 3.5: Schematic representation of the total travel time during the interval $(t_{n-1}, t_n)$ under normal-flow conditions. (Source: Vanajakshi et al., 2008, Figure 6a)

For this modified normal-flow model, the following factors are assumed: the known initial condition, the smooth cumulative flow at the time interval (constant $q(x_u, t_n), q(x_d, t_n)$) in the time $(t_{n-1}, t_n)$, and the same downstream flow rates at consecutive intervals ($q(x_d, t_n) = q(x_d, t_{n+1})$). During the time interval $(t_{n-1}, t_n)$, the total travel time $T(t_n)$ of all the vehicles $n(t_n)$ entering the link is shown as the shaded area in Figure 3.5 and is calculated as below.

$$T(t_n) = \frac{1}{2} \left[ (t^* - t_{n-1}) + (t^* - t_n) \right] n(t_n)$$

(3.65)

where
\( t^*\): expected departure time from the link of the first vehicle that enters the link at the time interval \((t_{n-1}, t_n]\)

\( t^*\): expected departure time from the link of the last vehicle that enters the link at the time interval \((t_{n-1}, t_n]\)

Also, the following equations can be derived from Figure 3.5:

\[
t^* - t_{n-1} = \frac{Q(x_n, t_{n-1}) - Q(x_d, t_{n-1})}{q(x_d, t_n)} = \frac{k(t_{n-1})\Delta x}{q(x_d, t_n)} \tag{3.66}
\]

\[
t^* - t_n = \frac{Q(x_n, t_n) - Q(x_d, t_n)}{q(x_d, t_{n+1})} = \frac{k(t_n)\Delta x}{q(x_d, t_{n+1})} \tag{3.67}
\]

Incorporating Equations 3.66 and 3.67, and assuming \(q(x_d, t_n) = q(x_d, t_{n+1})\) using Equation 3.65, the total travel time is represented as

\[
T(t_n) = \frac{1}{2} \left[ \frac{k(t_{n-1})\Delta x}{q(x_d, t_n)} + \frac{k(t_n)\Delta x}{q(x_d, t_{n+1})} \right] n(t_n)
\]

\[
= \frac{1}{2} \left[ \frac{k(t_{n-1})\Delta x}{q(x_d, t_n)} + \frac{k(t_n)\Delta x}{q(x_d, t_{n+1})} \right] n(t_n)
\]

\[
= \frac{\Delta x}{2} \left[ \frac{k(t_{n-1})}{q(x_d, t_n)} + \frac{k(t_n)}{q(x_d, t_{n+1})} \right] n(t_n) \tag{3.68}
\]

The average travel time \(tt(t_n)\) is the total travel time \(T(t_n)\) divided by \(n(t_n)\):
Comparing Equation 3.69 to Equation 3.64, the model for the normal-flow condition is the same as the model for the congestion condition. By considering all the entering vehicles during the same interval in the normal flow, the modified dynamic traffic flow model of Vanajakshi combines the two separate Nam and Drew models into one, which appears to be the most appropriate model to estimate the travel time for transition flow.

However, both the dynamic traffic flow model and the modified model assume that the flow rates of the downstream during consecutive time intervals are the same, which is not always applicable in the field. In reality, the flow rates vary under normal and transition flow conditions. Given the consecutive interval flow rate, a modification to the models is proposed in the next analysis.

Moreover, in the dynamic model, the distinction between normal and congested flow, which is based on the vehicle that enters and exits the link during the same interval, is not necessarily appropriate for all the conditions. For example, if the time interval is long enough, under congestion situations, some vehicles that enter the link can exit, while in the dynamic model this occurrence is considered to be the normal-flow condition. In the modified model, discussed in the next section, the number of vehicles that enter and exit during the same interval is not used to determine the traffic conditions; rather, the different cumulative flow diagrams and the modified models are based on the number of the vehicles.
(3) Modified Dynamic Traffic Flow Model by Yi

Figure 3.6 presents a diagram of the cumulative flow at two detection locations under varying traffic flow conditions, given the downstream flow rate of the subsequent time interval \( q(x_d, t_{n+1}) \) and \( q(x_d, t_n) \neq q(x_d, t_n) \), whereby \( m(t_n) > 0 \Rightarrow Q(x_d, t_n) > Q(x_u, t_{n-1}) \) and \( n(t_n) \) are considered in estimating the travel time.

![Figure 3.6: Schematic representation of the total travel time during the interval \((t_{n-1}, t_n)\) if \( m(t_n) > 0 \). (Source: Vanajakshi et al., 2008, Figure 6a)](image)

Given \( q(x_d, t_{n+1}) \) and \( q(x_d, t_{n+1}) \neq q(x_d, t_n) \), the total travel time \( T(t_n) \) of all the vehicles \( n(t_n) \) entering the link during the time interval \((t_{n-1}, t_n)\) is indicated as the shaded area in Figure 3.6 and is calculated as below.
where

\( t^* \): expected departure time from the link of the first vehicle that enters the link at the time interval \((t_{n-1}, t_n]\)

\( t'' \): expected departure time from the link of the last vehicle that enters the link at the time interval \((t_{n-1}, t_n]\)

\( t' \): entering time into the link of the last vehicle that exits the link during interval \((t_{n-1}, t_n]\)

Also, the following equations can be derived from Figure 3.5:

\[
t^* - t_{n-1} = \frac{Q(x_u, t_{n-1}) - Q(x_d, t_{n-1})}{q(x_d, t_n)} = \frac{k(t_{n-1})\Delta x}{q(x_d, t_n)}
\]

\(3.71\)

\[
t'' - t_n = \frac{Q(x_u, t_n) - Q(x_d, t_n)}{q(x_d, t_{n+1})} = \frac{k(t_n)\Delta x}{q(x_d, t_{n+1})}
\]

\(3.72\)

\[
t_n - t' = \frac{Q(x_u, t_n) - Q(x_d, t_n)}{q(x_u, t_n)} = \frac{k(t_n)\Delta x}{q(x_u, t_n)}
\]

\(3.73\)

Incorporating Equations 3.71, 3.72, and 3.73 into Equation 3.70, the total travel time is
The average travel time $t(t_n)$ is the total travel time $T(t_n)$ divided by $n(t_n)$:

$$tt(t_n) = \frac{T(t_n)}{n(t_n)} = \frac{\Delta x}{2q(x_d,t_n)} \left( k(t_{n-1}) + k(t_n) + \Delta x \left( \frac{k(t_n)^2}{q(x_d,t_{n+1})} - \frac{k(t_{n-1})^2}{q(x_d,t_n)} \right) \right)$$

Figure 3.7 presents a diagram of the cumulative flow at two detection locations whereby $m(t_n) \leq 0 \Rightarrow Q(x_d,t_n) \leq Q(x_u,t_{n-1})$ and $n(t_n)$ is considered in estimating the travel time.

Given $q(x_d,t_n)$ and $q(x_d,t_{n+1}) \neq q(x_d,t_n)$, the total travel time $T(t_n)$ of all the vehicles $n(t_n)$ entering the link during the time interval $(t_{n-1}, t_n)$ is indicated as the shaded area in

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Figure 3.7 and is calculated as below.

\[
T(t_n) = \frac{1}{2} \left[ (t' - t_{n-1}) + (t'' - t_n) \right] n(t_n)
\]

\[
= \frac{1}{2} \left[ \Delta t + (t' - t_n) + (t'' - t_n) \right] n(t_n)
\]

(3.75)

where

\( t' \): expected departure time from the link of the first vehicle that enters the link at the time interval \((t_{n-1}, t_n]\)

\( t'' \): expected departure time from the link of the last vehicle that enters the link at the time interval \((t_{n-1}, t_n]\)

Also, the following equations can be derived from Figure 3.7:

\[
t' - t_n = \frac{Q(x_n, t_{n-1}) - Q(x_d, t_n)}{q(x_d, t_{n+1})} = \frac{k(t_{n-1}) \Delta x - q(x_d, t_n) \Delta t}{q(x_d, t_{n+1})}
\]

(3.76)

\[
t'' - t_n = \frac{Q(x_n, t_n) - Q(x_d, t_n)}{q(x_d, t_{n+1})} = \frac{k(t_n) \Delta x}{q(x_d, t_{n+1})}
\]

(3.77)

Incorporating Equations 3.76 and 3.77 into Equation 3.75, the total travel time is
\[
T(t_n) = \frac{1}{2} \left[ \Delta t + \frac{k(t_{n-1})\Delta x - q(x_d, t_n)\Delta t}{q(x_d, t_{n+1})} + \frac{k(t_n)\Delta x}{q(x_d, t_{n+1})} \right] n(t_n)
\]

\[
= \frac{1}{2} \left[ \Delta t + \frac{k(t_{n-1})\Delta x + k(t_n)\Delta x - q(x_d, t_n)\Delta t}{q(x_d, t_{n+1})} \right] n(t_n)
\]

The average travel time \( tt(t_n) \) is the total travel time \( T(t_n) \) divided by \( n(t_n) \):

\[
tt(t_n) = \frac{T(t_n)}{n(t_n)} = \frac{\Delta t}{2} + \frac{k(t_{n-1})\Delta x + k(t_n)\Delta x - q(x_d, t_n)\Delta t}{2q(x_d, t_{n+1})}
\]

(3.78)

This modified model includes two cumulative flow diagrams, which are based on the vehicles \( n(t_n) \) that enter the link and can exit it during the same interval, and two different equations, which are derived to estimate the average travel time of all the vehicles that enter the link during the interval. The model avoids the distinction between traffic flow conditions based on \( n(t_n) \). Moreover, given the subsequent interval flow rate, the modification considers the varying flow rates to improve the accuracy of the travel time estimation.

However, in all the dynamic traffic flow models, the assumption of smooth cumulative flow curves is not practical for normal-flow conditions, especially for the low-flow condition, and thus, the dynamic traffic flow models are not appropriate for these particular conditions.

**3.1.4 Summary**

In this section, the three categorized methods of travel time estimation that are based on fixed-point data are qualitatively analyzed in detail in terms of each model’s theory, equation derivations, and possible modifications. The number of models to be compared in the
The simulation study is summarized in Table 3.1:

<table>
<thead>
<tr>
<th>Model</th>
<th>Number</th>
</tr>
</thead>
<tbody>
<tr>
<td>Speed extrapolation method</td>
<td></td>
</tr>
<tr>
<td>Speed extrapolation model 1</td>
<td>1</td>
</tr>
<tr>
<td>Speed extrapolation model 2</td>
<td>2</td>
</tr>
<tr>
<td>Speed extrapolation model 3</td>
<td>3</td>
</tr>
<tr>
<td>Dynamic traffic flow method</td>
<td></td>
</tr>
<tr>
<td>Dynamic traffic flow model</td>
<td>4</td>
</tr>
<tr>
<td>Modified dynamic traffic flow model</td>
<td>5</td>
</tr>
<tr>
<td>Statistical method</td>
<td></td>
</tr>
<tr>
<td>Cross-correlation method</td>
<td></td>
</tr>
<tr>
<td>Maximum cross-correlation model</td>
<td>6</td>
</tr>
<tr>
<td>Significant cross-correlation model</td>
<td>7</td>
</tr>
<tr>
<td>Probabilistic regression model</td>
<td></td>
</tr>
<tr>
<td>True TT</td>
<td>8</td>
</tr>
<tr>
<td>Estimated TT from upstream speed</td>
<td>9</td>
</tr>
<tr>
<td>Speed extrapolation method TT</td>
<td>10</td>
</tr>
<tr>
<td>True value of last interval</td>
<td>11</td>
</tr>
<tr>
<td>dynamic traffic flow method TT</td>
<td>12</td>
</tr>
<tr>
<td>Modified dynamic traffic flow method TT</td>
<td>13</td>
</tr>
</tbody>
</table>

### 3.2 Simulation Study

To compare the thirteen models outlined in the previous table in terms of quantity, a simulation study was conducted with the following six components: simulation design, data collection and aggregation, travel time estimation results, traffic condition determination, comparison of measurement performance, and conclusion.

In the simulation study, VISSIM 4.10 software is used to design various freeway links and traffic conditions, generate the traffic data and obtain the true simulated travel time. All the models were tested using the same set of traffic data to estimate the travel time. Also, by
analyzing the relationships among traffic conditions, traffic data, and true and estimated travel times, the appropriate parameters can be selected to determine the traffic conditions. Then, the measurement performance, based on MAE (mean absolute error) and MAPE (mean absolute percentage error), is used to compare the estimated travel time and the true value under various traffic conditions and with different time intervals. Finally, conclusions are drawn regarding the accuracy and application of all the models.

3.2.1 Simulation Design

To create the various traffic condition data for the freeway links, several freeway links with typically sampled link lengths and numbers of lane were designed in VISSIM 4.10. Also, various traffic conditions (free-flow, transition and congestion-flow) were simulated by changing the input traffic flow of the freeway links. The models for the software and details of the simulation design are described in the following section.

(1) VISSIM4.10 Software Introduction and the Inside Models

VISSIM 4.10 is the microscopic simulation software developed by the PTV AG Company. With this software, urban traffic and public transit operations can be developed by modeling each entity of all types of vehicles (car, truck, bus) under certain constraints, such as lane configurations, traffic composition, traffic signals, transit stops, and so on. These urban traffic and transit operations can also be analyzed by gathering the traffic information from the output files (PTV AG 2005).
In VISSIM, the models that determine vehicle movements include a car-following model and a lane-changing model. The car-following model for freeway links is based on the psycho-physical driver behavior model developed by Rainer Wiedemann in 1999. The basic concept of the so-called Wiedemann 99 model is that the driver maintains his desired speed if there is no observed preceding vehicle, or that the driver decelerates to reach and maintain the slower speed of the preceding vehicle within a desired safety distance. In the Wiedemann 99 model, the safety distance $dx_{\text{safe}}$ at given speed $v$ is computed as

$$dx_{\text{safe}} = CC0 + CC1 \times v$$  \hspace{1cm} (3.79)

where

- $CC0$: the standstill distance
- $CC1$: the headway time

Other parameters in the model include: following variation ($CC2$), threshold for entering following ($CC3$), following thresholds ($CC4$ and $CC5$), speed dependency of oscillation ($CC6$), oscillation acceleration ($CC7$), standstill acceleration ($CC8$) and acceleration at 80 km/h ($CC9$). A screen shot of the car-following parameters in the simulation design is shown in Figure 3.8.
As for the lane change model in VISSIM, there are two kinds of lane change logics: necessary lane change and free lane change. The necessary lane change allows the lane changer to reach the next connector of a route, which is accomplished by defining the maximum and accepted deceleration for the lane changer and the overtaken vehicle. The free lane change allows the lane changer to overtake freely in any lane to achieve a sufficient safety distance. The parameters of the lane change model are presented in Figure 3.9.
(2) Freeway Links with Different Lengths and Numbers of Lane

Figure 3.10 shows the various freeway links designed in VISSIM4.10 for the purposes of this study. The study area is the segment at the upstream of the on-ramp. Detectors are located at the upstream and downstream of the studied segment. The different freeway links are comprised of different link lengths between the detectors (500-meters, 750-meter and 1000-meter) and different numbers of lane (1 lane, 2 lanes and 3 lanes).
Figure 3.10: VISSIM freeway link designs with different lengths and lanes.

(3) Traffic Conditions Design within Time Intervals

To design the various traffic conditions, such as free-flow, transition and congestion, the input traffic flows of the major road and its on-ramp are changed according to the saturation flow rate of the freeway links.

As mentioned previously, the simulation model for the freeway link is based on the Wiedemann 99 car-following model in which the saturation flow rate is dependent on the safety distance, vehicle speed, truck percentage and number of lanes. According to Equation 3.79, the safety distance \( dx_{safe} \) is determined by the standstill distance \( CC0 \), headway time \( CC1 \) and the vehicle speed \( v \). In VISSIM, the vehicle speed is defined as the desired speed distribution, and the traffic composition is determined by the truck percentage.

There are ten different runs for each simulation states. Given the standstill distance and headway time, the various scenarios are determined and listed as follows:
• Desired speed distribution: $v = 60 \sim 90km / h$

• Traffic composition: 90% car and 10% truck

• Total simulation time length: 4 hours

• Time interval lengths: 2 minutes, 5 minutes, 10 minutes

• Data sampling interval of flow measurement: $\Delta = 1sec$

• One-lane link

  Traffic flow on major road: $q = 1000, 1200, 1400, 1600, 1800, 2000$ veh/h

  Traffic flow on ramp: $q_r = \frac{1}{2}q$

• Two-lane link

  Traffic flow on major road: $q = 2000, 3200, 3200, 2000, 4000, 2000$ veh/h

  Traffic flow on ramp: $q_r = \frac{1}{2}q$

• Three-lane link

  Traffic flow on major road: $q = 3000, 5400, 5400, 3000, 6600, 3000$ veh/h

  Traffic flow on ramp: $q_r = \frac{1}{3}q$
3.2.2 Data Collection and Aggregation

After running the simulation in VISSIM, the raw data measured from the two detectors at the upstream and downstream provide the time of each vehicle at the two locations, their spot speed, and occupancy. Then, the true travel time of each vehicle can be calculated from the time difference. Table 3.2 shows the raw data and true travel times of $m$ sample vehicles.

<table>
<thead>
<tr>
<th>Vehicle</th>
<th>Upstream</th>
<th>Downstream</th>
<th>Travel Time</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Time</td>
<td>Speed</td>
<td>Occupancy</td>
</tr>
<tr>
<td>1</td>
<td>$t_{u,1}$</td>
<td>$v_{u,1}$</td>
<td>$o_{u,1}$</td>
</tr>
<tr>
<td>2</td>
<td>$t_{u,2}$</td>
<td>$v_{u,2}$</td>
<td>$o_{u,2}$</td>
</tr>
<tr>
<td>....</td>
<td>....</td>
<td>....</td>
<td>....</td>
</tr>
<tr>
<td>m</td>
<td>$t_{u,m}$</td>
<td>$v_{u,m}$</td>
<td>$o_{u,m}$</td>
</tr>
</tbody>
</table>

If the time of the vehicle passing the upstream or downstream detectors is within some time interval $(A_{n,1}, A_{n})$, it would be classified as part of that time interval. Then, all the vehicles at the upstream and downstream are separately aggregated into the different time intervals. The results are shown in Table 3.3.

<table>
<thead>
<tr>
<th>Time Interval</th>
<th>Upstream</th>
<th>Downstream</th>
</tr>
</thead>
<tbody>
<tr>
<td>$(0, A_1)$</td>
<td>$t_{u,1}$</td>
<td>$v_{u,1}$</td>
</tr>
<tr>
<td></td>
<td>$t_{u,2}$</td>
<td>$v_{u,2}$</td>
</tr>
<tr>
<td></td>
<td>....</td>
<td>....</td>
</tr>
<tr>
<td></td>
<td>....</td>
<td>....</td>
</tr>
<tr>
<td></td>
<td>$(A_1, A_2)$</td>
<td>$t_{d,1}$</td>
</tr>
<tr>
<td></td>
<td>$t_{d,2}$</td>
<td>$v_{d,2}$</td>
</tr>
<tr>
<td></td>
<td>....</td>
<td>....</td>
</tr>
<tr>
<td></td>
<td>....</td>
<td>....</td>
</tr>
</tbody>
</table>
3.2.3 Travel Time Estimation Obtained from the Models

- Speed extrapolation models

In the speed extrapolation models, the space-mean speeds \( v_{u,n}, v_{d,n} \) of the upstream and downstream at the time interval \((t_{n-1}, t_n)\) are calculated using Equations 3.5 and 3.6, and then they are used to estimate the average travel time of the link \(tt(t_n)\) at the same interval by using Equations 3.14, 3.18 and 3.22 in the different speed extrapolation models.

<table>
<thead>
<tr>
<th>Time Interval</th>
<th>Space-Mean Speed</th>
<th>Speed Model 1 (tt(t_n))</th>
<th>Speed Model 2 (tt(t_n))</th>
<th>Speed Model 3 (tt(t_n))</th>
</tr>
</thead>
<tbody>
<tr>
<td>((0, t_1))</td>
<td>(v_{u,1}, v_{d,1})</td>
<td>(tt(t_1))</td>
<td>(tt(t_1))</td>
<td>(tt(t_1))</td>
</tr>
<tr>
<td>((t_1, t_2))</td>
<td>(v_{u,2}, v_{d,2})</td>
<td>(tt(t_2))</td>
<td>(tt(t_2))</td>
<td>(tt(t_2))</td>
</tr>
<tr>
<td>(\ldots \ldots)</td>
<td>(\ldots)</td>
<td>(\ldots)</td>
<td>(\ldots)</td>
<td>(\ldots)</td>
</tr>
<tr>
<td>((t_{n-1}, t_n))</td>
<td>(v_{u,n}, v_{d,n})</td>
<td>(tt(t_n))</td>
<td>(tt(t_n))</td>
<td>(tt(t_n))</td>
</tr>
</tbody>
</table>

- Dynamic traffic flow model and modified dynamic models

In the dynamic traffic flow model developed by Nam and Drew (1998), Equation 3.59 is used to estimate the travel time under normal-flow conditions, and Equation 3.64 is used to
estimate the travel time under congestion-flow conditions. In the modified dynamic model by Vanajakshi (2008), Equation 3.64 can estimate the average travel time of all the traffic conditions. The estimated travel time results for each time interval are found in Table 3.5.

Table 3.5 Travel Time Estimates by (Modified) Dynamic Traffic Flow Model

<table>
<thead>
<tr>
<th>Time Interval</th>
<th>Downstream Density k</th>
<th>tt(t_n)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(0, t_1)</td>
<td>q(x_d,t_1) k(t_1)</td>
<td>tt(t_1)</td>
</tr>
<tr>
<td>(t_1, t_2)</td>
<td>q(x_d,t_2) k(t_2)</td>
<td>tt(t_2)</td>
</tr>
<tr>
<td>....</td>
<td>....</td>
<td>....</td>
</tr>
<tr>
<td>(t_{n-1}, t_n)</td>
<td>q(x_d,t_n) k(t_n)</td>
<td>tt(t_n)</td>
</tr>
</tbody>
</table>

In the proposed modified dynamic traffic flow model, if some vehicles entering the link can exit during the same time interval, then Equation 3.74 is used to calculate the travel time. Then, the estimated travel time results for each time interval would be found in Table 3.6.

