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**A GENERALIZED NON-PARAMETRIC APPROACH FOR UNCERTAINTY  
EVALUATION IN TRAVEL TIME PREDICTION MODELS**

by

**BHAVEN NAIK**

A DISSERTATION

Presented to the Faculty of  
The Graduate College at the University of Nebraska  
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(Civil Engineering)

Under the Supervision of Professor Laurence R. Rilett

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A GENERALIZED NON-PARAMETRIC APPROACH FOR UNCERTAINTY  
EVALUATION IN TRAVEL TIME PREDICTION MODELS

Bhaven Naik, Ph.D.  
University of Nebraska, 2010

Advisor: Laurence R. Rilett

A core component within Advanced Traveler Information Systems is travel time information because it is easily understood and perceived by travelers. However, the suggested travel time information should be based not only on historical and real-time conditions, but also on forecasted or “unknown” future conditions.

Existing research has focused primarily on developing models that forecast point estimates of the mean travel time that are in close comparison to their respective field values. There has been limited research on any insight into the reliability or uncertainty margin that exists around the forecasted point estimate. As well, these researches have a limitation in that the methodologies suggested are applicable to datasets that are assumed to be independent and identically distributed. However, this is generally not the case for the readily and widely available Intelligent Transportation Systems’ data.

This dissertation identifies an approach that computes a forecasted travel time as well as an estimate of standard error (the basis for reliability measures in transportation) for highly nonlinear models. Additionally, the approach accounts for the dependent structure of a dataset. The approach is generic and could be applied to other estimation and prediction models as well as other traffic variables, such as flow and speed.

Whereas the ordinary bootstrap has been used previously for uncertainty modeling within the travel time prediction environment, it is ideal for dealing with data that are independent and identically distributed. The application of two other bootstrapping methods—the block bootstrap and the gapped bootstrap—is demonstrated. The block bootstrap is currently the best known method for implementing the bootstrap with

dependent data. The gapped bootstrap is a recently developed technique that is uniquely suited for handling uncertainties in dependent data.

The results suggest that, for the datasets used in this dissertation, the gapped bootstrap adequately captures the dependent structure when compared to the ordinary and block bootstrap methods. As well, unlike the ordinary bootstrap which is suitable only for data that are independent, it appears the gapped bootstrap can adequately address uncertainties for both independent and dependent structured datasets.

## DEDICATION

To the memory of my father and young brother

You left to be in the place of peace; I wished you had waited just a little more...

## ACKNOWLEDGEMENTS

As much as I might like to pretend I did all this on my own, it is far from the truth. A large group of different people helped me get through graduate school and the dissertation process, and I would like to take the pleasure of formally thanking them here.

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## CHAPTER 1

### 1.1 INTRODUCTION

The increasing reliance on Advanced Traveler Information Systems (ATIS) has heightened the need to estimate and predict travel times accurately and reliably (Ruimen 2003). Accurate and reliable travel times are necessary for a variety of real-time and off-line transportation applications. Real-time applications include route guidance, which allows road-users to make more informed route decisions (pre-trip and en-route), and that can potentially yield more stable and less congested traffic conditions. The off-line applications include system performance monitoring.

In 2006, 202 million licensed drivers traveled 262 billion miles in the United States alone (US Bureau of Transportation Statistics 2007; Federal Highway Administration 2007). This was an increase of six percent drivers and 22 percent vehicle miles traveled from year 2000 (190 million licensed drivers and 203 billion vehicle miles traveled). These increases in driver population and demand have not been matched by equivalent increase in the supply component. The end result was increasing congestion over time and space (Schrank and Lomax 2008). This can result in substantial cost, which has been estimated at \$78.2 billion (in 2005 dollar value) per year, on the US economy. This cost was due in part to 4.2 billion vehicle-hours of delay, resulting in 2.9 billion gallons of wasted fuel.

Several congestion management strategies target the demand and supply components of the transportation system. The supply side alternatives include increasing

the capacity by building more roads and building public transit. In many urban areas these are becoming infeasible due to increasing environmental awareness and concerns, the high costs of construction and difficulty in acquiring right-of-way. On the demand side, alternatives include car-pooling, the use of high occupancy vehicle facilities, roadway pricing and the use of ATIS.