Table 3.6 Travel Time Estimates by Proposed Modified Dynamic Traffic Flow Model

<table>
<thead>
<tr>
<th>Time Interval</th>
<th>Flow Rate q</th>
<th>Density k</th>
<th>tt(t_n)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Upstream</td>
<td>Downstream</td>
<td></td>
</tr>
<tr>
<td></td>
<td>q(x_u,t_n)</td>
<td>q(x_d,t_n)</td>
<td></td>
</tr>
<tr>
<td>(0, t_1)</td>
<td>q(x_u,t_1)</td>
<td>q(x_d,t_1)</td>
<td>tt(t_1)</td>
</tr>
<tr>
<td>(t_1, t_2)</td>
<td>q(x_u,t_2)</td>
<td>q(x_d,t_2)</td>
<td>tt(t_2)</td>
</tr>
<tr>
<td>....</td>
<td>....</td>
<td>....</td>
<td>....</td>
</tr>
<tr>
<td>(t_{n-1}, t_n)</td>
<td>q(x_u,t_n)</td>
<td>q(x_d,t_n)</td>
<td>tt(t_n)</td>
</tr>
</tbody>
</table>

If no vehicles entering the link can exit during the same time interval, then Equation 3.78 is used to calculate the travel time in the proposed dynamic traffic flow model. So, the
estimated result would be as Table 3.7.

<table>
<thead>
<tr>
<th>Time Interval</th>
<th>Downstream Density k</th>
<th>tt(tn)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(0, t1)</td>
<td>q(x_d, t1) q(x_d, t2)</td>
<td>k(t1) tt(t1)</td>
</tr>
<tr>
<td>(t1, t2)</td>
<td>q(x_d, t2) q(x_d, t3)</td>
<td>k(t2) tt(t2)</td>
</tr>
<tr>
<td>........</td>
<td>.........</td>
<td>....</td>
</tr>
<tr>
<td>(tn-1, tn)</td>
<td>q(x_d, t_n) q(x_d, t_n+1)</td>
<td>k(tn-1) tt(tn)</td>
</tr>
</tbody>
</table>

- Flow-based statistical models

In the probabilistic regression model, the raw data first are aggregated into flow measurements of one-second sampling intervals. The central value-of-fit range is defined as: the true travel time of the current time interval, the true value of the last interval, the estimated travel time based on the upstream speed, estimates from the speed extrapolation model, or estimated values from the (modified) dynamic traffic flow model. The fit range is fixed at 20 seconds. Then, the optimization arithmetic based on Equations 3.28 and 3.29 is used to estimate the average travel time of the different regression models.

In the maximum cross-correlation models, Equation 3.31 is used to determine the cross-correlation coefficients between the upstream and downstream flows, and the average travel time is the time delay of the maximum degree of correlation. In the significant cross-correlation model, the t-test statistic presented in Equation 3.43 is used to determine the significant coefficients, and then the average travel time is estimated from Equation 3.44.
3.2.4 Traffic Conditions Determination

To compare the travel time estimations under the various traffic conditions, the characteristics of the traffic conditions are studied and the parameters are selected to determine whether the traffic flow during the time interval is free-flow, transition or congestion.

Under free-flow conditions, there is little interaction, and drivers travel at their desired speed. Under congestion conditions, queues form behind active bottlenecks, and vehicles are always in stop-and-go traffic. Transition is the status between the free-flow and congestion conditions.

Traffic conditions can be determined by the relationships among traffic characteristics, such as flow, density and speed. Figure 3.11 presents a fundamental diagram of traffic flow characteristics and gives the relationships among the traffic conditions. It can be seen that with the change in traffic condition from free-flow to congestion, the space-mean speed decreases and the density increases. However, no significant
interaction exists between the flows and traffic conditions. Therefore, space-mean speed and density can be used to determine the traffic conditions.

Although the density of the link can be used to determine traffic conditions, numerous experiments should be conducted ahead of time to confirm the boundary of the density among the different traffic conditions. Such a task is complicated, and the boundary value of the density is not fixed even under the same traffic conditions due to the different link lengths and numbers of lanes. Therefore, the parameter of density is not applicable to the traffic condition determination.

In the simulation study, due to the design of the on-ramp that cause queues to form or disappear from downstream to upstream, the approximate range and significant difference of the average space-mean speed at the upstream and downstream can be used to determine the traffic conditions. This process is illustrated from an example of the simulation data, which is shown in Table 3.1. During the time intervals, 0~20 minutes, 55~60 minutes and 95~120 minutes, the space-mean speeds at the upstream and downstream are both in the desired speed range (60~90 km/h); thus, the traffic conditions are designated as the free-flow condition. During the time intervals, 25~50 minutes and 65~95 minutes, the space-mean speed at the upstream and downstream are both low (<34 km/h), and the traffic conditions can be defined as the congestion condition. During the other time intervals of 25~50 minutes and 65~95 minutes, the space-mean speed of one stream is within the desired speed range (>65 km/h), and the other stream space-mean speed is low (27~41 km/h). This space-mean speed difference is significant, and thus, the traffic conditions are designated as the transition
condition. Moreover, in the travel time estimation, the transition can be defined as the point at which the “best estimation” method switches from one method to another. As Table 3.8 shows, under the transition condition the estimation error switches sharply from one method to another.

From the above analysis, traffic conditions can be determined by the space-mean speed range and the speed difference between the two stations. Under the free-flow condition the space-mean speeds are within the desired speed range, under the congestion condition the space-mean speeds are all low, and in the transition condition the space-mean speeds are largely different (i.e., a low space-mean speed and free-flow speed).

<table>
<thead>
<tr>
<th>Time Interval (min)</th>
<th>$v_u$ (SMS) Km/h</th>
<th>$v_d$ (SMS) Km/h</th>
<th>MAE (sec) Method 1</th>
<th>MAE (sec) Method 2</th>
<th>MAPE (%) Method 1</th>
<th>MAPE (%) Method 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>68.621</td>
<td>66.756</td>
<td>10.6</td>
<td>0.1</td>
<td>39.6</td>
<td>0.4</td>
</tr>
<tr>
<td>10</td>
<td>68</td>
<td>66.36</td>
<td>2.4</td>
<td>0.1</td>
<td>8.8</td>
<td>0.4</td>
</tr>
<tr>
<td>15</td>
<td>69.624</td>
<td>67.023</td>
<td>3.9</td>
<td>0.1</td>
<td>14.8</td>
<td>0.2</td>
</tr>
<tr>
<td>20</td>
<td>68.481</td>
<td>67.474</td>
<td>5.5</td>
<td>0.1</td>
<td>20.8</td>
<td>0.5</td>
</tr>
<tr>
<td>25</td>
<td><strong>66.995</strong></td>
<td><strong>41.282</strong></td>
<td><strong>1.1</strong></td>
<td><strong>3.0</strong></td>
<td><strong>3.1</strong></td>
<td><strong>8.2</strong></td>
</tr>
<tr>
<td>30</td>
<td>34.32</td>
<td>22.682</td>
<td>2.8</td>
<td>17.2</td>
<td>3.4</td>
<td>21.4</td>
</tr>
<tr>
<td>35</td>
<td>21.184</td>
<td>19.717</td>
<td>9.7</td>
<td>0.4</td>
<td>11.1</td>
<td>0.5</td>
</tr>
<tr>
<td>40</td>
<td>22.623</td>
<td>21.269</td>
<td>2.7</td>
<td>10.5</td>
<td>2.9</td>
<td>11.3</td>
</tr>
<tr>
<td>45</td>
<td>26.567</td>
<td>19.991</td>
<td>2.5</td>
<td>1.3</td>
<td>3.3</td>
<td>1.7</td>
</tr>
<tr>
<td>50</td>
<td>31.735</td>
<td>23.814</td>
<td>1.6</td>
<td>2.9</td>
<td>2.3</td>
<td>4.3</td>
</tr>
<tr>
<td>55</td>
<td><strong>69.053</strong></td>
<td><strong>27.125</strong></td>
<td><strong>3.4</strong></td>
<td><strong>4.9</strong></td>
<td><strong>11.2</strong></td>
<td><strong>15.2</strong></td>
</tr>
<tr>
<td>60</td>
<td>69.987</td>
<td>67.972</td>
<td>1.8</td>
<td>0.1</td>
<td>6.8</td>
<td>0.4</td>
</tr>
<tr>
<td>65</td>
<td><strong>65.214</strong></td>
<td><strong>40.035</strong></td>
<td><strong>8.7</strong></td>
<td><strong>6.2</strong></td>
<td><strong>21.6</strong></td>
<td><strong>15.3</strong></td>
</tr>
<tr>
<td>70</td>
<td>24.274</td>
<td>22.28</td>
<td>6.8</td>
<td>10.8</td>
<td>7.7</td>
<td>12.2</td>
</tr>
<tr>
<td>75</td>
<td>25.749</td>
<td>23.996</td>
<td>8.0</td>
<td>14.7</td>
<td>9.2</td>
<td>16.9</td>
</tr>
<tr>
<td>80</td>
<td>24.289</td>
<td>24.135</td>
<td>12.1</td>
<td>15.6</td>
<td>13.5</td>
<td>17.3</td>
</tr>
<tr>
<td>85</td>
<td>26.378</td>
<td>21.559</td>
<td>6.1</td>
<td>3.5</td>
<td>8.5</td>
<td>4.9</td>
</tr>
</tbody>
</table>
Table 3.8 Continued

|    |    |    |    |    |    |    |    |    |
|----|----|----|----|----|----|----|----|
| 90 | 42.81 | 24.719 | 4.8 | 2.3 | 9.4 | 4.5 |  | Transition |
| 95 | 67.637 | 28.956 | 8.5 | 2.4 | 24.3 | 6.8 | Free-flow |
| 100 | 68.106 | 66.323 | 6.1 | 0.1 | 22.8 | 0.4 | |
| 105 | 68.13 | 66.346 | 4.6 | 0.0 | 17.2 | 0.1 | |
| 110 | 68.604 | 67.132 | 0.0 | 0.4 | 0.1 | 1.4 | |
| 115 | 69.104 | 66.615 | 3.6 | 0.1 | 13.4 | 0.3 | |
| 120 | 67.694 | 66.557 | 2.4 | 0.1 | 9.1 | 0.4 | |

3.2.5 Comparison of the Estimated Results

The true travel times (i.e., the true values) and the estimated travel times are shown in Figure 3.12 to Figure 3.38 (Appendix A), and the performance measures that are based on the estimation errors, MAE and MAPE, during varying traffic conditions are shown in Table 3.9 to Table 3.17 (Appendix A).

MAE is the mean absolute error for a data series and is calculated as

\[
\text{MAE} = \frac{\sum_{i=1}^{n} |T_i - \hat{T}_i|}{n} \tag{3.80}
\]

MAPE is the mean absolute percentage error and is calculated as:

\[
\text{MAPE} = \frac{\sum_{i=1}^{n} \left| \frac{T_i - \hat{T}_i}{T_i} \right| \times 100}{n} \tag{3.81}
\]

The comparison results of the thirteen models are illustrated using the data from various freeway links that are comprised of different link lengths and numbers of lane during
different time intervals. Also, the effects of link length, numbers of lane, and time interval on the accuracy of the models under different traffic conditions are discussed here.

(1) Comparison on 500-meter Freeway Links

Figures 3.12, 3.13 and 3.14 (Appendix A) show the plots of travel time estimates of the 500-meter, one-lane freeway link under normal flow and transition/congestion-flow at the 2-minute, 5-minute and 10-minute intervals. Table 3.9 shows the estimation errors, MAE and MAPE, under various traffic conditions. Figures 3.15, 3.16 and 3.17 show the plots of travel time estimates of the 500-meter, two-lane freeway link, and Table 3.10 presents the estimation errors, MAE and MAPE. Figures 3.18, 3.19 and 3.20 show the plots of travel time estimates of the 500-meter, three-lane freeway link, and the estimation errors, MAE and MAPE, are described in Table 3.11.

As Tables 3.9, 3.10 and 3.11 indicate, under the free-flow condition, the MAE (< 0.3 sec) and MAPE (< 0.9%) values of the speed extrapolation methods are the smallest; this finding is especially true of the speed method that assumes a constant acceleration rate with time. With the increase in time intervals and numbers of lanes, the errors and the differences among the three extrapolation models decrease. The measured errors of the probabilistic regression methods are small (MAE < 1.0 sec and MAPE < 4.0%), except those of the method whose central value is equal to the travel time obtained from the dynamic traffic flow models or from the true value at last time interval. The values obtained from cross correlation are acceptable during the 2-, 5- or 10-minute interval. The values obtained from the (modified)
dynamic flow methods are large, and thus these methods cannot be used to estimate the free-flow travel time. Using measured spot speeds, the speed extrapolation method is the best method for estimating the free-flow travel time. Without measured spot speeds, the travel time can be estimated using the probabilistic regression method with the central value-of-fit window estimated from the relationships of flow, occupancy and speed measured from the upstream detector. Applying the cross-correlation method to estimate the travel time in a large window length is also acceptable.

Under the transition condition, although the MAE and MAPE obtained from the probabilistic regression model whose central value is the measured value are the smallest, the probabilistic regression model is not practical because the travel time cannot be directly measured in practice. The values of the (modified) dynamic traffic flow method during the 2-minute interval are smaller than that of the 5-minute or 10-minute interval. The probabilistic regression model that uses the dynamic method travel time as the central value-of-fit range also produces acceptable results. However the MAE (4~6 sec) and MAPE (10%~14%) values of the 2-minute interval are not good due to the inconsistent traffic during this time interval. For example, during some time intervals (6480, 6600) on the 500-meter, two-lane freeway link, the speeds measured at the downstream detectors vary from congestion speed to free-flow speed, and the MAPE is over 30%. To improve the accuracy, the window of the length of time interval can be decreased to satisfy the same traffic distribution within the smaller time intervals.

Under congestion conditions, the estimation error of the travel time at a 2-minute interval
(MAE < 10 sec and MAPE < 9%) is the smallest when the (modified) dynamic traffic models are applied. The probabilistic regression model also affords good results if the central value is the travel time estimated from the (modified) dynamic method. The two methods can be used to estimate the travel time under congestion conditions. However, the accuracy of the two methods differs among the different numbers of lanes. The proposed dynamic traffic flow model is more accurate than the dynamic model by Nam and Drew (1998) and Vanajakshi (2008) for estimating the travel time of the 500-meter freeway link. The MAPE decreases from 8.1% to 5.5% with the one-lane link, 5.9% to 5.0% with the two-lane link and 6.1% to 5.6% with the three-lane link. On the 500-meter freeway link with fewer lanes, there are fewer vehicles that enter the link and can exit it during the same 2-minute interval. Further, there are no vehicles at all during some time intervals, and the downstream flow rate varies significantly, especially for the one-lane link. However, the dynamic model assumes that the flow rate is the same at the consecutive time interval \((q(x_d, t_n) = q(x_d, t_{n+1}))\). The proposed dynamic model modifies this assumption and improves the accuracy for travel time estimation.

(2) Comparison on 750-meter Freeway Links

Figures 3.21, 3.22 and 3.23 (Appendix A) compare the travel time estimates of the 750-meter, one-lane freeway link under various traffic conditions at different time intervals. Table 3.12 presents the estimation errors, MAE and MAPE, under different conditions. Figures 3.24, 3.25 and 3.26 represent the travel time estimation of the 750-meter, two-lane freeway link, and Table 3.13 describes the estimation errors, MAE and MAPE. Figures 3.27, 3.28 and 3.29
show the plots of the travel time estimates of the 750-meter, three-lane freeway link, and the estimation errors, MAE and MAPE, are described in Table 3.14.

Compared with the results indicated in the figures and tables for the 500-meter freeway links, the travel time estimation of the 750-meter freeway link reaches almost the same conclusions. However, with the increase of the link length, the average travel time increases and the estimation errors show certain trends, as discussed in the following.

Under free-flow conditions, although the errors of the speed extrapolation methods increase slightly in the 750-meter link compared to the 500-meter link, the MAE (< 0.5 sec) and MAPE (< 1.2%) are small, and with the increase of the time interval and numbers of lane, the errors are smaller. Therefore, given the measured spot speeds, the speed extrapolation methods are the best for travel time estimation. Without measured spot speeds, the travel time can be estimated by using the probabilistic regression method (whereby the central value-of-fit window is estimated from the relationships of the flow, occupancy and speed of the upstream detector, MAE < 2.0 sec and MAPE < 5.4%) or the cross-correlation method.

Under the transition condition, compared to the results for the 500-meter link, the values of the MAPE of the 750-meter freeway link decrease from 8.6%~13.9% to 5.7%~11.2% if using the (modified) dynamic traffic model or the probabilistic regression model with the dynamic method travel time as the central value at the 2-minute interval. The reason for this decrease is that the 2-minute interval is more comparable and suitable for the increased average travel time of the 750-meter link than for the 500-meter link due to the longer link.
Under congestion conditions, there are more 2-minute intervals during which the vehicles that enter the 750-meter one-lane and two-lane freeway links cannot exit, and the downstream flow rate changes much less frequently than that of the 500-meter link. The proposed dynamic model shows more accurate estimation results than the other dynamic models. The MAPE decreases from 9.1% to 4.2% with the one-lane link, 6.8% to 4.0% with the two-lane link and 5.4% to 4.4% with the three-lane link at 2-min time interval. Also, the accuracy of the modified model for the 750-meter link (MAPE 4.0%~4.4%) improves slightly more than for the 500-meter link (MAPE 5.0%~5.6%) when estimating the travel time per 2-minute interval. The modified dynamic-based regression model produces similar results.

(3) Comparison on 1000-meter Freeway Links

Figures 3.30, 3.31 and 3.32 describe the plots of travel time estimates of the 1000-meter, one-lane freeway link under different traffic conditions and time intervals (2 minutes, 5 minutes and 10 minutes). Table 3.15 presents the estimation errors, MAE and MAPE. Figures 3.33, 3.34 and 3.35 show the travel time estimations of the 1000-meter, two-lane freeway link, and the estimation errors are indicated in Table 3.16. Figures 3.36, 3.37 and 3.38 depict the plots of travel time estimates of the 1000-meter three-lane freeway link, and Table 3.17 shows the estimation errors, MAE and MAPE.

Compared to the estimation results of the 500-meter and 750-meter freeway links, the application of the models under various traffic conditions for the 1000-meter links does not
change much, and the estimation errors show almost the same trend as mentioned above.

Under free-flow conditions, with the increase of the freeway link length, the estimation errors for the 1000-meter link increase to 0.7 second (MAE) and 1.3% (MAPE) using the speed extrapolation methods. The accuracy is so good that these speed extrapolation methods are the best methods to estimate travel time using measured spot speeds. Without measured spot speeds, the travel time can be estimated using the probabilistic regression method with the central value estimated from the relationships of flow, occupancy and speed of the upstream detector due to good performance (MAE < 1.5 sec and MAPE < 3.0%).

Under transition conditions, if the (modified) dynamic traffic model or the probabilistic regression model based on the dynamic method is used, the 2-minute interval is more applicable to the 1000-meter freeway link, and thus the MAPE decreases to 4.5%~9.6%. With the increase of the link length, the vehicles that enter the 1000-meter, one-lane or two-lane link during some of the 2-minute intervals cannot exit, and the flow rate varies significantly. Thus, the proposed dynamic model shows the more accurate estimation results (MAPE 4.5%~7.0%) than the other dynamic model (MAPE 4.9%~9.6%). Under congestion conditions, more vehicles entering the 1000-meter, one-lane, two-lane, and even three-lane link cannot depart during the same 2-minute interval, and the flow rate cannot be assumed to be the same. If using the proposed dynamic traffic flow method, the MAPE decreases to 3.2%~4.6%, while the MAPE obtained from the other dynamic method is 5.1%~10.3%. Therefore, the proposed dynamic model and the modified dynamic-based regression model are the best models to accurately estimate travel time for the 1000-meter freeway link under
transition and congestion conditions.

3.2.6 Conclusions

From the simulation study, the measurement performances are provided and discussed using three categories of methods to estimate the link travel time for one, two, and three lanes during different time intervals and under various traffic conditions. The application range of these models and the effects of traffic conditions, numbers of lane, and link lengths can thereby be inferred.

- Free-flow condition:

Using spot speed measurements, the MAE and MAPE of the speed extrapolation models are smallest compared to the other models. The MAE is less than 0.7 second and the MAPE is less than 1.3%. With the increase in the time interval and numbers of lanes and the decrease in the link length, the MAE and MAPE values decrease. Therefore, the speed extrapolation models are the best methods to estimate the link travel time for one, two, or three lanes under free flow conditions.

Without speed information, the MAE and MAPE of the probabilistic regression model are small if the central value of the model is estimated from the relationships of the flow, occupancy and speed obtained from the upstream detector. The MAE is less than 1.0 seconds and the MAPE is less than 3.9%. Then, the probabilistic regression model can be used to estimate the travel time. The cross-correlation models with appropriate time delay range also
works for the travel time estimations for one- and two-lane links with a MAE less than 4.1 seconds and MAPE less than 8.0%.

- Transition and congestion conditions:

The MAE and MAPE values of the (modified) dynamic traffic flow models and the modified dynamic-based probabilistic regression model are smaller than those obtained from the other models. However, the accuracy of the models is affected by the time interval, link length and numbers of lanes.

Under transition conditions, the errors are significant if the time interval is 5 minutes or 10 minutes. During the 2-minute interval, with the decrease of the link length, the errors increase. The MAE is 3.3~8.6 seconds and the MAPE is 4.5%~9.6% for the 1000-meter freeway link during the 2-minute interval. For the 750-meter link the MAPE increases to 5.7%~11.2% and for the 500-meter link the MAPE increases to 8.6%~13.7%. Given the other parameters, the 2-minute interval is more suitable for the longer link due to the more stable traffic distribution. Also, to improve the accuracy of the 500-meter link under transition conditions, the window of the time interval should be decreased to 60 or 90 seconds.

Under congestion conditions, with an increase in the number of lanes and a decrease in the time interval, the errors decrease slightly. During the 2-minute interval, the MAE is less than 29.1 seconds and the MAPE is less than 10.3%. Also, with fewer lanes or longer links, there are more vehicles entering the link than cannot exit it during the same interval, and the
difference in the flow rates is more significant. Thus, the modified dynamic traffic model and the modified dynamic-based probabilistic regression model are more accurate than the dynamic traffic flow models. The MAPE can be decreased from 10.3% to 0.6%.

In summary, the (modified) dynamic traffic flow models and the modified dynamic-based probabilistic regression model can accurately estimate the travel time under transition and congestion conditions. Before using the models, the proper time interval (2 minutes or less) should be indicated according to link length and numbers of lane, and the modified dynamic model is preferred under certain conditions wherein the flow rates vary significantly.

3.3 Summary

This chapter focuses on an in-depth analysis of the three estimation categories of travel time estimation methods. In Section 3.1, the three methods are qualitatively analyzed in detail according to model theory, equation derivation, and possible modification. In Section 3.2, a simulation study is conducted to compare the three methods in terms of quantity, and is discussed in terms of simulation design, data collection and aggregation, travel time estimation results, determination of traffic conditions, and comparisons of measurement performance. Finally, the accuracy and application of all the models are examined under various traffic conditions and according to the effects of time interval, link length and numbers of lane. In Chapter 4, a systematic method will be proposed, and then utilized in the simulation data again to validate its accuracy for freeway links travel time estimation under various traffic conditions.
CHAPTER 4 SYSTEMATIC METHOD

In Chapter 3, the three categories of methods for travel time estimation based on fixed-point detector data were analyzed and compared to the model theory, and a simulation case study has been conducted to determine the limitations and applications of all thirteen models, including the modified model under various traffic conditions, time intervals and freeway links.

This chapter is devoted to the proposal of a systematic method that can accurately estimate the travel time for freeway links under all the traffic conditions in order to overcome the shortcomings associated with the previous models. First, the framework of the proposed systematic method is developed in Section 4.1. The following Sections 4.2, 4.3, 4.4 and 4.5 outline the procedures for developing this system. The preliminary findings of the systematic method tests using simulation data are discussed in Section 4.6. Finally, a summary is provided in Section 4.7.

4.1 Proposed Systematic Method Framework

The overall structure of the proposed systematic method is presented in Figure 4.1. There are three stages in this systematic method: 1) investigation and analysis of the traffic data, 2) determination of the traffic conditions, and 3) selection of the specific model for travel time estimation and performance measurement. The detailed procedure for each stage is discussed in the following sections.
Figure 4.1: Travel time estimation system structure
4.2 Traffic Data Investigation and Analysis

The previous simulation study determined that different time intervals, link lengths and numbers of lane have a significant effect on the accuracy of the travel time estimation. Also, the specific models chosen for the various traffic conditions are different. Therefore, in the systematic method, the traffic data should be investigated and analyzed in advance to determine the traffic scenario, so that the appropriate model is selected to fit the respective traffic condition.

Five steps are taken to conduct the traffic data investigation and analysis: (1) freeway link length and desired speed distribution determination, (2) raw data collection from fixed-point detectors, (3) raw data analysis, (4) time interval determination and (5) data aggregation. These procedures are described in Figure 4.2.

Generally, the common free-flow scenario of a freeway link whose length is \( \Delta x, \Delta x = x_d - x_u \) and desired speed limit is \( u_f \), has an average travel time \( \bar{t}_f, \bar{t}_f = \frac{\Delta x}{u_f} \) and desired free-flow speed range \( [u_f - \Delta u, u_f + \Delta u] \), which can be utilized as one of the determining factors for both the time interval length and traffic conditions. With the application of the dynamic traffic flow model, the relationship between the link length \( \Delta x \) and the time interval \( T \) (data aggregation interval) should be stated as \( T > \frac{\Delta x}{u_f} \) (Nam and Drew 1998). Herein, 2 minutes is the appropriate time interval if this relationship is satisfied. The desired speed distribution
\[ [u_f - \Delta u, u_f + \Delta u], \]
where \( \Delta u \) is defined as 15 or 20 mph, can be used to determine the varying traffic conditions between free-flow and transition/congestion. For instance, if the spot speeds measured at both detectors are in the range of the desired speed distribution, the traffic flow can be considered as the free-flow condition.

Some fixed-point detectors, such as single-loop detectors, measure raw data, including the time that each vehicle enters and exits the loop zone \((t_{on}), (t_{off})\). According to Equations 3.1 and 3.2, and given the assumed vehicle length \( L_v \), the spot speed \( v_i \) can be estimated from single-loop detector data. The dual-loop detectors directly measure the spot speed \( v_i \) based on the concepts of Equations 3.3 and 3.4. Also, for both loop detectors, the number of vehicles \( N_i \) or occupancy time \((t_{occ})_i\) can be calculated from the measured detector data. The estimated or calculated spot speed \( v_i \) and the number of vehicles can be used to provide the space-mean speed per time interval, which can determine the various traffic conditions and estimate travel time in free-flow scenarios. Moreover, the changing frequency of the traffic parameters should be studied to verify whether the traffic distribution is constant within the time interval to further improve the accuracy of travel time estimation.

Thus, in the raw data analysis, first the upstream and downstream space-mean speeds of the time intervals \( v_u, v_d \) are calculated from the spot speed \( v_i \), according to Equations 3.7, 3.8, 3.9 and 3.10. If one or both space-mean speeds fall out of the desired speed range \([u_f - \Delta u, u_f + \Delta u]\), the spot speed \( v_i \) and traffic flow \( q_i \) at the two stations will then be
examined to confirm the change in frequency.

If the change of any parameters $v_i, q_i$ is significant, the traffic distribution cannot be considered as constant during the whole time interval $T$. Therefore, to improve the accuracy of travel time estimation, the time window $T$ should be divided into smaller parts, $T_1, \ldots, T_n$. After the divisions of the time interval are further defined, the raw data are separately aggregated into the smaller time intervals. The flow rate $q_1, \ldots, q_n$ can be calculated separately, the travel times $t_{T_1}, \ldots, t_{T_n}$ are estimated at the smaller intervals $T_1, \ldots, T_n$, and the average travel time $tt$ at the time interval $T$ can be determined as $tt = \frac{q_1 \cdot t_{T_1} + \cdots + q_n \cdot t_{T_n}}{q_1 + \cdots + q_n}$. 
Figure 4.2: Traffic data investigation and analysis procedure.
4.3 Traffic Condition Determination

From the theory analysis and simulation results of the comparison of the three categories of methods discussed in Chapter 3, it is found that the accuracy and application of the models differs under various traffic conditions. So, the specific models chosen for travel time estimation are based on the determination of the traffic conditions.

In Section 3.2.4, the characteristics of the different traffic conditions are examined, and the parameters (flow, density and speed) are discussed in order to determine the traffic conditions. Under the free-flow condition, speeds are in the desired speed range, and the density is smaller than for the other conditions. Along with the change in traffic states from free-flow to congestion, speeds decrease sharply, and the density increases to jam density. But, for this change in condition, the flow increases first and then decreases afterwards.

Because the relationship between flow and traffic condition is not significant, flow is not considered a good indicator to determine traffic states. Also, density is not applicable for determining traffic conditions due to the complexity and diversity of the density ranges under different traffic conditions. However, the analysis discussed in Section 3.2.4 and the simulation results indicate that speed is an appropriate parameter to determine traffic conditions. As such, the traffic conditions are determined by the relationship between the desired speed distribution \((u_f - \Delta u, u_f + \Delta u)\) and the space-mean speeds of the two stations at some time interval, \(v_{u_1}, v_{d_1}, \ldots, v_{u_n}, v_{d_1}, \ldots, v_{d_n}\).

When both space-mean speeds are in the desired speed range, the traffic can be considered to
be in the free-flow condition. If one of the space-mean speeds is in the desired speed range and the other is not, the traffic condition is transition. If neither of the space-mean speeds is in the range, it is congestion.

Free-flow condition: \[ v_u \& v_d \in [u_f - \Delta u, u_f + \Delta u] \]

\[ v_u \in [u_f - \Delta u, u_f + \Delta u] \& \ v_d \in (0, u_f - \Delta u) \]

Transition condition: \[ v_d \in (0, u_f - \Delta u) \& \ v_u \in [u_f - \Delta u, u_f + \Delta u] \]

Congestion condition: \[ v_u \& v_d \in (0, u_f - \Delta u) \]

where, \( v_u \): the upstream space-mean speed

\( v_d \): the downstream space-mean speed

Following the data aggregation described in Section 4.2, the next procedure to determine traffic condition is described in Figure 4.3.
4.4 Specific Model Selection for Travel Time Estimation

From the comparison results of the simulation study found in Sections 3.2.5 and 3.2.6, the specific models can be chosen for the travel time estimation under various traffic conditions. Under the free-flow condition, the best model is the speed extrapolation model with measured spot speeds; the speed estimates-based probabilistic regression model or cross-correlation model is appropriate if direct speed measurements are not available. Under the transition and congestion conditions, the (modified) dynamic traffic flow models and the dynamic-based probabilistic regression model are most appropriate. If there is significant change of downstream traffic flow rates, then the preferred model is the modified dynamic model or the modified dynamic-based probabilistic regression model.
1. Model selection under the free-flow condition

With spot speed measurements taken at the upstream and downstream stations $v_{u_i}v_{d,j}$, the space-mean speeds $v_u v_d$ can be calculated from Equations 3.9 and 3.10. Then, the travel times can be estimated from the extrapolation modes, Equations 3.14, 3.18 and 3.22, which also can be described as the following:

\[
tt = \frac{2(x_d - x_u)}{v_d + v_u} \quad (3.14)
\]

\[
tt = (x_d - x_u) \left( \frac{\ln v_d - \ln v_u}{v_d - v_u} \right) \quad (3.18)
\]

\[
tt = \frac{\left[ \frac{\Delta x}{v_u} + \frac{\Delta x}{v_d} \right]}{2} \quad (3.22)
\]

Without spot speed measurements, and given the vehicle length $L_v$, the space-mean speeds $v_u v_d$ can be estimated from Equations 3.5 and 3.6. The travel time can be estimated from the probabilistic regression model, which is shown in Equations 3.30, 3.25 and 3.26. The travel time fit range $[a_i, a_z]$ is based on the upstream estimated space-mean $v_u$ and is shown in Equation 4.1. The aggregation time length $\Delta$ is 1 second.

\[
\sum_{t=b_i+a_1}^{b_i+a_2} \left( y(t) - \sum_{i=a_i}^{a_z} [x(t - i)f_i] \right)^2 \quad (3.30)
\]
subject to: \( f : f_i \geq 0, \sum_{i=a_1}^{a_2} f_i = 1 \) \hspace{1cm} (3.25)

\[
\begin{align*}
    a_1 &= \frac{x_d - x_u}{v_u} - 10 \\
    a_2 &= \frac{x_d - x_u}{v_u} + 10
\end{align*}
\] \hspace{1cm} (4.1)

\[
\sum_{i=a_1}^{a_2} f_i i
\] \hspace{1cm} (3.26)

The cross-correlation models can also be used to estimate the travel time under the low-flow condition without speed spot measurements, as seen in Equations 3.35, 3.36 and 3.44. The aggregation time length \( \Delta \) is 1 second. To improve the accuracy, the time delay \( k \) can be defined in a travel time fit range as in the above probabilistic regression model, seen in Equation 4.2.

\[
\rho_{xy}(k) = \frac{\sum_{t=h+k}^{b_2} (x(t-k) - \bar{x})(y(t) - \bar{y})}{\sqrt{\sum_{t=h+k}^{b_2} (x(t-k) - \bar{x})^2 \sum_{t=h+k}^{b_2} (y(t) - \bar{y})^2}}
\] \hspace{1cm} (3.35)

subject to \( k \in \left[ \frac{x_d - x_u}{v_u} - 20, \frac{x_d - x_u}{v_u} + 20 \right] \) \hspace{1cm} (4.2)

\[
\max^{-1} \left( \rho_{xy}(k) \right)
\] \hspace{1cm} (3.36)
\[
t = \frac{\sum_{i=m}^{i=m} (\hat{\rho}_y(c_i) * c_i)}{\sum_{i=1}^{i=m} \hat{\rho}_y(c_i)} \quad (3.44)
\]

2. Model selection under the transition and congestion conditions

When the downstream flow rate of one time interval is almost the same as that of the next time interval \( q(x_d, t_{n+1}) = q(x_d, t_n) \), then the dynamic traffic model modified by Vanajakshi et al. (2008) can be used to estimate the travel time, according to Equation 3.69. The probabilistic regression model is also appropriate here, as seen in Equations 3.30, 3.25 and 3.26, and the travel time fit range \([a_1, a_2] \) is based on the dynamic traffic model, as shown in Equation 4.3.

\[
t = \frac{\Delta x \ k(t_{n-1}) + k(t_n)}{2 \ q(x_d, t_n)} \quad (3.69)
\]

\[
\left\{ \begin{array}{l}
a_1 = \frac{\Delta x \ k(t_{n-1}) + k(t_n)}{2 \ q(x_d, t_n)} - 10 \\
a_2 = \frac{\Delta x \ k(t_{n-1}) + k(t_n)}{2 \ q(x_d, t_n)} + 10 
\end{array} \right. \quad (4.3)
\]

If the change in the downstream flow rate during consecutive time intervals is significant, that is \( q(x_d, t_{n+1}) \neq q(x_d, t_n) \), and given the downstream flow rate of the next time interval \( q(x_d, t_{n+1}) \), the travel time can be estimated from the modified dynamic traffic flow model shown in Equations 3.74 and 3.78 or from the modified dynamic-based probabilistic model.
whose central value is shown in Equation 4.4.

If \( Q(x_d, t_n) > Q(x_u, t_{n-1}) \):

\[
\Delta t = \frac{\Delta x}{2q(x_u, t_n)} \left\{ k(t_{n-1}) + k(t_n) + \frac{\Delta x}{\Delta t} \left( \frac{k(t_n)^2}{q(x_d, t_{n+1})} - \frac{k(t_{n-1})^2}{q(x_d, t_n)} \right) \right\} \tag{3.74}
\]

If \( Q(x_d, t_n) \leq Q(x_u, t_{n-1}) \):

\[
\Delta t = \frac{k(t_{n-1}) \Delta x + k(t_n) \Delta x - q(x_d, t_n) \Delta t}{2q(x_d, t_{n+1})} \tag{3.78}
\]

\[
\begin{align*}
\alpha_1 &= \Delta t - 10 \\
\alpha_2 &= \Delta t + 10 
\end{align*} \tag{4.4}
\]

3. Model modification using updating downstream data under transition and congestion conditions

From the diagram of the cumulative flows shown in Figure 3.6, besides the assumptions \( q(x_d, t_{n+1}) \neq q(x_d, t_n) \) and \( Q(x_d, t_n) > Q(x_u, t_{n-1}) \), Equation 3.74 also is based on the assumption that \( Q(x_d, t_{n+1}) > Q(x_u, t_n) \) or \( Q(x_d, t_{n+1}) \leq Q(x_u, t_n) \) & \( q(x_d, t_{n+2}) = q(x_d, t_{n+1}) \).

Given the updating downstream data, a complete diagram of the cumulative flows at two detection locations is shown in Figure 4.4. The necessary updated data include: 1) the time \( t_z \) that the downstream cumulative flow is equal to that of upstream at time \( t_n \); and 2) the
downstream cumulative flow $Q(x_d, t_{n+j+1})$ at time $t_{n+j+1}$ supposing $t_{n+j} \leq t_z \leq t_{n+j+1}$ $j = 1, 2, ...$.

Using the downstream flow rate data $q(x_d, t_{n+1}), q(x_d, t_{n+2}), ..., q(x_d, t_{n+j}), q(x_d, t_{n+j+1})$, $n(t_n)$ is introduced to estimate the travel time.

![Figure 4.4](image)

**Figure 4.4: Schematic representation of the total travel time during the interval $(t_{n-1}, t_n)$**.

The total travel time $TT$ of all the vehicles $n(t_n)$ that enter the link during the time interval $(t_{n-1}, t_n)$ is indicated in Figure 4.4 by the shaded area and is calculated as
\[
\begin{align*}
TT &= \frac{1}{2} \left[ \frac{Q(x_u,t_{n-1}) - Q(x_d,t_{n-1})}{q(x_u,t_n)} + \frac{Q(x_u,t_n) - Q(x_d,t_n)}{q(x_u,t_n)} \right] \left[ Q(x_d,t_n) - Q(x_u,t_{n-1}) \right] \\
&+ \frac{1}{2} \left[ \frac{Q(x_u,t_n) - Q(x_d,t_n)}{q(x_u,t_n)} + \Delta t + \frac{Q(x_u,t_n) - Q(x_d,t_{n+1})}{q(x_u,t_n)} \right] \left[ Q(x_d,t_{n+1}) - Q(x_u,t_n) \right] \\
&+ \frac{1}{2} \left[ \Delta t + \frac{Q(x_u,t_n) - Q(x_d,t_{n+1})}{q(x_u,t_n)} + 2\Delta t + \frac{Q(x_u,t_n) - Q(x_d,t_{n+2})}{q(x_u,t_n)} \right] \left[ Q(x_d,t_{n+2}) - Q(x_d,t_{n+1}) \right]
\end{align*}
\]

The average travel time \( tt \) is the total travel time \( TT \) divided by \( n(t_n) \):

\[
\begin{align*}
\frac{TT}{n(t_n)} &= \frac{1}{2q(x_u,t_n)\Delta t} \left[ \frac{Q(x_u,t_{n-1}) - Q(x_d,t_{n-1})}{q(x_u,t_n)} + \frac{Q(x_u,t_n) - Q(x_d,t_n)}{q(x_u,t_n)} \right] \left[ Q(x_d,t_n) - Q(x_u,t_{n-1}) \right] \\
&+ \left[ \Delta t + \frac{2Q(x_u,t_n) - Q(x_d,t_n) - Q(x_d,t_{n+1})}{q(x_u,t_n)} \right] q(x_d,t_{n+1})\Delta t \\
&+ \left[ 3\Delta t + \frac{2Q(x_u,t_n) - Q(x_d,t_{n+1}) - Q(x_d,t_{n+2})}{q(x_u,t_n)} \right] q(x_d,t_{n+2})\Delta t \\
&+ \left[ (2j-1)\Delta t + \frac{2Q(x_u,t_n) - Q(x_d,t_{n+j-1}) - Q(x_d,t_{n+j})}{q(x_u,t_n)} \right] q(x_d,t_{n+j})\Delta t \\
&+ \left[ 2j\Delta t + \frac{Q(x_u,t_n) - Q(x_d,t_{n+j})}{q(x_u,t_n)} + \frac{Q(x_u,t_n) - Q(x_d,t_{n+j+1})}{q(x_u,t_{n+j+1})} \right] \left[ Q(x_u,t_n) - Q(x_d,t_{n+j}) \right]
\end{align*}
\]
For the diagram of the cumulative flow shown in Figure 3.7, besides the assumption
\( q(x_d, t_n) \neq q(x_d, t_n) \) and \( Q(x_d, t_n) \leq Q(x_u, t_{n-1}) \leq Q(x_d, t_{n+1}) \), Equation 3.78 is also based on
the assumption that \( Q(x_d, t_n) > Q(x_u, t_n) \) or \( Q(x_d, t_n) \leq Q(x_u, t_n) \) & \( q(x_d, t_{n+2}) = q(x_d, t_{n+1}) \).

Given the updating downstream data, a complete diagram of the cumulative flows at two
detection locations is shown in Figure 4.5. The necessary updated data include: 1) the time
\( t_A \) that the downstream cumulative flow is equal to that of upstream at time \( t_{n-1} \); 2) and the
downstream cumulative flow \( Q(x_d, t_{n+i+1}) \) at time \( t_{n+i+1} \) with \( t_{n+i} \leq t_A \leq t_{n+i+1}, i = 1, 2, \ldots \); 3) the
time \( t_z \) that the downstream cumulative flow is equal to that of upstream at time \( t_n \); and 4)
and the downstream cumulative flow \( Q(x_d, t_{n+j+1}) \) at time \( t_{n+j+1} \) supposing \( t_{n+j} \leq t_z \leq t_{n+j+1} \),
\( j = 1, 2, \ldots \). Using the downstream flow rate data \( q(x_d, t_{n+1}), q(x_d, t_{n+2}), \ldots q(x_d, t_{n+j}), q(x_d, t_{n+1}), \ldots q(x_d, t_{n+j}), \ldots q(x_d, t_{n+j+1}), n(t_n) \) is introduced to estimate the travel time.