ATIS provide motorists with accurate and timely traffic information via media such as variable message signs, internet and radio. A vital component within ATIS is pre-trip travel time information. This predicted mean travel time information is obtained using numerous models that have been developed through extensive research in this area. However, a majority of these prediction models provide point estimates and do not give insight into the uncertainty margin around the estimates (Mazloumi et.al 2010; De Jong et al. 2007). The contribution of this research lies in developing and applying a methodology that will provide an accurate prediction of the mean travel time as well as a measure of the reliability, or confidence, in the predicted estimate. More importantly, it will provide a generic non-parametric approach to estimate uncertainties that is not a function of the travel time estimation or prediction model.

## **1.2 BACKGROUND**

### **1.2.1 Travel Time Prediction**

Advanced Traveler Information Systems offer an opportunity for understanding traffic and transit conditions, presenting multi-modal options to travelers, and improving the performance of the existing transportation infrastructure (Abdel et al. 1997). In other

words, ATIS aims to provide the public, businesses and commercial carriers with the right travel information (such as delays, next bus, and alternate routes) at the right time and right place; hence, improving the quality and convenience of their trips. A core component within ATIS is travel time information because it is easily understood and perceived by travelers. However, for ATIS to be successful, the suggested travel information should be based not only on historical and real-time travel times, but also on anticipatory travel time information. That is, travel times for “unknown” future traffic conditions. Two approaches of getting the expected travel times include: (i) indirect travel time prediction and (ii) direct travel time prediction (Van Lint 2004).

Indirect travel time prediction involves predicting traffic quantities (speeds, flows, and densities) from their measured values and then using standard formulations to estimate the future travel times. Hence, travel time estimation techniques can be used as components in travel time prediction models. With direct travel time prediction, future travel times are obtained without the intermediate step of predicting other traffic quantities. This means that future travel times are obtained using measured traffic quantities (speeds, flows, densities or travel times). A variety of models (direct and indirect) that predict the mean travel time are available in the literature. The next sections provide brief descriptions of the modeling approaches common to travel time prediction modeling. These modeling approaches include: time series analysis, neural network analysis and Kalman filtering.



### *1.2.1.1 Time Series Analysis*

In time series modeling a sequence of observations  $x_t$  are measured at successive time intervals  $t$  and plotted (Brockwell and Davies 2002). For the case of this dissertation these  $x_t$  values will be mean travel times that could either be measured or estimated. The time points at which the observations are made are discrete in most cases. A hypothetical probability model is then fitted to the measured data such that it represents the generating mechanism of the time series. Subsequently, the fitted model makes it possible to predict future observations. Time series models can have many forms and represent different stochastic processes (Box et al. 1994). Three broad classes include the autoregressive (AR) models, the moving average (MA) models and a combination of AR and MA known as the autoregressive integrated (ARIMA) models.

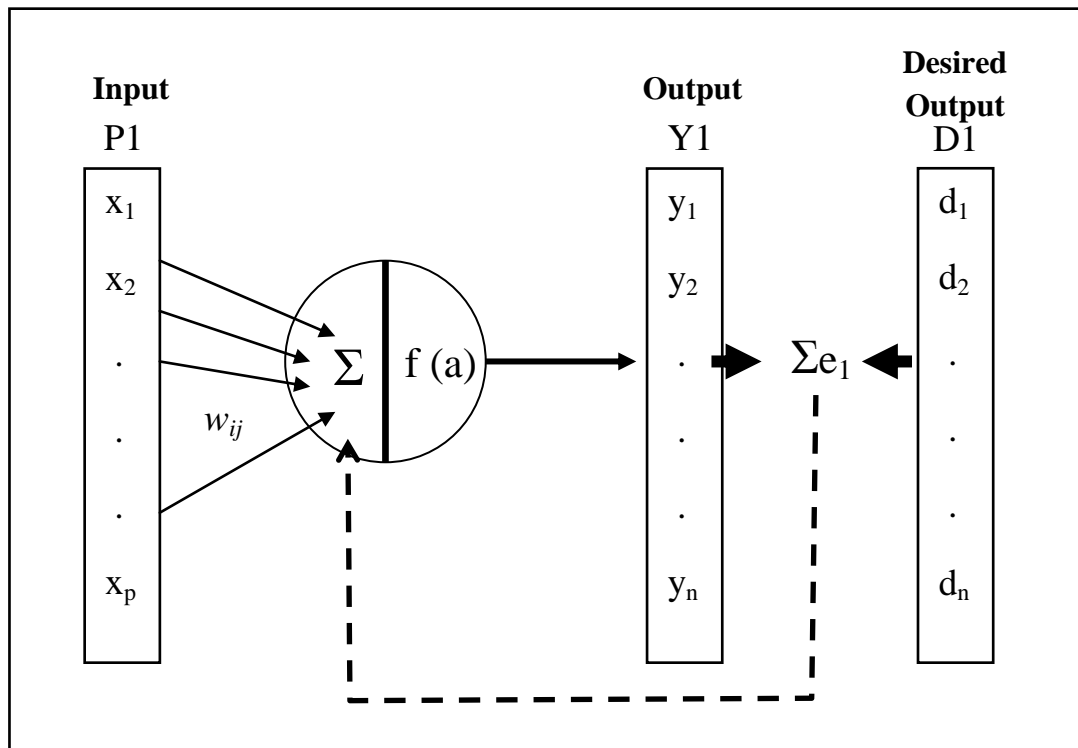
In time series analysis the assumption is that historic patterns will remain the same in the future. As such, the accuracy of these models is a function of the similarity between the real-time and historic patterns. Variations in historical data or changes in the relationship between historical data and real time data could cause significant inaccuracy in the prediction results. Travel time prediction using time series analysis has been reviewed in previous literature (Oda 1990; Andersen et al. 1994; Al-Deek et al. 1998; Yang 2005).