The total travel time \( TT \) of all the vehicles \( n(t_n) \) that enter the link during the time interval
\( (t_{n-1}, t_n) \) is seen in Figure 4.5 as the shaded area and is calculated as
\[
TT = \left\{ \begin{array}{l}
\frac{1}{2} \left[ (i+1)\Delta t + \frac{Q(x_u, t_{n-1}) - Q(x_d, t_{n+1})}{q(x_u, t_{n+1})} + (i+1)\Delta t + \frac{Q(x_u, t_n) - Q(x_d, t_{n+1})}{q(x_u, t_n)} \right] \\
* \left[ Q(x_d, t_{n+1}) - Q(x_u, t_{n-1}) \right] \\
+ \frac{1}{2} \left[ (i+1)\Delta t + \frac{Q(x_u, t_n) - Q(x_d, t_{n+1})}{q(x_u, t_n)} + (i+1)\Delta t + \frac{Q(x_u, t_n) - Q(x_d, t_{n+1})}{q(x_u, t_n)} \right] \\
* \left[ Q(x_d, t_{n+1}) - Q(x_u, t_{n-1}) \right] \\
\end{array} \right. \\
\left\{ \begin{array}{l}
\frac{1}{2} \left[ (j-1)\Delta t + \frac{Q(x_u, t_n) - Q(x_d, t_{n+j-1})}{q(x_u, t_n)} + j* \Delta t + \frac{Q(x_u, t_n) - Q(x_d, t_{n+j-1})}{q(x_u, t_n)} \right] \\
* \left[ Q(x_d, t_{n+j-1}) - Q(x_u, t_{n-1}) \right] \\
+ \frac{1}{2} \left[ j* \Delta t + \frac{Q(x_u, t_n) - Q(x_d, t_{n+j})}{q(x_u, t_n)} + j* \Delta t + \frac{Q(x_u, t_n) - Q(x_d, t_{n+j})}{q(x_u, t_n)} \right] \\
* \left[ Q(x_u, t_n) - Q(x_d, t_{n+j}) \right] \\
\end{array} \right. \\
\right. \\
\end{equation}

Figure 4.5: Schematic representation of the total travel time during the interval \((t_{n-1}, t_n)\).
The average travel time $tt$ is the total travel time $TT$ divided by $n(t_n)$:

$$tt = \frac{TT}{n(t_n)}$$

$$= \frac{1}{2q(x_u, t_n) \Delta t} \left[ 2(i + 1) \Delta t \frac{Q(x_u, t_{n-1}) - Q(x_d, t_{n+1})}{q(x_d, t_{n+1})} + \frac{Q(x_u, t_n) - Q(x_d, t_{n+1})}{q(x_d, t_n)} \right]$$

$$+ \left[ 2(i + 3) \Delta t + \frac{Q(x_u, t_n) - Q(x_d, t_{n+1}) - Q(x_d, t_{n+2})}{q(x_d, t_n)} \right] q(x_d, t_{n+2}) \Delta t$$

$$+ \left[ (2j - 1) \Delta t + \frac{Q(x_u, t_n) - Q(x_d, t_{n+1}) - Q(x_d, t_{n+j})}{q(x_u, t_n)} \right] q(x_u, t_{n+j}) \Delta t$$

$$+ \left[ 2j \Delta t + \frac{Q(x_u, t_n) - Q(x_d, t_{n+j})}{q(x_u, t_n)} + \frac{Q(x_u, t_n) - Q(x_d, t_{n+j})}{q(x_d, t_{n+j})} \right]$$

$$+ \left[ Q(x_u, t_n) - Q(x_d, t_{n+j}) \right]$$

(4.6)

Overall, after the traffic conditions are determined, the procedure for the selection of travel time estimation models can be presented, as seen in Figure 4.6.
Figure 4.6: Travel time estimation model selection procedure
4.5 Performance Measurements

After the application of the systematic method to estimate travel time per time interval \( tt(i_t) \), the estimation results should be compared to the true values \( tt(t_i) \) to measure the performance of the model. Besides the MAE and MAPE, shown in Equations 3.80 and 3.81 in Section 3.2.5, the absolute percentage error (APE) is also utilized to evaluate the travel time estimation of the proposed systematic method for each time interval.

The APE of the estimated travel time \( tt(i_t) \) is obtained from the real travel time \( tt(t_i) \) at a given time interval.

\[
\text{APE} = \left| \frac{tt(t_i) - tt(i_t)}{tt(t_i)} \right| \times 100 \tag{4.7}
\]

Given \( n \) as the number of the time interval, the MAE and MAPE are introduced.

\[
\text{MAE} = \frac{\sum_{i=1}^{n} |tt(t_i) - tt(i_t)|}{n} \tag{3.80}
\]

\[
\text{MAPE} = \frac{\sum_{i=1}^{n} \left| \frac{tt(t_i) - tt(i_t)}{tt(t_i)} \right| \times 100}{n} \tag{3.81}
\]

4.6 Preliminary Findings of Simulation Study using the Systematic Method

Using the simulation data for the 500-meter, 750-meter and 1000-meter freeway links, the
A systematic method can estimate the average travel time per time interval by choosing different models under six scenarios:

- **Scenario 1**: measured spot speeds, same downstream flow rates during consecutive times, and no updating downstream data.
  Model selection: speed extrapolation model (free-flow), dynamic traffic flow model or dynamic-based probabilistic regression model (transition and congestion).

- **Scenario 2**: estimated spot speeds, same downstream flow rates, no updating data.
  Model selection: Probabilistic regression model based on upstream estimated speed (free-flow), dynamic traffic flow model or dynamic-based probabilistic regression model (transition and congestion).

- **Scenario 3**: measured spot speeds, different downstream flow rates, no updating data.
  Model selection: Speed extrapolation model (free-flow), modified dynamic traffic flow model or modified dynamic-based probabilistic regression model (transition and congestion).

- **Scenario 4**: estimated spot speeds, different downstream flow rates, no updating data.
  Model selection: Probabilistic regression model based on upstream estimated speed (free-flow), modified dynamic traffic flow model or modified dynamic-based probabilistic regression model.

- **Scenario 5**: measured spot speeds, with updating downstream data.
  Model selection: Speed extrapolation model (free-flow), modified dynamic traffic flow model or modified dynamic-based probabilistic regression model (transition and congestion).
congestion).

- Scenario 6: estimated spot speeds, with updating downstream data.

  Model selection: Probabilistic regression model based on upstream estimated speed (free-flow), modified dynamic traffic flow model or modified dynamic-based probabilistic regression model (transition and congestion)

Figures 4.7, 4.8 and 4.9 in Appendix B show the plots of travel time estimates for the 500-meter freeway link using the systematic method for each of the six cases; Table 4.1 presents the estimation errors, MAE and MAPE. Figures 4.10, 4.11 and 4.12 show the plots of travel time estimates for the 750-meter freeway link; Table 4.2 presents the estimation errors, MAE and MAPE. Figures 4.13, 4.14 and 4.15 show the plots of travel time estimates for the 1000-meter freeway link; Table 4.3 presents the estimation errors, MAE and MAPE. The preliminary findings are listed below.

1. Even without updating downstream data, the systematic method improves the accuracy of the models for travel time estimation under the transition condition through parameter changing test and time interval division. The comparison results are shown in Table 4.4.
Table 4.4 Error Comparison under Transition Condition

<table>
<thead>
<tr>
<th>Freeway links</th>
<th>Statistic</th>
<th>Dynamic traffic flow model</th>
<th>Modified dynamic traffic flow model</th>
<th>Systematic Method Dynamic traffic flow model</th>
<th>Modified traffic flow model</th>
</tr>
</thead>
<tbody>
<tr>
<td>500 m</td>
<td>One-lane</td>
<td>MAE sec 5.5</td>
<td>5.6</td>
<td>4.4</td>
<td>2.8</td>
</tr>
<tr>
<td></td>
<td></td>
<td>MAPE % 12.6</td>
<td>12.8</td>
<td>9.6</td>
<td>6.8</td>
</tr>
<tr>
<td></td>
<td>Two-lane</td>
<td>MAE sec 5.4</td>
<td>5.6</td>
<td>3.6</td>
<td>1.8</td>
</tr>
<tr>
<td></td>
<td></td>
<td>MAPE % 13.6</td>
<td>14.5</td>
<td>6.4</td>
<td>4.1</td>
</tr>
<tr>
<td></td>
<td>Three-lane</td>
<td>MAE sec 5.4</td>
<td>5.7</td>
<td>2.1</td>
<td>2.1</td>
</tr>
<tr>
<td></td>
<td></td>
<td>MAPE % 14.7</td>
<td>15.9</td>
<td>5.9</td>
<td>6.1</td>
</tr>
<tr>
<td>750 m</td>
<td>One-lane</td>
<td>MAE sec 5.2</td>
<td>5.6</td>
<td>5.4</td>
<td>3.4</td>
</tr>
<tr>
<td></td>
<td></td>
<td>MAPE % 8.4</td>
<td>8.6</td>
<td>7.5</td>
<td>5.5</td>
</tr>
<tr>
<td></td>
<td>Two-lane</td>
<td>MAE sec 8.3</td>
<td>5.4</td>
<td>6.9</td>
<td>2.6</td>
</tr>
<tr>
<td></td>
<td></td>
<td>MAPE % 11.9</td>
<td>10.2</td>
<td>7.9</td>
<td>3.7</td>
</tr>
<tr>
<td></td>
<td>Three-lane</td>
<td>MAE sec 4.1</td>
<td>4.4</td>
<td>2.2</td>
<td>2.0</td>
</tr>
<tr>
<td></td>
<td></td>
<td>MAPE % 7.5</td>
<td>8.3</td>
<td>3.9</td>
<td>3.1</td>
</tr>
<tr>
<td>1000 m</td>
<td>One-lane</td>
<td>MAE sec 9.3</td>
<td>5.6</td>
<td>9.6</td>
<td>7.2</td>
</tr>
<tr>
<td></td>
<td></td>
<td>MAPE % 10.1</td>
<td>6.5</td>
<td>8.8</td>
<td>6.0</td>
</tr>
<tr>
<td></td>
<td>Two-lane</td>
<td>MAE sec 10.5</td>
<td>5.7</td>
<td>9.4</td>
<td>7.5</td>
</tr>
<tr>
<td></td>
<td></td>
<td>MAPE % 8.7</td>
<td>6.0</td>
<td>7.6</td>
<td>5.1</td>
</tr>
<tr>
<td></td>
<td>Three-lane</td>
<td>MAE sec 4.6</td>
<td>4.6</td>
<td>3.4</td>
<td>2.9</td>
</tr>
<tr>
<td></td>
<td></td>
<td>MAPE % 5.9</td>
<td>6.1</td>
<td>4.4</td>
<td>3.4</td>
</tr>
</tbody>
</table>

From the table, it can be seen that for the travel time estimation obtained from the 500-meter freeway link data, the MAPE decreases from 12.6%~14.7% to 9.6%~5.9% using the dynamic traffic flow model and from 12.8%~15.9% to 6.8%~4.1% using the modified dynamic traffic flow model. For the 750-meter data, the MAPE decreases from 11.9%~7.5% to 7.5%~3.9% and from 10.2%~8.3% to 3.7%~3.1%. Overall, the errors decrease significantly when using the systematic method.

2. Using updating downstream data, the systematic method can estimate the travel time of each time interval more accurately under the congestion condition by improving the modified dynamic traffic flow model. The comparison results are shown in Table 4.5.
Table 4.5 Error Comparison under Congestion Condition

<table>
<thead>
<tr>
<th>Freeway links</th>
<th>Statistic</th>
<th>No updating data</th>
<th>With updating data</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Dynamic traffic flow model</td>
<td>Modified traffic flow model</td>
<td>Modified traffic flow model</td>
</tr>
<tr>
<td>500m</td>
<td>One-lane MAE (sec)</td>
<td>12.9</td>
<td>7.4</td>
</tr>
<tr>
<td></td>
<td>MAPE %</td>
<td>9.4</td>
<td>6.2</td>
</tr>
<tr>
<td></td>
<td>Two-lane MAE (sec)</td>
<td>8.3</td>
<td>5.1</td>
</tr>
<tr>
<td></td>
<td>MAPE %</td>
<td>7.2</td>
<td>4.5</td>
</tr>
<tr>
<td></td>
<td>Three-lane MAE (sec)</td>
<td>4.8</td>
<td>4.8</td>
</tr>
<tr>
<td></td>
<td>MAPE %</td>
<td>5.9</td>
<td>6.1</td>
</tr>
<tr>
<td>750m</td>
<td>One-lane MAE (sec)</td>
<td>21.9</td>
<td>9.2</td>
</tr>
<tr>
<td></td>
<td>MAPE %</td>
<td>10.8</td>
<td>4.7</td>
</tr>
<tr>
<td></td>
<td>Two-lane MAE (sec)</td>
<td>12.5</td>
<td>6.4</td>
</tr>
<tr>
<td></td>
<td>MAPE %</td>
<td>7.1</td>
<td>3.7</td>
</tr>
<tr>
<td></td>
<td>Three-lane MAE (sec)</td>
<td>4.8</td>
<td>4.5</td>
</tr>
<tr>
<td></td>
<td>MAPE %</td>
<td>4.1</td>
<td>3.8</td>
</tr>
<tr>
<td>1000m</td>
<td>One-lane MAE (sec)</td>
<td>9.6</td>
<td>5.4</td>
</tr>
<tr>
<td></td>
<td>MAPE %</td>
<td>6.2</td>
<td>3.5</td>
</tr>
<tr>
<td></td>
<td>Two-lane MAE (sec)</td>
<td>29.1</td>
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<td></td>
<td>MAPE %</td>
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<td>5.8</td>
</tr>
<tr>
<td></td>
<td>Three-lane MAE (sec)</td>
<td>17.0</td>
<td>9.7</td>
</tr>
<tr>
<td></td>
<td>MAPE %</td>
<td>7.1</td>
<td>4.0</td>
</tr>
</tbody>
</table>

From the table, it can be seen that the MAE and MAPE from the dynamic traffic flow model are in the acceptable range (MAE, 4.8~29.1 seconds; MAPE 4.1%~11.0%), and the MAE and MAPE from the modified dynamic model are more accurate (MAE, 4.5~15.5 seconds; MAPE 3.5%~6.2%). Moreover, using the updating downstream data, the MAE and MAPE decrease to 1.8~3.9 seconds and 1.6%~4.1%, respectively.

Also, an example of the APE per time interval for the 750-meter, one-lane link under the congestion condition is shown in Figure 4.16 to verify the accuracy of the modified dynamic model using updating downstream data. Other examples can be found in the Appendix B Figures 4.17 - 4.25. Although the MAPE (10.8%) from the dynamic flow model is acceptable, and the MAPE (4.7%) from the modified dynamic flow model without updated data seems
accurate, the APE of the two models during some time intervals is large (20%~80%). With the updated data, the APEs of the proposed model per time interval are all less than 5%. It can be seen that the proposed modified dynamic model is the most accurate and appropriate model to estimate the travel time using the updated data.

![Figure 4.16: MAPE of 750m one-lane link under congestion flow](image)

3. Under the free-flow condition, the systematic method uses the speed extrapolation models with measured speeds or the probabilistic regression model based on estimated upstream speeds to estimate the travel time. As seen in Tables 4.1, 4.2 and 4.3 in the Appendix B, the errors of the MAE (0.10~0.77 second, 0.70~1.37 seconds) and MAPE (0.40%~1.49%, 2.67%~3.66%) are small, and thus the estimation of the travel time is accurate.

4. Compared with the other models, the systematic method is applicable under various conditions.
traffic conditions and for different freeway links. Moreover, the accuracy of the method improves significantly with the updating data. Tables 4.6, 4.7 and 4.8 summarize the comparison with the performance measurements for the different link lengths (500-meter, 750-meter and 1000-meter) and numbers of lanes (one lane, two lanes and three lanes) under all traffic conditions. From these tables, the MAE (1.0~3.3 seconds) and MAPE (1.3%~3.9%) of the systematic method are the smallest, especially using the updated data. The simulation study proves that the systematic method is more accurate and applicable for travel time estimation than the other methods.

Table 4.6 Error Comparison of the 500-Meter Freeway Link

<table>
<thead>
<tr>
<th>Models</th>
<th>MAE (sec)</th>
<th>MAPE (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1-lane</td>
<td>2-lane</td>
</tr>
<tr>
<td>Speed Extrapolation Model 1</td>
<td>10.8</td>
<td>11.6</td>
</tr>
<tr>
<td>Speed Extrapolation Model 2</td>
<td>11.3</td>
<td>12.1</td>
</tr>
<tr>
<td>Speed Extrapolation Model 3</td>
<td>15.4</td>
<td>14.7</td>
</tr>
<tr>
<td>Dynamic Traffic flow</td>
<td>9.1</td>
<td>6.2</td>
</tr>
<tr>
<td>Modified Dynamic Traffic flow</td>
<td>6.2</td>
<td>4.5</td>
</tr>
<tr>
<td>Probabilistic Regression Method Central value-of-fit window True TT</td>
<td>1.4</td>
<td>1.6</td>
</tr>
<tr>
<td>Upstream TT</td>
<td>26.5</td>
<td>19.9</td>
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<tr>
<td>Speed Extrapolation TT</td>
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</tr>
<tr>
<td>Modified Dynamic TT</td>
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<td>3.9</td>
</tr>
</tbody>
</table>

Systematic Method

<table>
<thead>
<tr>
<th></th>
<th>Measured spot speeds</th>
<th>Estimated spot speeds</th>
</tr>
</thead>
<tbody>
<tr>
<td>No update data</td>
<td>Dynamic flow model</td>
<td>Dynamic flow model</td>
</tr>
<tr>
<td></td>
<td>7.0</td>
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<td></td>
<td>4.1</td>
<td>7.2</td>
</tr>
<tr>
<td></td>
<td>4.2</td>
<td>4.2</td>
</tr>
<tr>
<td>With update data</td>
<td>Measured spot speeds</td>
<td>Estimated spot speeds</td>
</tr>
<tr>
<td></td>
<td>2.3 2.6 1.4</td>
<td>2.7 2.8 2.3</td>
</tr>
<tr>
<td></td>
<td>2.5 2.9 1.8</td>
<td>3.4 3.9 3.8</td>
</tr>
</tbody>
</table>
Table 4.7 Error Comparison of 750-Meter Freeway Link

<table>
<thead>
<tr>
<th>Models</th>
<th>MAE (sec)</th>
<th></th>
<th>MAPE (%)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>1-lane</td>
<td>2-lane</td>
<td>3-lane</td>
</tr>
<tr>
<td>Speed Extrapolation Model 1</td>
<td></td>
<td>18.0</td>
<td>20.1</td>
<td>8.4</td>
</tr>
<tr>
<td>Speed Extrapolation Model 2</td>
<td></td>
<td>16.8</td>
<td>19.8</td>
<td>7.9</td>
</tr>
<tr>
<td>Speed Extrapolation Model 3</td>
<td></td>
<td>16.4</td>
<td>20.0</td>
<td>7.4</td>
</tr>
<tr>
<td>Dynamic Traffic flow</td>
<td></td>
<td>13.8</td>
<td>8.6</td>
<td>4.1</td>
</tr>
<tr>
<td>Modified Dynamic Traffic flow</td>
<td></td>
<td>7.4</td>
<td>5.2</td>
<td>4.0</td>
</tr>
<tr>
<td>Probabilistic Regression Method</td>
<td>True TT</td>
<td>1.5</td>
<td>1.7</td>
<td>1.6</td>
</tr>
<tr>
<td>Central value-of-fit window</td>
<td>Upstream TT</td>
<td>26.5</td>
<td>27.3</td>
<td>14.0</td>
</tr>
<tr>
<td>Systematic Method</td>
<td>Last Interval True TT</td>
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<td>13.6</td>
<td>8.9</td>
</tr>
<tr>
<td>No update data</td>
<td>Dynamic TT</td>
<td>13.1</td>
<td>8.1</td>
<td>3.5</td>
</tr>
<tr>
<td>Measured spot speeds Dynamic flow model</td>
<td>Modified TT</td>
<td>8.6</td>
<td>5.1</td>
<td>3.4</td>
</tr>
<tr>
<td>With update data</td>
<td>True TT</td>
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<td>1.7</td>
<td>1.6</td>
</tr>
<tr>
<td>Measured spot speeds Dynamic flow model</td>
<td>Upstream TT</td>
<td>26.5</td>
<td>27.3</td>
<td>14.0</td>
</tr>
<tr>
<td>Estimated spot speeds Dynamic flow model</td>
<td>Last Interval True TT</td>
<td>10.9</td>
<td>13.6</td>
<td>8.9</td>
</tr>
<tr>
<td>Estimated spot speeds Modified model</td>
<td>Dynamic TT</td>
<td>13.1</td>
<td>8.1</td>
<td>3.5</td>
</tr>
<tr>
<td>Estimated spot speeds Modified model</td>
<td>Modified TT</td>
<td>8.6</td>
<td>5.1</td>
<td>3.4</td>
</tr>
</tbody>
</table>

Table 4.8 Error Comparison of 1000-Meter Freeway Link

<table>
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<tr>
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<th>MAPE (%)</th>
<th></th>
</tr>
</thead>
<tbody>
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<td></td>
<td></td>
<td>1-lane</td>
<td>2-lane</td>
<td>3-lane</td>
</tr>
<tr>
<td>Speed Extrapolation Model 1</td>
<td></td>
<td>28.1</td>
<td>31.9</td>
<td>10.5</td>
</tr>
<tr>
<td>Speed Extrapolation Model 2</td>
<td></td>
<td>27.4</td>
<td>31.5</td>
<td>9.9</td>
</tr>
<tr>
<td>Speed Extrapolation Model 3</td>
<td></td>
<td>27.1</td>
<td>33.8</td>
<td>9.7</td>
</tr>
<tr>
<td>Dynamic Traffic flow</td>
<td></td>
<td>18.3</td>
<td>10.8</td>
<td>6.0</td>
</tr>
<tr>
<td>Modified Dynamic Traffic flow</td>
<td></td>
<td>10.8</td>
<td>6.8</td>
<td>4.6</td>
</tr>
<tr>
<td>Probabilistic Regression Method</td>
<td>True TT</td>
<td>1.8</td>
<td>1.8</td>
<td>1.8</td>
</tr>
<tr>
<td>Central value-of-fit window</td>
<td>Upstream TT</td>
<td>41.1</td>
<td>53.7</td>
<td>18.8</td>
</tr>
<tr>
<td>Systematic Method</td>
<td>Speed Extrapolation TT</td>
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<td>32.5</td>
<td>11.1</td>
</tr>
<tr>
<td>No update data</td>
<td>Last Interval True TT</td>
<td>13.2</td>
<td>16.4</td>
<td>10.4</td>
</tr>
<tr>
<td>Measured spot speeds Dynamic flow model</td>
<td>Dynamic TT</td>
<td>17.5</td>
<td>10.5</td>
<td>5.4</td>
</tr>
<tr>
<td>Estimated spot speeds Modified model</td>
<td>Modified Dynamic TT</td>
<td>10.2</td>
<td>6.5</td>
<td>4.1</td>
</tr>
<tr>
<td>With update data</td>
<td>True TT</td>
<td>1.8</td>
<td>1.8</td>
<td>1.8</td>
</tr>
<tr>
<td>Measured spot speeds Dynamic flow model</td>
<td>Upstream TT</td>
<td>41.1</td>
<td>53.7</td>
<td>18.8</td>
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<tr>
<td>Estimated spot speeds Dynamic flow model</td>
<td>Last Interval True TT</td>
<td>13.2</td>
<td>16.4</td>
<td>10.4</td>
</tr>
<tr>
<td>Estimated spot speeds Modified model</td>
<td>Dynamic TT</td>
<td>17.5</td>
<td>10.5</td>
<td>5.4</td>
</tr>
<tr>
<td>Estimated spot speeds Modified model</td>
<td>Modified Dynamic TT</td>
<td>10.2</td>
<td>6.5</td>
<td>4.1</td>
</tr>
</tbody>
</table>
4.7 Summary

Based on the comparison of different estimation models discussed in Chapter 3, Chapter 4 proposed a systematic method to estimate the travel times for different freeway links under various traffic conditions. In this proposed systematic estimation method, raw traffic data have been investigated and analyzed in advance to select a speed as the appropriate parameter to determine the traffic conditions. Under different traffic conditions, the traffic data have been further aggregated to meet the demand of constant flow in each time interval. Then, a specific model was assigned to each traffic scenario to estimate the travel time.

In summary, the preliminary findings show that the accuracy of the systematic method is verified using simulation data. In Chapter 5, the proposed systematic method will be implemented and tested using field traffic data.
CHAPTER 5 FIELD DATA STUDY

In Chapter 4, a systematic method for the travel time estimation of freeway links under all traffic conditions was proposed and also was verified by the simulation data. This chapter discusses the implementation and testing of the proposed systematic method using real traffic data. Real traffic data collected from different highways and used in the Next Generation Simulation (NGSIM) program are described in Section 5.1. The procedure for developing the estimation system for the field data is presented in Sections 5.2 and 5.3. In Section 5.4, the comparison of the estimated results and measured performance results from different methods is discussed to verify the accuracy of the systematic method. Finally, a summary is provided in Section 5.5.

5.1 Field Data Description

The real traffic data are collected from the NGSIM program, which is used to develop a core of open behavioral algorithms for improving the quality and performance of traffic simulation tools. This program is based on supporting documents and validation datasets that describe the interactions of multi-model travelers, vehicles and highway systems. Besides the wide-area detector data, the datasets include detailed vehicle trajectory data. The true travel time can be measured from these detailed data, and thus the NGSIM data can be utilized to develop and test the proposed estimation system. The field data selected from the NGSIM datasets consist of U.S. Highway 101 (US 101) data, Interstate 80 prototype data and new I-80 data.
5.1.1 NGSIM US 101 Data

The traffic data were collected by the NGSIM team using video cameras on a segment of U.S. Highway 101 (the Hollywood Freeway) in Los Angeles, California. Figure 5.1 provides a schematic illustration of the location for this dataset. The detection site is 2100 feet in length, with an on-ramp at Ventura Boulevard and an off-ramp at Cahuenga Boulevard. This section has five lanes with an extra sixth lane between the two ramps. Video data were collected on June 15, 2005 using eight video cameras. Complete vehicle trajectory data were transcribed at a resolution of 10 frames per second, and data for 45-minute periods, from 7:50 a.m. to 8:35 a.m., present transitional and congested flow conditions.

This research focuses on the freeway links without on- or off-ramps between the detectors; thus, the study area for the US 101 data is the segment between the two ramps, as shown in Figure 5.1. The study area is approximately 698 feet (213 meters) in length with six lanes.

Some terminology found in the text file of the vehicle trajectories is relevant to the research; these terms are listed below. The process for obtaining the relevant raw data uses SAS scripts, and this code is shown in Appendix C.1.

- Vehicle ID: vehicle identification number.
- Frame ID: frame identification number, which is set to the time with unit 1/10 second.
- Local Y: longitudinal coordinate of the vehicle with respect to the entry edge of the section, which is set to the detector station. The data of $Y = 578'$ or $Y = 1276'$ are loaded as the two station detector locations of the study area.
- Vehicle Velocity: instantaneous velocity of the vehicle, which is set to the spot speed.

Figure 5.1: Study area schematic for NGSIM US 101 data. (Source: Cambridge Systematic, Inc., 2005, Figure 1)
5.1.2 NGSIM Prototype I-80 Data

The prototype I-80 data were collected as part of the NGSIM prototype data collection by Cambridge Systematic, Inc. and the California Center for Innovative Transportation at the University of California, Berkeley. These prototype data were collected at the Berkeley Highway Laboratory (BHL) site, which is located at a segment of eastbound I-80 in Emeryville, California. Figure 5.2 shows a schematic illustration of the detection location for this prototype I-80 dataset. The detection site is approximately 2950 feet in length, with an on-ramp at Powell Street and an off-ramp at Ashby Avenue. There are six lanes in this section before the off-ramp and five lanes at the downstream of the off-ramp. Video data were collected using six video cameras, and the vehicle trajectory data were transcribed at a temporal resolution of 15 frames per second. The data collection time is approximately 30 minutes, from 2:35 p.m. to 3:05 p.m.; these data present normal and transition flow conditions.

As shown in Figure 5.2, the study area for the prototype I-80 dataset focuses on the segment between the on-ramp and off-ramp, which is approximately 1300 feet (369 meters) in length with six lanes. The items chosen from the text file of the I-80 trajectories are the same as those from US 101: vehicle ID; frame ID with unit 1/15 second; local Y with upstream location \( Y = 755' \) and downstream location \( Y = 2360' \); and vehicle velocity. Also, the process for the SAS code is presented in Appendix C.2.
5.1.3 New I-80 Data

The newly developed I-80 data were collected at the Berkeley Highway Laboratory (BHL) site on April 13, 2005. Compared to the prototype I-80 data, the detection area for the new I-80 data is just at the merge section of the BHL site, which is illustrated in the schematic of Figure 5.3. The merge site is only approximately 1650 feet in length with an on-ramp at
Powell Street. The off-ramp at Ashby Avenue is located at the downstream of the detection area. There are six lanes throughout the detection section. Video data were collected using seven video cameras, and the vehicle trajectory data were transcribed at a resolution of 10 frames per second. There are a total of 45 minutes of data collected during the afternoon peak hours: 1) 4:00 p.m. to 4:15 p.m.; 2) 5:00 p.m. to 5:15 p.m.; and 3) 5:15 p.m. to 5:30 p.m. The data for the 4:00 p.m. to 4:15 p.m. period primarily represent transitional traffic conditions. The remaining two periods represent congested traffic conditions.

An illustration of the study area for the new I-80 data is provided in Figure 5.3. The study area is the merge segment of the on–ramp downstream, which is about 1230 feet (375 meters) in length with six lanes. Compared to the selected items in the text file of the prototype I-80 data, the unit of the frame ID is 1/10 second, and the local Y is $Y = 420'$ and $Y = 1650'$. The SAS script and its code in Appendix C.3 are used to obtain the relevant raw data.
5.2 Field Data Analysis and Traffic Condition Determination

For the three field datasets described in Section 5.1, i.e., the U.S. Highway 101 data, the I-80 first prototype data and the new I-80 data, the study areas are all weaving segments between an on-ramp and an off-ramp of the freeway. Weaving segments require intense lane-changing maneuvers, and thus, traffic in a weaving segment is more turbulent than that normally
present on basic freeway segments (HCM 2000). Therefore, in the field data investigation and analysis, besides the basic procedure mentioned in Section 4.2, some specific processes are included, such as time interval identification, testing of the change in the frequency of certain traffic parameters, and data aggregation. Then, the traffic conditions per time interval, or even smaller time intervals, are determined.

5.2.1 Time Interval Length Identification

As discussed in Section 4.2, given the relationship among time interval length, link length, and desired speed, \( T > \frac{\Delta x}{u_f} \), the recommended time interval is 2 minutes. Therefore, to determine the appropriate time interval, first the relationships should be identified.

For the US 101 dataset, the freeway link length \( \Delta x \) is 698 feet, the desired speed \( u_f \) is almost 65 mph, and then: \( \frac{\Delta x}{u_f} = \frac{698 \text{ ft}}{65 \text{ mph}} \approx 8 \text{ sec} \), which is less than 2 minutes. For the prototype I-80 dataset, the freeway link length \( \Delta x \) is 1300 feet, the desired speed \( u_f \) is 65 mph, and \( \frac{\Delta x}{u_f} = \frac{1300 \text{ ft}}{65 \text{ mph}} \approx 14 \text{ sec} \) is less than 2 minutes. For the new I-80 dataset, the freeway link length \( \Delta x \) is 1230 feet, the desired speed \( u_f \) is almost 65 mph, and \( \frac{\Delta x}{u_f} = \frac{1230 \text{ ft}}{65 \text{ mph}} \approx 13 \text{ sec} < 2 \text{ min} \). Overall, the relationship \( T > \frac{\Delta x}{u_f} \) is satisfied, and thus the suggested time interval \( T = 2 \text{ min} \) is appropriate for the field data analysis. Moreover, smaller time intervals, such as 1 minute, 30 seconds and even 15 seconds, could likewise be
applicable because they also satisfy the relationship, i.e.,

$$T(1\text{ min}, 30\text{ sec}, 15\text{ sec}) > \frac{\Delta v}{u_f}(8\text{ sec}, 13\text{ sec}, 14\text{ sec}).$$

In the present field data analysis, besides the time interval of 2 minutes, the smaller ones of 1 minute, 30 seconds and 15 seconds are also tested; then, the results of the travel time estimation are compared to verify the models of the systematic method.

### 5.2.2 Testing of Frequency Changes in the Traffic Parameters

In the systematic method, to improve the accuracy of the travel time estimation, the changes in frequency of the traffic parameters, such as the space-mean speed $v_i$ and flow rates $q_i$, should be tested to verify the constant traffic distribution during the whole time interval. If the change in any of the parameters $v_i, q_i$ is significant, the traffic distribution within the time interval is not constant, and so the time interval is divided into smaller parts. In this field data analysis, due to the turbulent traffic within the weaving segments, the traffic dynamics data per 1-minute, 30-second and even 15-second intervals are collected and compared to test the change in frequency within the 2-minute intervals.

Figures 5.4, 5.5 and 5.6 (Appendix D) describe the plots of the traffic parameters (i.e., the upstream and downstream flow rates $q_{u,i}, q_{d,i}$ and space-mean speeds $v_{u,i}, v_{d,i}$) obtained from NGSIM US101 data. Within each 2-minute interval, if the four plot lines are flat, the traffic parameters ($q_{u,i}, q_{d,i}, v_{u,i}, v_{d,i}$) change less. However, as Figures 5.4, 5.5 and 5.6 indicate, the flow rates or space-mean-speeds change significantly at each 1-minute, 30-second, and even
15-second interval, especially after 12 minutes. Therefore, the 2-minute interval can be divided into eight 15-second intervals. The other divisions, i.e., two 1-minute intervals and four 30-second intervals, can also be utilized in the subsequent data analysis to compare performances with the different time interval divisions.

Figures 5.7, 5.8 and 5.9 (Appendix D) show the changes in frequency of the flow rates and space-mean speeds at two stations obtained from the new I-80 data. It can be seen that the changes of the parameters per 1-minute, 30-second or 15-second intervals are significant. Moreover, compared to those flow rates prior to 26 minutes, the flow rates after 26 minutes change more significantly, i.e., between 26 minutes and 45 minutes. Thus, the time interval divisions in the new I-80 data analysis can be the same as those in the US 101 data analysis. However, in the comparison with the US 101 data, the space-mean speeds of the new I-80 dataset are lower and the link length is longer, and thus, the 15-second division is not necessary. In the latter analysis for the new I-80 data, the preferred time division interval is 30 seconds.

Figures 5.10, 5.11 and 5.12 (Appendix D) depict the plots of flow rates and space-mean speeds obtained from the prototype I-80 dataset. Compared with the space-mean speeds indicated in the other figures, the space-mean speeds prior to the 20-minute interval are in the range of the desired speed distribution, i.e., $[50mph,80mph]$. According to the traffic analysis procedure found in Section 4.2, the change in frequency of the parameters during the time intervals does not require testing, and the time interval can be 2 minutes. However, due to the large traffic volume during this interval, which is close to capacity, and the significant
change in the flow rates, the 2-minute interval is divided into 15-second divisions for verifying the (modified) dynamic traffic model. After 20 minutes, due to the space-mean speed \( (v_s, v_d \in (0,50\text{mph})) \) and significant changes in flow rates or space-mean speeds, the time division can also be 15 seconds.

### 5.2.3 Data Aggregation and Traffic Condition Determination

As discussed in Section 5.2.2, for the US 101 dataset and the prototype I-80 dataset, the 2-minute interval is divided into 15-second intervals, and for the new I-80 dataset the appropriate time division is 30 seconds. During the determined time interval division \( T_i \) (15 seconds or 30 seconds), the raw field data, which includes the number of vehicles \( N_i \) and spot speeds \( v_i \) passing the two stations (no occupancy data due to the use of the camera detector), are converted to the aggregated data, which consist of traffic flow \( q \) and space-mean speeds \( v \). The aggregation is performed according to Equations 5.1 and 5.2.

\[
q = \frac{N_i \times 3600}{T_i} \text{ (vph)} \tag{5.1}
\]

\[
v = \frac{N_i}{\sum_{i=1}^{N} \frac{1}{v_i}} \text{ (mph)} \tag{5.2}
\]

Also, to use the probabilistic regression model, the raw data are aggregated to the 1-second traffic volume data. All the data aggregation is performed using MATLAB R2006, and the code is shown in Appendix C.
As indicated from the analysis discussed in Section 4.3, the traffic conditions are determined by the relationship between the desired speed distribution \([u_f - \Delta u, u_f + \Delta u]\) and the space-mean speeds at two stations \(v_u, v_d\). For the field data, the desired speed distribution is \([50mph, 80mph]\). If both the space-mean speeds are in the desired range, the traffic condition for the time interval is free-flow; otherwise, it is transition/congestion. Table 5.1 in Appendix D shows the traffic condition per time division for the US 101 dataset, prototype I-80 dataset and the new I-80 dataset. It can be concluded that the traffic condition for US 101 per 15-second division is congestion. For the new I-80 dataset, before the time of 20 minutes, the traffic condition is free-flow; after 20 minutes, the traffic condition per 15-second interval is transition/congestion.

### 5.3 Travel Time Estimation and Performance Measurement

As analyzed in Section 4.4, after the determination of the traffic condition per time division interval \(T_i\) (15 seconds or 30 seconds), specific models are selected to estimate the travel time at each time division \(t_{it}\), and then, the average travel time in 2-minute intervals \(t_t\) is calculated using Equation 5.3.

\[
 t_t = \frac{t_{i1} \cdot q_{u,1} + t_{i2} \cdot q_{u,2} + \ldots + t_{in} \cdot q_{u,n}}{q_{u,1} + q_{u,2} + \ldots + q_{u,n}} 
\]

(5.3)

The estimated travel time and measurement errors (MAE, MAPE and APE) for the US 101 dataset, prototype I-80 dataset and new I-80 dataset are discussed in the following sections.
US 101 dataset

For the US 101 dataset, each 2-minute interval is divided into eight 15-second intervals, and the traffic condition per 15-second interval is congestion. Therefore, the (modified) dynamic traffic model or (modified) dynamic-based probabilistic regression models are used to estimate the travel time per 15-second interval, i.e., \( t_i, i = 1, 2, ..., 8 \), and the average travel time is

\[
\bar{t} = \frac{t_{i,1} * q_{u,1} + t_{i,2} * q_{u,2} + ... + t_{i,8} * q_{u,8}}{q_{u,1} + q_{u,2} + ... + q_{u,8}}
\]  (5.4)

Figure 5.13 shows the estimated travel times and true values for the US 101 freeway segment at each 2-minute interval. Figure 5.14 describes the APE. Table 5.2 summarizes the mean measurement errors, MAE and MAPE.

![Figure 5.13: Travel time estimates at 2-minute intervals for the US-101 link.](image-url)
Table 5.2 MAE and MAPE of Travel Time Estimation for US 101 Dataset

<table>
<thead>
<tr>
<th>Model</th>
<th>MAE (sec)</th>
<th>MAPE (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Modified Dynamic Model-updating data</td>
<td>0.1</td>
<td>0.6</td>
</tr>
<tr>
<td>Modified Dynamic Model</td>
<td>0.4</td>
<td>1.5</td>
</tr>
<tr>
<td>Dynamic Flow Model (Nam and Drew, Vanajakshi)</td>
<td>1.2</td>
<td>4.2</td>
</tr>
<tr>
<td>Modified dynamic-based Petty model-updating data</td>
<td>0.8</td>
<td>3.6</td>
</tr>
<tr>
<td>Modified dynamic-based Petty model</td>
<td>1.0</td>
<td>4.0</td>
</tr>
<tr>
<td>Dynamic-based Petty Model</td>
<td>1.9</td>
<td>6.9</td>
</tr>
</tbody>
</table>

For the US 101 dataset, there are six models in the systematic method that can be used to estimate travel time under different scenarios:

Given the necessary updated downstream data, as discussed in Section 4.4, the modified dynamic model by Yi is used for travel time estimation. From Figure 5.3, Figure 5.4 and Table 4.6, it can be seen that the estimated travel times are very close to the true values, with
the smallest mean error of the MAE (0.1 second) and MAPE (0.6%); even the APEs per time interval are all less than 2%.

The probabilistic regression model based on the above modified dynamic model is also applicable, with a MAE of 0.8 second and MAPE of 3.6%, and APEs less than 9%. However, the fit range of the central value should be changed to 10 seconds due to the travel time range of $16\text{ sec} < tt < 32\text{ sec}$ . If using 20 seconds as the fit range, the errors of the estimated travel time increase: the MAE is 2.1 seconds, MAPE is 8.9% and APEs are less than 18%.

Without the necessary updated downstream data, due to the change in frequency of the flow rates per 15-second interval, the proposed modified dynamic model is more accurate than the dynamic traffic model by Nam and Drew (1998), or Vanajakshi (2008). Also, the probabilistic regression models based on the modified dynamic model are applicable with a MAE of 1.0 second, MAPE of 4.0% and APEs less than 10%. The results from the dynamic traffic model are acceptable, except for high APEs (15%, 18%) at some time intervals.

In the US 101 data analysis, almost all the updated data needed for the 2-minute intervals are part of the next time interval downstream flow; thus, it is not time consuming to obtain the necessary data. Even without the updated data, due to the division of the time interval into several 15-second intervals, the travel time estimation is affected only for the last few 15-second intervals; and the travel time estimation for these intervals can be obtained from the modified traffic model without updated data. Therefore, the proposed modified dynamic
model is the most accurate and appropriate model to estimate the travel time for the US 101 dataset.

**New I-80 dataset**

For the new I-80 dataset, as discussed in Section 5.2, each 2-minute interval is divided into four 30-second intervals, and the traffic condition of each 30-second interval is congestion. Therefore, the (modified) dynamic traffic model or (modified) dynamic-based probabilistic regression models are used to estimate the travel time per 30-second intervals, \( tt_i, i = 1, 2, 3, 4 \), and the average travel time is

\[
\bar{tt} = \frac{tt_1 \cdot q_{u,1} + tt_2 \cdot q_{u,2} + tt_3 \cdot q_{u,3} + tt_4 \cdot q_{u,4}}{q_{u,1} + q_{u,2} + q_{u,3} + q_{u,4}} \quad (5.5)
\]

Figure 5.15 shows the estimated travel times and true values for the new I-80 dataset. Figure 5.16 describes the APEs. Table 5.3 summarizes the mean measurement errors, MAE and MAPE.
Figure 5.15: Travel time estimates at 2-minute intervals for the US-101 link.

Figure 5.16: APE at 2-minute intervals for the new I-80 dataset.

Table 5.3 MAE and MAPE of Travel Time Estimation for New I-80 Dataset

<table>
<thead>
<tr>
<th>Model</th>
<th>MAE (sec)</th>
<th>MAPE (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Modified Dynamic Model-updating data</td>
<td>1.8</td>
<td>2.5</td>
</tr>
<tr>
<td>Modified Dynamic Model</td>
<td>2.4</td>
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</tr>
<tr>
<td>Dynamic Flow Model (Nam and Drew, Vanajakshi)</td>
<td>5.6</td>
<td>7.9</td>
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<tr>
<td>Modified dynamic-based Petty model-updating data</td>
<td>2.6</td>
<td>3.9</td>
</tr>
<tr>
<td>Modified dynamic-based Petty model</td>
<td>3.1</td>
<td>4.3</td>
</tr>
<tr>
<td>Dynamic-based Petty Model</td>
<td>6.1</td>
<td>8.7</td>
</tr>
</tbody>
</table>
Given all the necessary updated downstream data, which are nearly part of the next 1-minute downstream flow, the average travel time estimated from the modified dynamic model by Yi is accurate; the mean estimation errors, MAE of 1.8 seconds and MAPE of 2.5%, are small, and the APEs are less than 10%. Also, the probabilistic regression model based on the proposed modified dynamic model is appropriate, with a MAE of 2.6 seconds and MAPE of 3.9%, and APEs less than 11%.

Without the necessary updated downstream data, the modified dynamic model by Yi considers the change in downstream flow rates, and thus, it is more accurate than the dynamic traffic model by Nam and Drew, or Vanajakshi, in which the APEs (20%, 50%) at some time intervals are large. The dynamic-based probabilistic regression model also has relatively large estimation errors, i.e., a MAE of 6.1 seconds, MAPE of 8.7% and high APEs at some time intervals.

**Prototype I-80 dataset**

Out of the total 30 minutes of the prototype I-80 dataset, during the first 20 minutes, the traffic is under free-flow conditions, and the travel time per 2-minute interval can be estimated from the speed extrapolation models. During the last 10 minutes, the 2-minute interval is divided into eight 15-second intervals, and the traffic for those 15-second intervals is under transition or congestion conditions. Therefore, the (modified) dynamic traffic model or (modified) dynamic-based probabilistic regression models are used for travel time estimates per 15-second interval, i.e., \( tt_i, i = 1, 2, \ldots, 8 \), and the average travel time is
Figure 5.17 shows the estimated travel times and true values for the prototype I-80 dataset. Figure 5.18 describes the APE per time interval. Table 5.4 summarizes the mean measurement errors, MAE and MAPE.

\[
\text{tt} = \frac{tt_1 \cdot q_{u,1} + tt_2 \cdot q_{u,2} + \ldots + tt_8 \cdot q_{u,8}}{q_{u,1} + q_{u,2} + \ldots + q_{u,8}}
\]  

(5.6)

**Figure 5.17:** Travel time estimates at 2-minute intervals for the prototype I-80 dataset.
For the prototype I-80 dataset, the speed extrapolation model is used to estimate the travel time for the first 20 minutes, and the (modified) dynamic traffic model or (modified) dynamic-based probabilistic regression models are used for travel time estimates for the last 10 minutes. The mean errors, MAE 0.5–0.7 sec and MAPE 3.9%–4.2%, are small and APEs of all time intervals are less than 7.8%. Therefore, the systematic method can accurately estimate the average travel time for the prototype I-80 data.