### *1.2.1.2 Neural Network Analysis*

Neural networks are data models that are able to capture and represent complex input/output relationships (NeuroSolutions 2008). In its most general form, a neural network (NN) model aims at mimicking the human brain in performing a particular task

or function of interest. NNs thus resemble the brain in two particular respects: (i) they acquire knowledge through training, and (ii) weights are used to store the acquired knowledge (Haykin 1999).

A NN model is comprised of several building blocks called neurons. Each neuron has inputs  $PI$  (such as measured speeds or volumes) that are multiplied with weights  $w_{ij}$  and then summed, as shown in Figure 1-1. An activation function  $f(a)$  is then applied to the summed and weighted input to produce an output  $YI$ . Given that the output  $YI$  is not the same as the desired output  $DI$  an apparent error will be present. This error is fed back to the model and the weights are readjusted. This process is called training and is repeated until the model performance is acceptable. Once the model has been trained, the model parameters, or weights, are set and the model can be used for the prediction task.



**FIGURE 1-1: Neural network computation scheme**

While NN models can represent both linear and non-linear relationships, their advantage lies in the ability to learn these relationships directly from the data being modeled. NN models have been developed for use in the area of transportation since the early 1990's. These models have been used to predict travel time (Park et al. 1998; Park and Rilett 1998; Rilett and Park 2001; Van Lint et al. 2002; Kisgyorgy and Rilett 2002; Huisken and Berkum 2003) and also traffic conditions (Taylor and Meldrum 1995; Dia 2001; Innamaa 2001) on motorways.

### *1.2.1.3 Kalman Filtering*

Kalman filtering (Kalman 1960) combines available measured data, regardless of their accuracy (such as speeds, flows or densities) with prior knowledge about the system and measuring devices, to estimate a desired variable of interest (such as travel time) in such a manner that the error is minimized. The two main features of the Kalman formulation and solution to the problem are (i) vector modeling of the random processes under consideration, and (ii) recursive processing of the noisy measurement (input) data. The model is essentially a set of recursive mathematical equations (or sub models) that when used together will model and accurately estimate the movement of a dynamic system.

The process model provides an *a priori* estimate of the state of the process, whereas the measurement model takes actual measurements of the state of the process. The information contained in the actual measurements is then incorporated into the *priori* estimate to update it, resulting in the *a posteriori* estimate. The *a posteriori* estimate is then used to make a new *a priori* estimate of the state of the process at  $t + \Delta t$ , where  $\Delta t$

is the time interval between two adjacent time steps. A Kalman filter model can be summed as an optimal recursive computation of the least squares algorithm.

This modeling approach has been used in the prediction of traffic volumes (Okutani and Stephanedes 1984), real-time demand diversion (Stephanedes and Kwon 1993) and the estimation of trip-distribution and traffic density (Okutani and Stephanedes 1987). More recently, the Kalman filter has been used to develop travel time prediction models (Chen and Chien 2002; Chien and Kuchipudi 2003; Chien et al. 2003; Lianyu et al. 2005).