Due to the traffic effect of the on-ramp and off-ramp in the weaving segment, the speeds along the freeway segment do not linearly change as they do under normal free-flow.
conditions. The space-mean speeds at the upstream and downstream stations are lower than those at other weaving segments, and thus the estimated travel time is larger than the true travel time shown in Figure 5.17. The modified dynamic traffic model by Yi is more accurate than speed extrapolation model. The measurement errors are smaller: MAE of 0.2 second, MAPE of 1.2%, and APEs per time interval less than 3%. Although the errors of the modified dynamic model are smaller the speed model for the field data under free-flow condition, the model are based on the parameters changing test and time interval division in the systematic method. Without the process of the systematic method, the errors of the modified model are large under free-flow condition (APE 2% ~40%), while the speed model are still appropriate (APE 2%~8%).

Overall, under free-flow conditions the speed model is more easily implemented for the field data and the performance is satisfied. Therefore, the model chosen is correct and the systematic method is appropriate for the travel time estimation.

5.4 Conclusions

As discussed in Sections 5.2 and 5.3, once the proposed systematic method is applied to the field traffic data, i.e., the US 101 data, prototype I-80 data and new I-80 data, the travel times can be estimated using the proposed estimation system, and the estimation results are accurate according to the performance measurements, MAE, MAPE and APE.

In addition, the proposed systematic method is compared with other methods in terms of estimation accuracy. Table 5.5 summarizes the comparison of the mean measurement errors,
MAE and MAPE, for the different methods. Figures 5.19, 5.20 and 5.21 show the comparison of the APEs per time interval for the US 101 data, prototype I-80 data and new I-80 data.

As Table 5.5 and Figures 5.19, 5.20 and 5.21 indicate, although the measurement errors of the speed models for the US 101 dataset and the prototype I-80 dataset are acceptable (MAE 0.7 sec~1.6 sec, MAPE 4.8%~4.9% and APEs <18%, 8%), the method is not applicable to the new I-80 dataset (MAE 12sec~16sec, MAPE 18%~26%, and APEs of several time intervals 50%~60%). The mean errors for the (modified) dynamic traffic flow models are acceptable, but the APEs at several time intervals are large, i.e. 20%~30% for the US 101 dataset, 40%~60% for the new I-80 dataset and 20%~40% for the prototype I-80 dataset. The probabilistic regression methods are based on the estimated values from the other models, and the accuracy is lower than that of the models.

Compared to the other methods, the systematic method produces the smallest measurement errors for all the real traffic data, i.e., MAE 0.1sec~1.8sec, MAPE 0.6%sec~3.9% and APEs <2%, 10%, 8% for the US 101, new I-80, and prototype I-80 datasets. Therefore, the proposed systematic method can accurately estimate travel times for different freeway links under various traffic conditions.
Table 5.5 Mean Error Comparison for Real Traffic Data

<table>
<thead>
<tr>
<th>Models</th>
<th>MAE (sec)</th>
<th>MAPE (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>US101 data</td>
<td>I-80 new data</td>
</tr>
<tr>
<td>Speed Extrapolation Model 1</td>
<td>1.6</td>
<td>11.8</td>
</tr>
<tr>
<td>Speed Extrapolation Model 2</td>
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<td>13.3</td>
</tr>
<tr>
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<td>16.5</td>
</tr>
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<td>6.4</td>
</tr>
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<td>Modified Dynamic Traffic flow</td>
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<td>Probabilistic Regression Method</td>
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<td>Central value-of-fit window</td>
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<td>True TT</td>
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</tr>
<tr>
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<td>16.4</td>
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<td>Speed Extrapolation TT</td>
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<td>6.4</td>
<td>10.8</td>
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<td>Dynamic TT</td>
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<td>6.5</td>
</tr>
<tr>
<td>Modified Dynamic TT</td>
<td>2.1</td>
<td>5.3</td>
</tr>
<tr>
<td>Systematic Method</td>
<td>0.1</td>
<td>1.8</td>
</tr>
</tbody>
</table>

Figure 5.19: APE comparison of all methods for US 101 dataset.
Figure 5.20 APE comparison of all methods for new I-80 dataset.

Figure 5.21 APE comparison of all methods for prototype I-80 dataset.
5.5 Summary

Chapter 5 demonstrates the implementation and testing of the proposed travel time estimation system using the field data. The areas of study for the US 101 dataset, prototype I-80 dataset and new I-80 dataset are different freeway segments with different link lengths, multiple lanes and various traffic conditions (Section 5.1). After the field data investigation and analysis, smaller time divisions within the 2-minute interval are then decided, after which the traffic condition per time division is determined (Section 5.2). Specific models in the systematic method are used for the travel time estimation, and the measurement errors (MAE, MAPE and APE) are calculated using the true values of the field data (Section 5.3). Comparing the measurement errors for all the estimation methods, it is concluded that the proposed systematic method is an accurate method for travel time estimation for different freeway links under various traffic conditions (Section 5.4).
CHAPTER 6 CONCLUSIONS

6.1 Summary

This dissertation proposes a travel time estimation system for freeway management systems with fixed point detection. Travel time is a fundamental element of advanced transportation information systems. Accurate travel times, especially section travel time over a short distance, can provide important information for travel routes, transportation schedules and incident detection, which in turn can mitigate congestion problems in urban freeway systems. Section travel time over a short distance is the basis of travel time of various freeway links and even freeway network. Direct measurement methods to obtain accurate travel time data are not widely used due to their costs and the privacy concerns inherent of such methods. Fixed-point detectors are widely used on freeways and provide continuous traffic flow, occupancy and/or spot speed data. If travel time can be accurately estimated from fixed-point detector data, then use of indirect estimation methods is cost-effective and widely applicable. Various estimation methods are described in terms of three specifications: estimation variables, time scale and adaptability. The characteristics of the ideal estimation method are claimed to be accuracy, efficiency and adaptability. This dissertation develops a systematic method for accurately estimating the travel time of different freeway links under various traffic conditions using fixed-point detector data.

The foundation of the proposed estimation system is a thorough analysis and comparison of the three categories of travel time estimation methods, i.e. speed extrapolation models, flow-
based statistic models and dynamic traffic flow models. The applications and limitations of each model have been analyzed in terms of theory and equation derivation, and possible modifications have been presented. Through a simulation study, the various models have been compared according to performance measurements under various traffic conditions, time intervals and freeway links. Finally, the applications of these models and the effects of traffic condition, number of freeway lanes and link length are discussed.

The proposed systematic method includes three stages: 1) investigation and analysis of the traffic data, 2) determination of the traffic conditions, and 3) selection of the specific model for travel time estimation and performance measurement. In the data investigation and analysis stage, data for the freeway link lengths and the desired speed distribution are collected to identify the appropriate time intervals; testing for changes in the frequency of the traffic parameters is used to determine the appropriate time interval divisions and verify the constant traffic distribution per time interval or per smaller time divisions; and then the raw data were aggregated. The traffic conditions per time interval are determined by the relationship of the aggregated space-mean speeds at the two stations and the desired speed distribution. The specific models are assigned to the various traffic conditions to estimate the average travel time per time interval, which is then compared to the true travel time to measure the performance of the systematic method.

The proposed systematic method was tested using both simulation data and real traffic data. For the simulation data for the 500-meter, 750-meter and 1000-meter freeway links, the travel times were estimated using the systematic method by choosing different models under
six scenarios: with and without spot speeds, change and no change in downstream flow rates, with and without updated downstream flow rates. A comparison of the estimated results and measurement errors helps to show the accuracy of the proposed systematic method for estimating the travel times of freeway links under various traffic conditions.

The real traffic data incorporated the US 101 dataset, prototype I-80 dataset and new I-80 dataset, collected using the NGSIM program. The areas of research present different freeway weaving segments comprised of different link lengths, numbers of lane and various traffic conditions. Once the field data investigation and analysis are completed, the 2-minute interval is divided into smaller time divisions, and the traffic conditions per time division are determined. Specific models in the proposed systematic method are used for the travel time estimation, and the measurement errors are calculated using the true values of the field data. By comparing the measurement errors of all the estimation methods, it is verified that the proposed systematic method can accurately estimate the travel times of freeway links under various traffic conditions.

6.2 Major Findings and Contributions

The major findings and contributions of this study are listed as follows:

- Travel time estimation methods that use fixed-point detector data can be divided into three categories: speed extrapolation models, flow-based statistic models and dynamic traffic flow models. In the dissertation, the three categories are analyzed and compared in detail through theory study, simulation study and field study.
• The three different statistical measurement errors (MAE, MAPE, and APE) can be used to assess the travel time estimation. By comparing the three estimation methods, the applications and limitations of the different models under various traffic conditions are decided, the effects of time interval, number of freeway lanes and link length are concluded, and the appropriate time interval is recommended.

• The accuracy of the probabilistic regression model is based on the central value of fit range, which is verified by the estimation results of the model using true value as its central value. Also, the research improves the model’s accuracy by using the appropriate central value according to: 1) the upstream estimated space-mean speed, 2) speed extrapolation Model 1, 3) the dynamic traffic flow model, or 5) the modified traffic flow model.

• The accuracy of the dynamic traffic flow models by Nam and Drew, or the modified model by Vanajakshi et al., is limited due to the assumption of constant downstream flow rates. The study considers the changes in cumulative downstream flow rates, proposes a modified dynamic traffic flow model, and then improves the modified dynamic traffic model using updated downstream data.

• The accuracy of the cross-correlation models is related to the value of the time delay. The study improves the models by choosing the appropriate range of time delay.

• Under various traffic conditions, the characteristic of traffic parameters are different. The study determines the traffic states by using the relationship between the desired speed distribution and the space-mean speeds in the upstream and downstream.

• Neither of the previous models or methods is fit for estimating travel time under
different traffic conditions. In the research, a prototype systematic method is proposed, and the framework and the detailed procedures are developed for accurate travel time estimation of different freeway links under various traffic condition.

- In the proposed systematic method, first, the data for freeway link lengths and desired speed distribution are collected to identify the recommended time interval. To confirm the constant traffic distribution, testing for changes in the frequency of traffic parameters should be undertaken, and the time intervals should be divided into smaller time divisions. The traffic conditions per time interval, or per small time division, are then determined. After the appropriate model is chosen and the travel time estimation is determined at the smaller time divisions, the average travel time can be calculated.

- For the simulation data of six different scenarios, a comparison of the estimated results and the measurement errors shows the accuracy of the systematic method for estimating travel times of freeway links under various traffic conditions.

- For the real traffic data, from the testing for frequency changes in the traffic parameters, the determined 2-minute interval is divided into smaller time divisions. By comparing the measurement errors of all the estimation methods, it is verified that the proposed systematic method is appropriate for travel time estimation of freeway links.

Overall, through a thorough analysis, comparison and possible modifications of the three categories of travel time estimation methods, the study presents a prototype of the travel time
estimation system. The accuracy of the systematic method is verified using both simulation data and real traffic data.

6.3 Future Research

The systematic method, as a prototype development, is not perfect and should be improved in the future study. Based on the findings from this study, the following recommendations for future research are put forward.

- Although the proposed method is appropriate for the field data, the chosen speed model is not the best under free-flow condition. For the prototype I-80 dataset, due to the large traffic volume of the weaving segment, and the modified dynamic model by Yi is more appropriate for the traffic state by using the time interval division process of the systematic method. In the simulation study, the design is only for freeway links upstream of ramp. Therefore, more simulation and field studies are needed to evaluate and improve the prototype systematic method in terms of other segment types of freeway links and more detailed traffic conditions.

- The study proposes a systematic method for the accurate estimation of travel times of freeway links under various traffic conditions. However the system depends entirely on correct fixed-point data. The errors in measured spot speeds and occupancy due to detector inaccuracies would be reflected in any estimates of link travel time. The flow data would be affected even more than the occupancy and speed data if detector malfunctions should occur. Therefore, future work is needed to verify and improve
the proposed systematic method in the case of incomplete or wrong simulation or field fixed-point detector data. Possible enhancements of fixed-point detectors should be studied to provide high quality datasets for the proposed systematic method.

The proposed systematic method is used to estimate the average travel times of all the lanes in the freeway link, because the data used in the study are obtained from all the detectors in the freeway lanes, which are each assumed to be a single lane. However, the travel times for the different lanes are different. Future work should be done to develop a revised model within the proposed systematic method that can take into account the lane-changing characteristics and analyze the data on a lane-by-lane basis.
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APPENDIX A TRAVEL TIME ESTIMATION AND PERFORMANCE MEASURE IN CHAPTER 3
Figure 3.12 Travel time estimates of 500m one-lane link at 2min interval
Figure 3.13 Travel time estimates of 500m one-lane link at 5min interval
Figure 3.14 Travel time estimates of 500m one-lane link at 10min interval
Figure 3.15 Travel time estimates of 500m two-lane link at 2min interval
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Figure 3.30 Travel time estimates of 1000m one-lane link at 2min interval
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Figure 3.34 Travel time estimates of 1000m two-lane link at 5min interval
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Figure 3.36 Travel time estimates of 1000m three-lane link at 2min interval
Figure 3.37 Travel time estimates of 1000m three-lane link at 5min interval
Figure 3.38 Travel time estimates of 1000m three-lane link at 10min interval
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<p>| 5min         | Speed Extrapolation 1 | 0.312 (0.05) | 16.8 (7.0) | 30.6 (3.2) | 0.602 (0.1) | 17.1 (5.8) | 14.3 (1.3) |
|              | Speed Extrapolation 2 | 0.316 (0.05) | 15.0 (6.8) | 29.6 (3.1) | 0.611 (0.1) | 16.5 (6.1) | 13.7 (1.3) |
|              | Speed Extrapolation 3 | 0.326 (0.05) | 15.1 (5.4) | 27.8 (2.7) | 0.630 (0.1) | 19.4 (6.4) | 12.8 (1.2) |
|              | Dynamic Traffic flow | 9.1 (2.0) | 6.8 (1.5) | 13.0 (2.4) | 17.6 (4.0) | 9.9 (2.9) | 6.0 (0.9) |
|              | Modified Dynamic Traffic flow | 8.9 (2.0) | 6.5 (1.7) | 9.6 (1.6) | 17.3 (3.9) | 9.7 (2.9) | 4.6 (0.7) |
|              | Max Cross-Correlation Significant C-C | 1.9 (0.3) | 5.0 (0.6) | 3.9 (0.5) |</p>
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APPENDIX B MEASUREMENT RESULTS FROM SIMULATION DATA USING SYSTEMATIC METHOD IN CHAPTER 4
Figure 4.7 Travel time estimates of 500m one-lane link by systematic method

Figure 4.8 Travel time estimates of 500m two-lane link by systematic method
Figure 4.9 Travel time estimates of 500m three-lane link by systematic method

Figure 4.10 Travel time estimates of 750m one-lane link by systematic method
Figure 4.11 Travel time estimates of 750m two-lane link by systematic method

Figure 4.12 Travel time estimates of 750m three-lane link by systematic method
Figure 4.13 Travel time estimates of 1000m one-lane link by systematic method

Figure 4.14 Travel time estimates of 1000m two-lane link by systematic method
Figure 4.15 Travel time estimates of 1000m three-lane link by systematic method

Figure 4.17 APE of 500m one-lane link under congested flow by systematic method
Figure 4.18 APE of 500m two-lane link under congested flow by systematic method

Figure 4.19 APE of 500m three-lane link under congested flow by systematic method
Figure 4.16 APE of 750m one-lane link under congested flow by systematic method

Figure 4.20 APE of 750m two-lane link under congested flow by systematic method
Figure 4.21 APE of 750m three-lane link under congested flow by systematic method

Figure 4.22 APE of 1000m one-lane link under congested flow by systematic method
Figure 4.23 APE of 1000 m two-lane link under congested flow by systematic method

Figure 4.24 APE of 1000 m three-lane link under congested flow by systematic method
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Table 4.2 Estimation Errors of 750m freeway link by Systematic Method

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Table 4.3 Estimation Errors of 1000m freeway link by Systematic Method

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APPENDIX C

C.1 CODE for NGSIM US101 DATA

1. Use SAS to Transfer original NGSIM data (US101 trajectory data) to relevant raw data

Code:

```sas
data test;
infil "C:\Documents and Settings\US101\vehicle-trajectory-data.txt";
input x1-x18 @@;
run;

data subtest(keep=x1 x2 x3 x6 x12 x14);
set test;
run;

data subtest;
set subtest;
rename x1=id
x2=t
x3=tt
x6=y
x12=s
x14=l;
run;

data try1;
set subtest;
if y>578 then output;

data try1;
set try1;
by id;
first=first.id;
last=last.id;
data try1;
set try1;
if first then output;
run;

data try2;
set subtest;
if y>1276 then output;

data try2;
set try2;
by id;
first=first.id;
last=last.id;
data try2;
```
set try2;
if first then output;
run;

2. Use Matlab to get the traffic flow and SMS data of 15 sec interval

Code:

A=load('data.txt');
t_enter1=A(:,1);
t_leave1=A(:,2);
v1=A(:,3);
t_enter2=A(:,4);
t_leave2=A(:,5);
v2=A(:,6);

for j=1:180
    n=0;a=0;b=0;
    for i=1:length(A)
        if((t_enter1(i)>=15*(j-1))&&(t_enter1(i)<15*j))
            a=a+1/v1(i);b=b+t_leave1(i);n=n+1;
        end
    end
    N(j)=n;B(j)=n/a;C(j)=b/n;F(j)=15*j;
end

for j=2:180
    n=0;a=0;b=0;
    for i=1:length(A)
        if((t_enter2(i)>=15*(j-1))&&(t_enter2(i)<15*j))
            a=a+1/v2(i);b=b+t_leave2(i);n=n+1;
        end
    end
    Q(j)=n;D(j)=n/a;E(j)=b/n;
end

Run: M=[F;N;B;C;Q;D;E]';
save output2.txt M -ASCII

3. Use Matlab to get the vehicle data of 1 sec

Code:

A=load('data.txt');
t1_enter=A(:,1);
t2_enter=A(:,4);
for i=1:2760
    n1=0;n2=0;
    for j=1:length(A)
        if ((t1_enter(j)>=(i-1))&&(t1_enter(j)<i))
            n1=n1+1;
        end
    end
    if (i==2760)
        n2=n2+1;
    end
end
if ((t2_enter(j) >= (i-1)) && (t2_enter(j) < i))
    n2 = n2 + 1;
end
end
N(i, 1) = n1; N(i, 2) = n2;
End
diary on
N
diary off

Run: save output3.txt N -ASCII

4. Use Matlab to estimate the travel time from Dynamic flow model and Modified dynamic flow model in 15sec

Code:

A = load('output2.txt');
B(:, 1:2) = A(:, 1:2);
B(:, 6) = A(:, 5);

Q1(1) = B(1, 2);
Q2(1) = B(1, 6);

for i = 1:length(A) - 1
    Q1(i + 1) = Q1(i) + B(i + 1, 2);
    Q2(i + 1) = Q2(i) + B(i + 1, 6);
end

kt_1(1) = 0;
for j = 1:length(A) - 1
    kt_1(j + 1) = Q1(j) - Q2(j);
end

kt = Q1 - Q2;
B(:, 10) = (kt_1' + kt')./(2*B(:, 6))*120;

for j = 1:length(A) - 1
    q2_1(j) = B(j, 6);
    q2_2(j) = B(j + 1, 6);
end

q2_1(length(A)) = B(length(A), 6);
q2_2(length(A)) = B(length(A), 6);

B(:, 14) = 0.5 * (kt_1' + kt')./B(:, 2) * 120 - 0.5./B(:, 2).* (kt_1'.^2./q2_1'.^120-kt'.^2./q2_2'.^120);
B(:, 15) = 60 - (q2_1' - kt_1' - kt')./q2_2'*60;
5. Use Matlab to estimate the travel time from the proposed dynamic flow model (with updating data) in 15 sec

```matlab
A = load('data.txt');
deltat=15;
q1=A(:,1);q2=A(:,2);
Q1(1)=q1(1);Q2(1)=q2(1);
for i=1:length(q1)-1
    Q1(i+1,1)=Q1(i,1)+q1(i+1);
    Q2(i+1,1)=Q2(i,1)+q2(i+1);
end

a(1)=-1;
for i=2:length(Q1)
    for j=1:length(Q2)
        if (Q1(i-1)-Q2(j)<=0)
            a(i)= -1+(j-i);
            break;
        end
    end
end

for i=1:length(Q1)-2
    c(i)=a(i+1)+1;
end

for i=2:length(Q1)-2
    if c(i)==a(i)+1
        t(i)=((2*(a(i)+1)+(Q1(i-1)-Q2(i+a(i)))/q2(i+a(i)+1)+(Q1(i)-Q2(a(i)+i+1))/q1(i))*Q2(i+a(i)+1)-Q1(i-1))+2*(a(i)+1)+(Q1(i)-Q2(a(i)+i+1))/q1(i)+Q1(i)-Q2(a(i)+i+1))/q2(i+a(i)+2)*deltat;
    elseif c(i)==a(i)
        t(i)=([2*a(i)+1+[Q1(i-1)-Q2(i+a(i))]/q2(i+a(i)+1)+[Q1(i)-Q2(a(i)+i)]]/q2(i+a(i)+1))*deltat/2;
    else c(i)>a(i)+2
        b(i-1)=0;
        for j=2*a(i)+3:2*c(i)-1
            b(j)=b(i-1)+(2*a(i)+3+(2*Q1(i)-Q2(i+a(i)+1))-Q2(i+a(i)+1))/q1(i))*q2(i+a(i)+2);
        end
        t(i)=((2*(a(i)+1)+(Q1(i-1)-Q2(i+a(i)))/q2(i+a(i)+1)+(Q1(i)-Q2(a(i)+i+1))/q1(i))*Q2(i+a(i)+1)-Q1(i-1))+b(j)+(2*c(i)+(Q1(i)-Q2(i+c(i)))/q1(i)+Q1(i)-Q2(i+c(i)))/q2(i+c(i)+1))*deltat/(2*q1(i));
    end
end
```
6. Use Matlab to estimate the travel time from Probabilistic Regression Method per 2 minute

```matlab
A=load('output3.txt');
B=load('output4.txt');
y=A(:,1);z=A(:,2);
r1=5;r2=10;
for n=1:22
    a=B(n,9)-r1;b=a+r2;TB=120*(n-1)+1;TF=120*n;
    d=zeros(TF+a-TB-b+1,1);
    for i=(TB+b):(TF+a)
        d(i+1-TB-b)=z(i);
    end
    C=zeros(TF+a-TB-b+1,b-a+1);
    for i=1:(TF+a-TB-b+1)
        for j=1:(b-a+1)
            C(i,j)=y(TB+b-a+i-j);
        end
    end
    x0=[0.05*ones(b-a+1,1)];
    Aeq=ones(1,b-a+1);beq=1;lb=zeros(b-a+1,1);ub=ones(b-a+1,1);
    options=optimset('LargeScale','off');
    x=lsqlin(C,d,[],[],Aeq,beq,lb,ub,x0,options);
    for i=1:(b-a+1)
        u(i)=x(i);
        v(i)=a+i-1;
    end
    p(n)=sum(u.*v);
    q(n)=sum(u);
end
```

```matlab
for n=1:22
    a=B(n,5)-r1;b=a+r2;TB=120*(n-1)+1;TF=120*n;
    d=zeros(TF+a-TB-b+1,1);
    for i=(TB+b):(TF+a)
        d(i+1-TB-b)=z(i);
    end
    C=zeros(TF+a-TB-b+1,b-a+1);
    for i=1:(TF+a-TB-b+1)
```
for j=1:(b-a+1)
    C(i,j)=y(TB+b-a+i-j);
end
end

x0=[0.05*ones(b-a+1,1)];
Aeq=ones(1,b-a+1);beq=1;lb=zeros(b-a+1,1);ub=ones(b-a+1,1);
options=optimset('LargeScale','off');
x=lsqmin(C,d,[],[],Aeq,beq,lb,ub,x0,options);

for i=1:(b-a+1)
    u(i)=x(i);
    v(i)=a+i-1;
end

p1(n)=sum(u.*v);
q1(n)=sum(u);
end

for n=1:22
    a=B(n,11)-r1;b=a+r2;TB=120*(n-1)+1;TF=120*n;
d=zeros(TF+a-TB-b+1,1);
    for i=(TB+b):(TF+a)
        z(i)=d(i+1-TB-b);
    end

    C=zeros(TF+a-TB-b+1,b-a+1);
    for i=1:(TF+a-TB-b+1)
        for j=1:(b-a+1)
            C(i,j)=y(TB+b-a+i-j);
        end
    end

    x0=[0.05*ones(b-a+1,1)];
    Aeq=ones(1,b-a+1);beq=1;lb=zeros(b-a+1,1);ub=ones(b-a+1,1);
    options=optimset('LargeScale','off');
    x=lsqmin(C,d,[],[],Aeq,beq,lb,ub,x0,options);

    for i=1:(b-a+1)
        u(i)=x(i);
        v(i)=a+i-1;
    end

    p2(n)=sum(u.*v);
    q2(n)=sum(u);
end

for n=2:22
    a=B(n-1,9)-r1;b=a+r2;TB=120*(n-1)+1;TF=120*n;
d=zeros(TF+a-TB-b+1,1);
    for i=(TB+b):(TF+a)
d(i+1-TB-b)=z(i);
end

C=zeros(TF+a-TB-b+1,b-a+1);
for i=1:(TF+a-TB-b+1)
    for j=1:(b-a+1)
        C(i,j)=y(TB+b-a+i-j);
    end
end

x0=[0.05*ones(b-a+1,1)];
Aeq=ones(1,b-a+1);beq=1;lb=zeros(b-a+1,1);ub=ones(b-a+1,1);
options=optimset('LargeScale','off');
x=lsqlin(C,d,[],[],Aeq,beq,lb,ub,x0,options);

for i=1:(b-a+1)
    u(i)=x(i);
    v(i)=a+i-1;
end

p3(n)=sum(u.*v);
q3(n)=sum(u);
end

for n=1:22
    a=B(n,10)-r1;b=a+r2;TB=120*(n-1)+1;TF=120*n;
    d=zeros(TF+a-TB-b+1,1);
    for i=(TB+b):(TF+a)
        d(i+1-TB-b)=z(i);
    end

    C=zeros(TF+a-TB-b+1,b-a+1);
    for i=1:(TF+a-TB-b+1)
        for j=1:(b-a+1)
            C(i,j)=y(TB+b-a+i-j);
        end
    end

    x0=[0.05*ones(b-a+1,1)];
    Aeq=ones(1,b-a+1);beq=1;lb=zeros(b-a+1,1);ub=ones(b-a+1,1);
    options=optimset('LargeScale','off');
    x=lsqlin(C,d,[],[],Aeq,beq,lb,ub,x0,options);

    for i=1:(b-a+1)
        u(i)=x(i);
        v(i)=a+i-1;
    end

    p4(n)=sum(u.*v);
    q4(n)=sum(u);
end
for n=1:22
    a=B(n,14)-r1;b=a+r2;TB=120*(n-1)+1;TF=120*n;
    d=zeros(TF+a-TB-b+1,1);
    for i=(TB+b):(TF+a)
        d(i+1-TB-b)=z(i);
    end
    C=zeros(TF+a-TB-b+1,b-a+1);
    for i=1:(TF+a-TB-b+1)
        for j=1:(b-a+1)
            C(i,j)=y(TB+b-a+i-j);
        end
    end
    x0=[0.05*ones(b-a+1,1)];
    Aeq=zeros(1,b-a+1);beq=1;lb=zeros(b-a+1,1);ub=ones(b-a+1,1);
    options=optimset('LargeScale','off');
    x=lsqlin(C,d,[],[],Aeq,beq,lb,ub,x0,options);
    for i=1:(b-a+1)
        u(i)=x(i);
    end
    p5(n)=sum(u.*v);
    q5(n)=sum(u);
end

for n=1:22
    a=B(n,15)-r1;b=a+r2;TB=120*(n-1)+1;TF=120*n;
    d=zeros(TF+a-TB-b+1,1);
    for i=(TB+b):(TF+a)
        d(i+1-TB-b)=z(i);
    end
    C=zeros(TF+a-TB-b+1,b-a+1);
    for i=1:(TF+a-TB-b+1)
        for j=1:(b-a+1)
            C(i,j)=y(TB+b-a+i-j);
        end
    end
    x0=[0.05*ones(b-a+1,1)];
    Aeq=zeros(1,b-a+1);beq=1;lb=zeros(b-a+1,1);ub=ones(b-a+1,1);
    options=optimset('LargeScale','off');
    x=lsqlin(C,d,[],[],Aeq,beq,lb,ub,x0,options);
    for i=1:(b-a+1)
        u(i)=x(i);
\[ v(i) = a + i - 1; \]
\[ p6(n) = \text{sum}(u.*v); \]
\[ q6(n) = \text{sum}(u); \]
\end{verbatim}

\begin{verbatim}
for n=1:22
    a=B(n,16)-r1; b=a+r2; TB=120*(n-1)+1; TF=120*n;
    d=zeros(TF+a-TB-b+1,1);
    for i=(TB+b):(TF+a)
        d(i+1-TB-b)=z(i);
    end

    C=zeros(TF+a-TB-b+1,b-a+1);
    for i=1:(TF+a-TB-b+1)
        for j=1:(b-a+1)
            C(i,j)=y(TB+b-a+i-j);
        end
    end

    x0=[0.05*ones(b-a+1,1)];
    Aeq=ones(1,b-a+1); beq=1; lb=zeros(b-a+1,1); ub=ones(b-a+1,1);
    options=optimset('LargeScale','off');
    x=lsqlin(C,d,[],[],Aeq,beq,lb,ub,x0,options);
    for i=1:(b-a+1)
        u(i)=x(i);
        v(i)=a+i-1;
    end

    p7(n) = \text{sum}(u.*v);
    q7(n) = \text{sum}(u);
end
\end{verbatim}

Run: M=[p;p1;p2;p3;p4;p5;p6;p7];
save output6.txt M -ASCII

7. Use Matlab to compare estimated travel time of all methods with true value

\begin{verbatim}
A=load('output4.txt');
C=load('output6.txt');
E(:,1)=abs(B(:,10)-B(:,9));
E(:,2)=abs(B(:,11)-B(:,9));
E(:,3)=abs(B(:,12)-B(:,9));
E(:,4)=abs(B(:,13)-B(:,9));
E(:,5)=abs(B(:,14)-B(:,9));
E(:,6)=abs(B(:,15)-B(:,9));
\end{verbatim}
E(:,7)=abs(C(:,1)-B(:,9));
E(:,8)=abs(C(:,2)-B(:,9));
E(:,9)=abs(C(:,3)-B(:,9));
E(:,10)=abs(C(:,4)-B(:,9));
E(:,11)=abs(C(:,5)-B(:,9));
E(:,12)=abs(C(:,6)-B(:,9));
E(:,13)=(E(:,1)./B(:,9).*100;
E(:,14)=(E(:,2)./B(:,9).*100;
E(:,15)=(E(:,3)./B(:,9).*100;
E(:,16)=(E(:,4)./B(:,9).*100;
E(:,17)=(E(:,5)./B(:,9).*100;
E(:,18)=(E(:,6)./B(:,9).*100;
E(:,19)=(E(:,7)./B(:,9).*100;
E(:,20)=(E(:,8)./B(:,9).*100;
E(:,21)=(E(:,9)./B(:,9).*100;
E(:,22)=(E(:,10)./B(:,9).*100;
E(:,23)=(E(:,11)./B(:,9).*100;
E(:,24)=(E(:,12)./B(:,9).*100;

Run: save output6.txt E -ASCII

Run: M=mean(E(2:22,:));
save output.txt M -ASCII

C.2 CODE for NGSIM I-80 FIRST PROTOTYPE DATA

1. Transfer original NGSIM data (I80 trajectory data) to relevant raw data

Code:

data test;
infile "C:\Documents and Settings\I80 prototype\vehicle-trajectory-data.txt";
input x1-x16 @@;
run;

data subtest(keep=x1 x2 x3 x5 x12 x14);
set test;
run;

data subtest;
set subtest;
rename x1=id
x2=tt
x3=t
x5=y
x12=s
x14=1;
run;

data try1;
set subtest;
if y>755 then output;
data try1;
set try1;
by id;
first=first.id;
last=last.id;
data try1;
set try1;
if first then output;
run;

data try2;
set subtest;
if y<2055 then output;
data try2;
set try2;
by id;
first=first.id;
last=last.id;
data try2;
set try2;
if last then output;
run;

2. Use Matlab to get the traffic flow and SMS data of 15sec interval

Code:

A=load('data.txt');
t_enter1=A(:,1);
t_leave1=A(:,2);
v1=A(:,3);
t_enter2=A(:,4);
t_leave2=A(:,5);
v2=A(:,6);

for j=1:119
n=0;a=0;b=0;
for i=1:length(A)
    if((t_enter1(i)>=15*(j-1))&&(t_enter1(i)<15*j))
        a=a+1/v1(i);b=b+t_leave1(i);n=n+1;
    end
end
N(j)=n;B(j)=n/a;C(j)=b/n;F(j)=15*j;
end
for j=2:119
    n=0;a=0;b=0;
    for i=1:length(A)
        if((t_enter2(i)>=15*(j-1))&&(t_enter2(i)<15*j))
            a=a+1/v2(i);b=b+t_leave2(i);n=n+1;
        end
    end
    Q(j)=n;D(j)=n/a;E(j)=b/n;
end

Run: M=[F;N;B;C;Q;D;E]';
save output2.txt M -ASCII

3. Use Matlab to get the vehicle data of in 1 sec

Code:
A=load('data.txt');
t1_enter=A(:,1);
t2_enter=A(:,4);
for i=1:2760
    n1=0;n2=0;
    for j=1:length(A)
        if ((t1_enter(j)>=(i-1))&&(t1_enter(j)<i))
            n1=n1+1;
        end
        if ((t2_enter(j)>=(i-1))&&(t2_enter(j)<i))
            n2=n2+1;
        end
    end
    N(i,1)=n1;N(i,2)=n2;
end
diary on
N
diary off
Run: save output3.txt N -ASCII

4. Use Matlab to estimate the travel time of Extrapolation model, Dynamic flow model and Modified dynamic flow model in 15 second

Code:
A=load('output2.txt');
B(:,1:2)=A(:,1:2);
B(:,3)=A(:,3)*5280./3600.;
B(:,4)=A(:,3);
B(:,5)=698./B(:,3);
B(:,6)=A(:,5);
B(:,7)=A(:,6)*5280./3600.;
B(:,8)=A(:,6);
B(:,9)=A(:,4);
%------------------------%
Q1(1)=B(1,2);
Q2(1)=B(1,6);

for i=1:length(A)-1
    Q1(i+1)=Q1(i)+B(i+1,2);
    Q2(i+1)=Q2(i)+B(i+1,6);
end

kt_1(1)=0;
for j=1:length(A)-1
    kt_1(j+1)=Q1(j)-Q2(j);
end

kt=Q1-Q2;
B(:,10)=(kt_1'+kt')./(2*B(:,6))*15;
B(:,11)=2*698./(B(:,3)+B(:,7));
B(:,12)=698.*((log(B(:,7))-log(B(:,3)))./(B(:,7)-B(:,3)));
B(:,13)=0.5*(698./B(:,3)+698./B(:,7));

for j=1:length(A)-1
    q2_1(j)=B(j,6);
    q2_2(j)=B(j+1,6);
end
q2_1(length(A))=B(length(A),6);
q2_2(length(A))=B(length(A),6);

B(:,14)=0.5*(kt_1'+kt')./(B(:,2)*15-0.5./B(:,2)).*(kt_1'.^2./q2_1'.*15-
          kt'.^2./q2_2'.*15);
B(:,15)=7.5-(q2_1'-kt_1'-kt')./q2_2'*7.5;

Run: save output4.txt B -ASCII
(Transfer output4.txt to output4A. txt )

5. Use Matlab to estimate the travel time from the proposed dynamic flow model (with
   updating data) in 15 sec  (PS: no significant difference with results in 4)

A = load(data.txt');
deltat=15;
q1=A(:,1);q2=A(:,2);
Q1(1)=q1(1);Q2(1)=q2(1);
for i=1:length(q1)-1
    Q1(i+1,1)=Q1(i,1)+q1(i+1);
    Q2(i+1,1)=Q2(i,1)+q2(i+1);
end

a(1)=-1;
for i=2:length(Q1)
    for j=i:length(Q2)
if (Q1(i-1)-Q2(j)<=0) 
a(i) = -1+(j-i);
break;
end

for i=1:length(Q1)-2 
c(i)=a(i+1)+1;
end

for i=2:length(Q1)-2 
if c(i)==a(i)+1 
    t(i)=((2*(a(i)+1)+(Q1(i-1)-Q2(i+a(i)))/q2(i+a(i)+1)+(Q1(i)-Q2(a(i)+i+1))/q1(i)))*(Q2(i+a(i)+1)-Q1(i-1))/2/q1(i)*deltat;
elseif c(i)==a(i) 
    t(i)=[2*a(i)+1+[Q1(i-1)-Q2(i+a(i))]/q2(i+a(i)+1)+[Q1(i)-Q2(a(i)+i)]/q2(i+a(i)+1)]*deltat/2;
else c(i)>=a(i)+2 
    b(i-1)=0;
    for j=2*a(i)+3:2*c(i)-1
        b(j)=b(i-1)+(2*a(i)+3+(2*Q1(i)-Q2(i+a(i)+1)-Q2(i+a(i)+2))/q1(i))*q2(i+a(i)+2);
    end
    t(i)=((2*(a(i)+1)+(Q1(i-1)-Q2(i+a(i)))/q2(i+a(i)+1)+(Q1(i)-Q2(a(i)+i+1))/q1(i)))*(Q2(i+a(i)+1)-Q1(i-1))+b(j)+(2*c(i)+(Q1(i)-Q2(c(i)+i))/q1(i)+(Q1(i)-Q2(c(i)+i))/q2(i+c(i)+1))*(Q1(i)-Q2(i+c(i)))/2/q1(i)*deltat;
end
end

M=t';
save output5.txt M –ASCII

6. Use Matlab to estimate the travel time of Probabilistic Regression Method in 2min

A=load('output3.txt');
B=load('output4A.txt');
y=A(:,1);z=A(:,2);
rl=5;rr=10;

for n=1:15
    a=B(n,9)-rl;b=a+rr;TB=120*(n-1)+1;TF=120*n;
d=zeros(TF+a-TB-b+1,1);
    for i=(TB+b):(TF+a)
\[ d(i+1-TB-b)=z(i); \]
\[ \text{end} \]

\[ C=\text{zeros}(TF+a-TB-b+1,b-a+1); \]
\[ \text{for } i=1:(TF+a-TB-b+1) \]
\[ \text{for } j=1:(b-a+1) \]
\[ C(i,j)=y(TB+b-a+i-j); \]
\[ \text{end} \]
\[ \text{end} \]

\[ x0=[0.05*\text{ones}(b-a+1,1)]; \]
\[ \text{Aeq=ones}(1,b-a+1); \text{beq}=1; \text{lb}=[\text{zeros}(b-a+1,1)]; \text{ub}=[\text{ones}(b-a+1,1)]; \]
\[ \text{options=optimset('LargeScale','off');} \]
\[ x=\text{lsq}lin(C,d,[],[],\text{Aeq},\text{beq},\text{lb},\text{ub},x0,\text{options}); \]

\[ \text{for } i=1:(b-a+1) \]
\[ u(i)=x(i); \]
\[ v(i)=a+i-1; \]
\[ \text{end} \]

\[ p(n)=\text{sum}(u.*v); \]
\[ q(n)=\text{sum}(u); \]
\[ \text{end} \]

\[ \text{for } n=1:15 \]
\[ a=B(n,5)-r1;b=a+r2;TB=120*(n-1)+1;TF=120*n; \]
\[ d=\text{zeros}(TF+a-TB-b+1,1); \]
\[ \text{for } i=(TB+b):(TF+a) \]
\[ d(i+1-TB-b)=z(i); \]
\[ \text{end} \]
\[ C=\text{zeros}(TF+a-TB-b+1,b-a+1); \]
\[ \text{for } i=1:(TF+a-TB-b+1) \]
\[ \text{for } j=1:(b-a+1) \]
\[ C(i,j)=y(TB+b-a+i-j); \]
\[ \text{end} \]
\[ \text{end} \]

\[ x0=[0.05*\text{ones}(b-a+1,1)]; \]
\[ \text{Aeq=ones}(1,b-a+1); \text{beq}=1; \text{lb}=[\text{zeros}(b-a+1,1)]; \text{ub}=[\text{ones}(b-a+1,1)]; \]
\[ \text{options=optimset('LargeScale','off');} \]
\[ x=\text{lsq}lin(C,d,[],[],\text{Aeq},\text{beq},\text{lb},\text{ub},x0,\text{options}); \]

\[ \text{for } i=1:(b-a+1) \]
\[ u(i)=x(i); \]
\[ v(i)=a+i-1; \]
\[ \text{end} \]

\[ p1(n)=\text{sum}(u.*v); \]
\[ q1(n)=\text{sum}(u); \]
\[ \text{end} \]
for n=1:15
    a=B(n,11)-r1;b=a+r2;TB=120*(n-1)+1;TF=120*n;
    d=zeros(TF+a-TB-b+1,1);
    for i=(TB+b):(TF+a)
        d(i+1-TB-b)=z(i);
    end

    C=zeros(TF+a-TB-b+1,b-a+1);
    for i=1:(TF+a-TB-b+1)
        for j=1:(b-a+1)
            C(i,j)=y(TB+b-a+i-j);
        end
    end

    x0=[0.05*ones(b-a+1,1)];
    Aeq=ones(1,b-a+1);beq=1;lb=[zeros(b-a+1,1)];ub=[ones(b-a+1,1)];
    options=optimset('LargeScale','off');
    x=lsqlin(C,d,[],[],Aeq,beq,lb,ub,x0,options);

    for i=1:(b-a+1)
        u(i)=x(i);
        v(i)=a+i-1;
    end

    p2(n)=sum(u.*v);
    q2(n)=sum(u);
end

for n=2:15
    a=B(n-1,9)-r1;b=a+r2;TB=120*(n-1)+1;TF=120*n;
    d=zeros(TF+a-TB-b+1,1);
    for i=(TB+b):(TF+a)
        d(i+1-TB-b)=z(i);
    end

    C=zeros(TF+a-TB-b+1,b-a+1);
    for i=1:(TF+a-TB-b+1)
        for j=1:(b-a+1)
            C(i,j)=y(TB+b-a+i-j);
        end
    end

    x0=[0.05*ones(b-a+1,1)];
    Aeq=ones(1,b-a+1);beq=1;lb=[zeros(b-a+1,1)];ub=[ones(b-a+1,1)];
    options=optimset('LargeScale','off');
    x=lsqlin(C,d,[],[],Aeq,beq,lb,ub,x0,options);

    for i=1:(b-a+1)
        u(i)=x(i);
        v(i)=a+i-1;
    end

end
end

p3(n)=sum(u.*v);
q3(n)=sum(u);
end

for n=1:15
    a=B(n,10)-r1;b=a+r2;TB=120*(n-1)+1;TF=120*n;
    d=zeros(TF+a-TB-b+1,1);
    for i=(TB+b):(TF+a)
        d(i+1-TB-b)=z(i);
    end

    C=zeros(TF+a-TB-b+1,b-a+1);
    for i=1:(TF+a-TB-b+1)
        for j=1:(b-a+1)
            C(i,j)=y(TB+b-a+i-j);
        end
    end

    x0=[0.05*ones(b-a+1,1)];
    Aeq=ones(1,b-a+1);beq=1;lb=zeros(b-a+1,1);ub=ones(b-a+1,1);
    options=optimset('LargeScale','off');
    x=lsqlin(C,d,[],[],Aeq,beq,lb,ub,x0,options);
    for i=1:(b-a+1)
        u(i)=x(i);
        v(i)=a+i-1;
    end

    p4(n)=sum(u.*v);
    q4(n)=sum(u);
end

for n=1:15
    a=B(n,14)-r1;b=a+r2;TB=120*(n-1)+1;TF=120*n;
    d=zeros(TF+a-TB-b+1,1);
    for i=(TB+b):(TF+a)
        d(i+1-TB-b)=z(i);
    end