### **1.2.2 Assessment of Model Uncertainty**

Generally when calculating an estimate  $\hat{\theta}$  of a statistic such as the mean of a given sample data, an initial model based on a fixed set of variables and model parameters is developed. Subsequently, the developed model is used to estimate the statistic of interest. In doing this, it is assumed that an exact or “true value” of the population parameter  $\theta$  exists. Model uncertainty is the best measure or quantification of how far the estimated statistic might be from its “true value” (i.e.,  $\theta - \hat{\theta}$ ). The estimated statistic is thus reported by specifying a range of values which are likely to enclose the “true value” (i.e., best estimate  $\pm$  uncertainty).

The uncertainty is often calculated by repeating the estimating process a number of times to get a good estimate of the standard deviation, the square root of the variance, of the measured values. However, if the measured values are averaged, then the mean measurement value has a much smaller uncertainty; namely, it is equal to the standard

error of the mean, which is the standard deviation divided by the square root of the number of measurements. The standard error is a crude but useful measure of statistical accuracy and is frequently used to provide a confidence interval for an unknown parameter  $\theta$  (Efron and Tibshirani 1985).

A confidence interval is a range of values that is likely to include the “true value” of the population parameter. The width of the confidence interval provides a measure of the uncertainty in the population parameter. A wider interval indicates greater uncertainty in the estimated parameter whereas a narrow interval indicates lesser uncertainty. The confidence interval also provides a measure of the reliability of an estimate and, depending on the confidence level, indicates how likely the estimated parameter will fall within the interval. For example, at a confidence level of 95%, if the experiment was repeated a 100 times and the confidence interval calculated each time, then the confidence interval thus calculated would contain the value of the estimated parameter 95 out of 100 times.

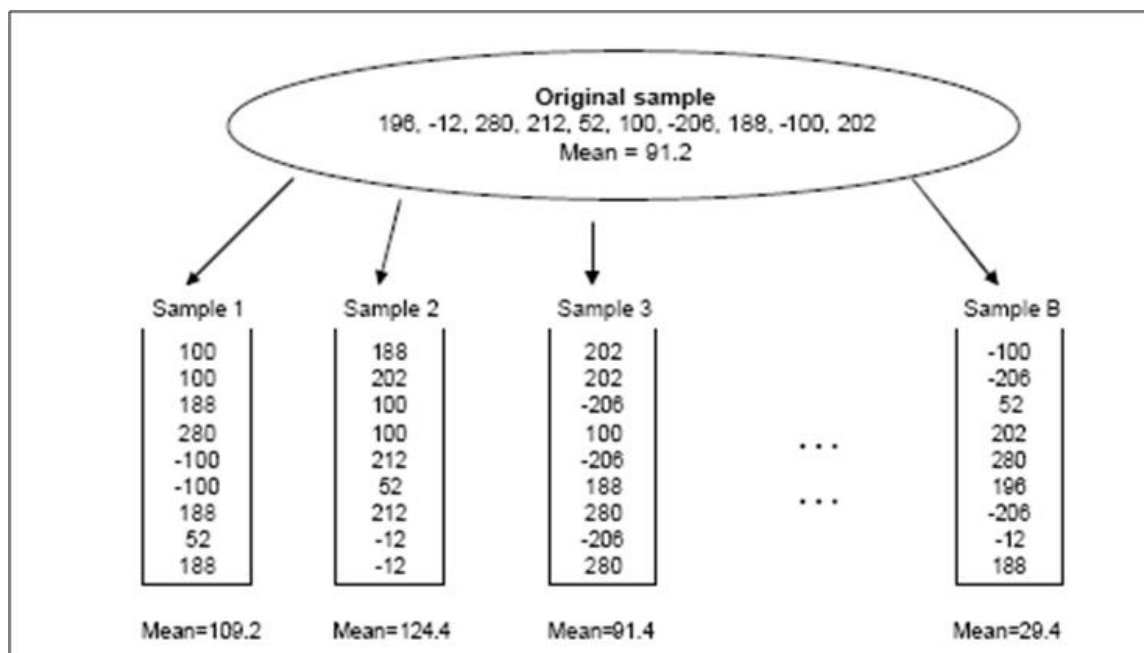
### **1.2.3 Uncertainty Assessment with Bootstrapping**

Bootstrapping is a data-based simulation technique for assigning measures of accuracy to statistical estimates (Barker 2005). It is a computationally intensive, nonparametric technique that can produce probability based inferences (standard errors and confidence intervals) about a population-related parameter based on a sample estimate (Mooney and Duval 1993). Bootstrapping is useful in examining the performance of statistical methods by applying them repeatedly to bootstrap pseudo data, known as "resamples" (Mammen and Nandi 2008). The inspection of the outcomes for

the different bootstrap samples allows the statistician to get a reliable measure on the performance of the statistical procedure. The common implementations of the bootstrap are ordinary bootstrap and block bootstrap methods. The appropriate type of bootstrap method to be implemented is dependent on the structure of the data (i.e., independent and identically distributed data or dependent data).