    C=zeros(TF+a-TB-b+1,b-a+1);
    for i=1:(TF+a-TB-b+1)
        for j=1:(b-a+1)
            C(i,j)=y(TB+b-a+i-j);
        end
    end

    x0=[0.05*ones(b-a+1,1)];
    Aeq=ones(1,b-a+1);beq=1;lb=zeros(b-a+1,1);ub=ones(b-a+1,1);
    options=optimset('LargeScale','off');
    x=lsqlin(C,d,[],[],Aeq,beq,lb,ub,x0,options);

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x=lsqlin(C,d,[],[],Aeq,beq,lb,ub,x0,options);

for i=1:(b-a+1)
    u(i)=x(i);
    v(i)=a+i-1;
end

p5(n)=sum(u.*v);
q5(n)=sum(u);
end

for n=1:15
    a=B(n,15)-r1;b=a+r2;TB=120*(n-1)+1;TF=120*n;
    d=zeros(TF+a-TB-b+1,1);
    for i=(TB+b):(TF+a)
        d(i+1-TB-b)=z(i);
    end

    C=zeros(TF+a-TB-b+1,b-a+1);
    for i=1:(TF+a-TB-b+1)
        for j=1:(b-a+1)
            C(i,j)=y(TB+b-a+i-j);
        end
    end

    x0=[0.05*ones(b-a+1,1)];
    Aeq=ones(1,b-a+1);beq=1;lb=[zeros(b-a+1,1)];ub=[ones(b-a+1,1)];
    options=optimset('LargeScale','off');
    x=lsqlin(C,d,[],[],Aeq,beq,lb,ub,x0,options);

    for i=1:(b-a+1)
        u(i)=x(i);
        v(i)=a+i-1;
    end

    p6(n)=sum(u.*v);
    q6(n)=sum(u);
end

for n=1:15
    a=B(n,16)-r1;b=a+r2;TB=120*(n-1)+1;TF=120*n;
    d=zeros(TF+a-TB-b+1,1);
    for i=(TB+b):(TF+a)
        d(i+1-TB-b)=z(i);
    end

    C=zeros(TF+a-TB-b+1,b-a+1);
    for i=1:(TF+a-TB-b+1)
        for j=1:(b-a+1)
            C(i,j)=y(TB+b-a+i-j);
        end
    end

end
end

x0=[0.05*ones(b-a+1,1)];
Aeq=ones(1,b-a+1);beq=1;lb=zeros(b-a+1,1);ub=[ones(b-a+1,1)];
options=optimset('LargeScale','off');
x=lsqlin(C,d,[],[],Aeq,beq,lb,ub,x0,options);

for i=1:(b-a+1)
    u(i)=x(i);
    v(i)=a+i-1;
end

p7(n)=sum(u.*v);
q7(n)=sum(u);
end

Run: M=[p;p1;p2;p3;p4;p5;p6;p7];
save output5A.txt M –ASCII

7. Use Matlab to compare estimated travel time of all methods with true value

A=load('output4.txt');
B=A(1:8,:);
C=load('output6.txt');

E(:,1)=abs(B(:,10)-B(:,9));
E(:,2)=abs(B(:,11)-B(:,9));
E(:,3)=abs(B(:,12)-B(:,9));
E(:,4)=abs(B(:,13)-B(:,9));
E(:,5)=abs(B(:,14)-B(:,9));
E(:,6)=abs(B(:,15)-B(:,9));
E(:,7)=abs(C(:,1)-B(:,9));
E(:,8)=abs(C(:,2)-B(:,9));
E(:,9)=abs(C(:,3)-B(:,9));
E(:,10)=abs(C(:,4)-B(:,9));
E(:,11)=abs(C(:,5)-B(:,9));
E(:,12)=abs(C(:,6)-B(:,9));

E(:,13)=E(:,1)./B(:,9).*100;
E(:,14)=E(:,2)./B(:,9).*100;
E(:,15)=E(:,3)./B(:,9).*100;
E(:,16)=E(:,4)./B(:,9).*100;
E(:,17)=E(:,5)./B(:,9).*100;
E(:,18)=E(:,6)./B(:,9).*100;
E(:,19)=E(:,7)./B(:,9).*100;
E(:,20)=E(:,8)./B(:,9).*100;
E(:,21)=E(:,9)./B(:,9).*100;
E(:,22)=E(:,10)./B(:,9).*100;
E(:,23)=E(:,11)./B(:,9).*100;
E(:,24)=E(:,12)./B(:,9).*100;

Run: save output7.txt E –ASCII

C.3 CODE for NGSIM I-80 NEW DATA

1. Transfer original NGSIM data (I80 trajectory data) to relevant raw data

Code:

data test;
infile "C:\Documents and Settings\i80\vehicle-trajectory-data.txt";
input x1-x18 @@;
run;

data subtest(keep=x1 x2 x3 x6 x12 x14);
set test;
run;

data subtest;
set subtest;
rename x1=id
x2=t
x3=tt
x6=y
x12=s
x14=l;
run;

data try1;
set subtest;
if y>420 then output;
data try1;
set try1;
by id;
first=first.id;
last=last.id;
data try1;
set try1;
if first then output;
run;

data try2;
set subtest;
if y>1650 then output;
data try2;
set try2;
by id;
first=first.id;
last=last.id;
data try2;
set try2;
if first then output;
run;

2. Use Matlab to get the traffic flow and SMS data of 30sec interval

Code:
A=load('data.txt');
t_enter1=A(:,1);
t_leave1=A(:,2);
v1=A(:,3);
t_enter2=A(:,4);
t_leave2=A(:,5);
v2=A(:,6);

for j=1:91
    n=0;a=0;b=0;
    for i=1:length(A)
        if((t_enter1(i)>=30*(j-1))&&(t_enter1(i)<30*j))
            a=a+1/v1(i);b=b+t_leave1(i);n=n+1;
        end
    end
    N(j)=n;B(j)=n/a;C(j)=b/n;F(j)=30*j;
end

for j=2:91
    n=0;a=0;b=0;
    for i=1:length(A)
        if((t_enter2(i)>=30*(j-1))&&(t_enter2(i)<30*j))
            a=a+1/v2(i);b=b+t_leave2(i);n=n+1;
        end
    end
    Q(j)=n;D(j)=n/a;E(j)=b/n;
end

Run: M=[F;N;B;C;Q;D;E]';
save output2.txt M -ASCII

3. Use Matlab to get the vehicle data of in 1 sec

Code:
A=load('data.txt');
t1_enter=A(:,1);
t2_enter=A(:,4);
for i=1:2880
    n1=0;n2=0;

for j=1:length(A)
    if ((t1_enter(j)>=i-1)&&(t1_enter(j)<i))
        n1=n1+1;
    end
    if ((t2_enter(j)>=i-1)&&(t2_enter(j)<i))
        n2=n2+1;
    end
end
N(i,1)=n1;N(i,2)=n2;
diary on
N
diary off

Run: save output3.txt N -ASCII

4. Use Matlab to estimate the travel time of Dynamic flow model and Modified dynamic flow model in 30 sec

Code:

A=load('output2.txt');
B(:,1:2)=A(:,1:2);
B(:,3)=A(:,3)*5280./3600.;
B(:,4)=A(:,3);
B(:,5)=1230./B(:,3);
B(:,6)=A(:,5);
B(:,7)=A(:,6)*5280./3600.;
B(:,8)=A(:,6);
B(:,9)=A(:,4);

%------------------------%
Q1(1)=B(1,2);
Q2(1)=B(1,6);

for i=1:length(A)-1
    Q1(i+1)=Q1(i)+B(i+1,2);
    Q2(i+1)=Q2(i)+B(i+1,6);
end

kt_1(1)=0;
for j=2:length(A)-1
    kt_1(j+1)=Q1(j)-Q2(j);
end

kt=Q1-Q2;
B(:,10)=(kt_1'+kt')./(2*B(:,6))*60;
B(:,11)=2*1230./(B(:,3)+B(:,7));
B(:,12)=1230.*((log(B(:,7))-log(B(:,3)))./(B(:,7)-B(:,3)));
B(:,13)=0.5*(1230./B(:,3)+1230./B(:,7));

for j=1:length(A)-1
q2_1(j)=B(j,6);
q2_2(j)=B(j+1,6);
end

q2_1(length(A))=B(length(A),6);
q2_2(length(A))=B(length(A),6);

B(:,14)=0.5*(kt_1'+kt')./B(:,2).*60-0.5./B(:,2).*(kt_1'.^2./q2_1'.*60-
kt'.^2./q2_2'.*60);
B(:,15)=30-(q2_1'-kt_1'-kt')./q2_2'*30;

Run: save output4.txt B -ASCII
(Transfer output4.txt to output4A.txt)

5. Use Matlab to estimate the travel time from the proposed dynamic flow model (with
updating data) in 30 sec

A = load('data.txt');
deltat=30;
q1=A(:,1);q2=A(:,2);
Q1(1)=q1(1);Q2(1)=q2(1);
for i=1:length(q1)-1
    Q1(i+1,1)=Q1(i,1)+q1(i+1);
    Q2(i+1,1)=Q2(i,1)+q2(i+1);
end
a(1)=-1;
for i=2:length(Q1)
    for j=i:length(Q2)
        if (Q1(i-1)-Q2(j)<=0)
            a(i) = -1+(j-i);
            break;
        end
    end
end

for i=1:length(Q1)-1
    c(i)=a(i+1)+1;
end
for i=2:length(Q1)-2
    if c(i)==a(i)+1
        t(i)=(2*(a(i)+1)+(Q1(i-1)-Q2(i+a(i)))/q2(i+a(i)+1)+(Q1(i)-
        Q2(a(i)+i+1))/q1(i))*(Q2(i+a(i)+1)-Q1(i-1))+(2*(a(i)+1)+(Q1(i)-
        Q2(a(i)+i+1))/q1(i)+(Q1(i)-Q2(a(i)+i+1))/q2(i+a(i)+2))*(Q1(i)-
        Q2(i+a(i)+1)))/2/q1(i)*deltat;
    elseif c(i)==a(i)
        t(i)=[2*a(i)+1+[Q1(i-1)-Q2(i+a(i))]/q2(i+a(i)+1)+[Q1(i)-
        Q2(a(i)+i)]/q2(i+a(i)+1)]*deltat/2;
    end
else c(i) >= a(i) + 2

    b(i-1) = 0;
    for j = 2*a(i) + 3:2*c(i) - 1
        b(j) = b(i-1) + (2*a(i) + 3 + (2*Q1(i) - Q2(i+a(i)+1) - Q2(i+a(i)+2))/q1(i)) * q2(i+a(i)+2);
    end

    t(i) = ((2*(a(i)+1) + (Q1(i-1) - Q2(i+a(i)))/q2(i+a(i)+1) + (Q1(i) - Q2(i+a(i)+1))/q1(i)) * (Q2(i+a(i)+1) - Q1(i-1)) + b(j) + (2*c(i) + (Q1(i) - Q2(i+c(i)))/q1(i) + (Q1(i) - Q2(c(i)+i))/q2(i+c(i)+1)) * (Q1(i) - Q2(i+c(i)))) * deltat / (2*q1(i));
end
end

M = t';
save output5.txt M -ASCII

6. Use Matlab to estimate the travel time of Probabilistic Regression Method in 2min

A = load('output3.txt');
B = load('output4A.txt');
y=A(:,1); z=A(:,2);
r1=5; r2=10;

for n = 1:22
    a = B(n,9) - r1; b = a + r2; TB = 120*(n-1) + 1; TF = 120*n;
    d = zeros(TF + a - TB - b + 1, 1);
    for i = (TB + b) : (TF + a)
        d(i + 1 - TB - b) = z(i);
    end

    C = zeros(TF + a - TB - b + 1, b - a + 1);
    for i = 1 : (TF + a - TB - b + 1)
        for j = 1 : (b - a + 1)
            C(i, j) = y(TB + b - a + i - j);
        end
    end

    x0 = [0.05 * ones(b - a + 1, 1)];
    Aeq = ones(1, b - a + 1); beq = 1; lb = [zeros(b - a + 1, 1)]; ub = [ones(b - a + 1, 1)];
    options = optimset('LargeScale', 'off');
    x = lsqlin(C, d, [], [], Aeq, beq, lb, ub, x0, options);

    for i = 1 : (b - a + 1)
        u(i) = x(i);
        v(i) = a + i - 1;
    end
\[ p(n) = \sum (u \cdot v); \]
\[ q(n) = \sum u; \]
\[ \text{end} \]

\begin{verbatim}
for n=1:22
  a=B(n,5)-r1;b=a+r2;TB=120*(n-1)+1;TF=120*n;
  d=zeros(TF+a-TB-b+1,1);
  for i=(TB+b):(TF+a)
    d(i+1-TB-b)=z(i);
  end

  C=zeros(TF+a-TB-b+1,b-a+1);
  for i=1:(TF+a-TB-b+1)
    for j=1:(b-a+1)
      C(i,j)=y(TB+b-a+i-j);
    end
  end

  x0=[0.05*ones(b-a+1,1)];
  Aeq=ones(1,b-a+1);beq=1;lb=[zeros(b-a+1,1)];ub=[ones(b-a+1,1)];
  options=optimset('LargeScale','off');
  x=lsqlin(C,d,[],[],Aeq,beq,lb,ub,x0,options);
  for i=1:(b-a+1)
    u(i)=x(i);
    v(i)=a+i-1;
  end

  p1(n)=sum(u.*v);
  q1(n)=sum(u);
end
\end{verbatim}

\begin{verbatim}
for n=1:22
  a=B(n,11)-r1;b=a+r2;TB=120*(n-1)+1;TF=120*n;
  d=zeros(TF+a-TB-b+1,1);
  for i=(TB+b):(TF+a)
    d(i+1-TB-b)=z(i);
  end

  C=zeros(TF+a-TB-b+1,b-a+1);
  for i=1:(TF+a-TB-b+1)
    for j=1:(b-a+1)
      C(i,j)=y(TB+b-a+i-j);
    end
  end

  x0=[0.05*ones(b-a+1,1)];
  Aeq=ones(1,b-a+1);beq=1;lb=[zeros(b-a+1,1)];ub=[ones(b-a+1,1)];
  options=optimset('LargeScale','off');
  x=lsqlin(C,d,[],[],Aeq,beq,lb,ub,x0,options);
\end{verbatim}
for i=1:(b-a+1)
    u(i)=x(i);
    v(i)=a+i-1;
end
p2(n)=sum(u.*v);
q2(n)=sum(u);
end
for n=2:22
    a=B(n-1,9)-r1;b=a+r2;TB=120*(n-1)+1;TF=120*n;
d=zeros(TF+a-TB-b+1,1);
    for i=(TB+b):(TF+a)
        d(i+1-TB-b)=z(i);
    end
    C=zeros(TF+a-TB-b+1,b-a+1);
    for i=1:(TF+a-TB-b+1)
        for j=1:(b-a+1)
            C(i,j)=y(TB+b-a+i-j);
        end
    end
    x0=[0.05*ones(b-a+1,1)];
    Aeq=ones(1,b-a+1);beq=1;lb=[zeros(b-a+1,1)];ub=[ones(b-a+1,1)];
    options=optimset('LargeScale','off');
    x=lsqlin(C,d,[],[],Aeq,beq,lb,ub,x0,options);
end
for i=1:(b-a+1)
    u(i)=x(i);
    v(i)=a+i-1;
end
p3(n)=sum(u.*v);
q3(n)=sum(u);
end
for n=1:22
    a=B(n,10)-r1;b=a+r2;TB=120*(n-1)+1;TF=120*n;
d=zeros(TF+a-TB-b+1,1);
    for i=(TB+b):(TF+a)
        d(i+1-TB-b)=z(i);
    end
    C=zeros(TF+a-TB-b+1,b-a+1);
    for i=1:(TF+a-TB-b+1)
        for j=1:(b-a+1)
            C(i,j)=y(TB+b-a+i-j);
        end
    end
    x0=[0.05*ones(b-a+1,1)];
    Aeq=ones(1,b-a+1);beq=1;lb=[zeros(b-a+1,1)];ub=[ones(b-a+1,1)];
    options=optimset('LargeScale','off');
    x=lsqlin(C,d,[],[],Aeq,beq,lb,ub,x0,options);
for i=1:(b-a+1)
    u(i)=x(i);
    v(i)=a+i-1;
end

p4(n)=sum(u.*v);
q4(n)=sum(u);
end

for n=1:22
    a=B(n,14)-r1;b=a+r2;TB=120*(n-1)+1;TF=120*n;
    d=zeros(TF+a-TB-b+1,1);
    for i=(TB+b):(TF+a)
        d(i+1-TB-b)=z(i);
    end
    C=zeros(TF+a-TB-b+1,b-a+1);
    for i=1:(TF+a-TB-b+1)
        for j=1:(b-a+1)
            C(i,j)=y(TB+b-a+i-j);
        end
    end
    x0=[0.05*ones(b-a+1,1)];
    Aeq=ones(1,b-a+1);beq=1;lb=zeros(b-a+1,1);
    ub=ones(b-a+1,1);
    options=optimset('LargeScale','off');
    x=lsqlin(C,d,[],[],Aeq,beq,lb,ub,x0,options);
    for i=1:(b-a+1)
        u(i)=x(i);
        v(i)=a+i-1;
    end
    p5(n)=sum(u.*v);
    q5(n)=sum(u);
end

for n=1:22
    a=B(n,15)-r1;b=a+r2;TB=120*(n-1)+1;TF=120*n;
    d=zeros(TF+a-TB-b+1,1);
    for i=(TB+b):(TF+a)
        d(i+1-TB-b)=z(i);
    end
    C=zeros(TF+a-TB-b+1,b-a+1);
    for i=1:(TF+a-TB-b+1)
        for j=1:(b-a+1)
            C(i,j)=y(TB+b-a+i-j);
        end
    end
    x0=[0.05*ones(b-a+1,1)];
Aeq=ones(1,b-a+1);beq=l;lb=[zeros(b-a+1,1)];ub=[ones(b-a+1,1)];
options=optimset('LargeScale','off');
x=lsqlin(C,d,[],[],Aeq,beq,lb,ub,x0,options);

for i=1:(b-a+1)
    u(i)=x(i);
    v(i)=a+i-1;
end

p6(n)=sum(u.*v);
q6(n)=sum(u);
end

for n=1:22
    a=B(n,16)-r1;b=a+r2;TB=120*(n-1)+1;TF=120*n;
    d=zeros(TF+a-TB-b+1,1);
    for i=(TB+b):(TF+a)
        d(i+1-TB-b)=z(i);
    end
    C=zeros(TF+a-TB-b+1,b-a+1);
    for i=1:(TF+a-TB-b+1)
        for j=1:(b-a+1)
            C(i,j)=y(TB+b-a+i-j);
        end
    end
    x0=[0.05*ones(b-a+1,1)];
    Aeq=ones(1,b-a+1);beq=l;lb=[zeros(b-a+1,1)];ub=[ones(b-a+1,1)];
    options=optimset('LargeScale','off');
    x=lsqlin(C,d,[],[],Aeq,beq,lb,ub,x0,options);

    for i=1:(b-a+1)
        u(i)=x(i);
        v(i)=a+i-1;
    end

    p7(n)=sum(u.*v);
    q7(n)=sum(u);
end

Run: M=[p;p1;p2;p3;p4;p5;p6;p7];
save output5A.txt M –ASCII

7. Use Matlab to compare estimated travel time of all methods with true value

A=load('output4.txt');
B=A(1:22,:);
C=load('output6.txt');
E(:,1) = abs(B(:,10) - B(:,9));
E(:,2) = abs(B(:,11) - B(:,9));
E(:,3) = abs(B(:,12) - B(:,9));
E(:,4) = abs(B(:,13) - B(:,9));
E(:,5) = abs(B(:,14) - B(:,9));
E(:,6) = abs(B(:,15) - B(:,9));
E(:,7) = abs(C(:,1) - B(:,9));
E(:,8) = abs(C(:,2) - B(:,9));
E(:,9) = abs(C(:,3) - B(:,9));
E(:,10) = abs(C(:,4) - B(:,9));
E(:,11) = abs(C(:,5) - B(:,9));
E(:,12) = abs(C(:,6) - B(:,9));
E(:,13) = E(:,1) ./ B(:,9) .* 100;
E(:,14) = E(:,2) ./ B(:,9) .* 100;
E(:,15) = E(:,3) ./ B(:,9) .* 100;
E(:,16) = E(:,4) ./ B(:,9) .* 100;
E(:,17) = E(:,5) ./ B(:,9) .* 100;
E(:,18) = E(:,6) ./ B(:,9) .* 100;
E(:,19) = E(:,7) ./ B(:,9) .* 100;
E(:,20) = E(:,8) ./ B(:,9) .* 100;
E(:,21) = E(:,9) ./ B(:,9) .* 100;
E(:,22) = E(:,10) ./ B(:,9) .* 100;
E(:,23) = E(:,11) ./ B(:,9) .* 100;
E(:,24) = E(:,12) ./ B(:,9) .* 100;

Run: save output7.txt E –ASCII
APPENDIX D TRAFFIC FREQUENCY CHANGING TESTING AND TRAFFIC CONDITION DETERMINATION IN FIELD DATA
Figure 5.4: Traffic changing frequency per 1 minute for NGSIM US101 data

Figure 5.5: Traffic changing frequency per 30 sec for NGSIM US101 data

Figure 5.6: Traffic changing frequency per 15 sec for NGSIM US101 data
Figure 5.7: Traffic changing frequency per 1min for NGSIM I80 new data

Figure 5.8: Traffic changing frequency per 30sec for NGSIM I80 new data

Figure 5.9: Traffic changing frequency per 15sec for NGSIM I80 new data
Figure 5.10: Traffic changing frequency per 1min for NGSIM I80 first prototype data

Figure 5.11: Traffic changing frequency per 30sec for NGSIM I80 first prototype data

Figure 5.12: Traffic changing frequency per 15sec for NGSIM I80 first prototype data
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PS: F- Free-flow condition

T/C- Transition/Congestion Condition