#### *1.2.3.1 The Ordinary Bootstrap*

The ordinary bootstrap is the simpler and more general version of bootstrapping that is applied to independently and identically-distributed data (i.i.d). The methodology involves starting with an original sample, then creating a new sample (bootstrap sample) by sampling with replacement from the original sample. The process is repeated a number of times (generally 1000) to generate a series of bootstrapped samples, and the statistic of interest (such as the mean) is computed for each bootstrapped sample. Figure 1-2 illustrates this process. Note that because the resampling is done with replacement, bootstrap samples can duplicate observations from the original sample. The standard error (standard deviation of the mean) is then calculated by finding the standard deviation of the bootstrapped means.



**FIGURE 1-2: Illustration of the ordinary bootstrap method<sup>1</sup>**

### *1.2.3.2 The Block Bootstrap*

The block bootstrap is the most popular method for implementing the bootstrap with time-series (dependent) data (Hardle et al. 2003). The basic concepts of the block bootstrap are similar to those of the ordinary bootstrap discussed earlier. Both procedures are based on sampling observations with replacement. However, in the block bootstrap method, the data are divided into contiguous blocks that are randomly sampled in order to construct the bootstrap samples. The blocks can be created using different methods as described in previous studies on the subject (Hall 1985; Carlstein 1986; Kunsch 1989) and (Politis and Romano 1994).

<sup>1</sup> Image source: Barker 2005

This blocking is done to capture the dependent structure; hence, the resulting estimates from the block bootstrap tend to be less biased than those from an ordinary bootstrap. Nonetheless, as Lahiri finds, “a bias correction is needed for the block bootstrap to accurately estimate uncertainties and the bias correction is often laborious even for estimators as simple as the sample mean” (1999).

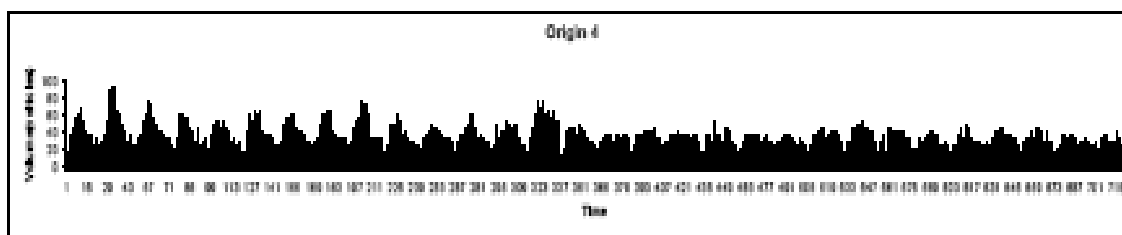
#### **1.2.4 Multivariate Data Structure**

In many dynamical systems, multivariate data are readily available for estimating model parameters. These multivariate data exhibit two distinct characteristics: (i) nonlinearity: there is no direct or straight line relationship between variables; and (ii) nonstationarity: the statistical characteristics (mean and variance) change over time due to either internal or external nonlinear dynamics. For stationary data the probability density function remains equal regardless of any shift in time to its time origin (Haag 2008), but this is not the case for nonstationary data. An example of nonstationary data can be found in environmental systems for spatial-temporal modeling where data might be several pollutants species measured over time at many locations or for receptor modeling where similar data may be obtained at just one pollution receptor over time.

The widespread deployment of Intelligent Transportation Systems (ITS) has enabled traffic data such as volume, speed and occupancy to be readily available. These data are often used in prediction models to provide estimates of mean travel time to road users. The volume, speed and occupancy data have a nonstationary distribution and exhibit a general periodicity. That is, considering a time series of volume data, Monday’s data are similar to every other Monday, but data from Monday morning and Monday



afternoon can be different. Figure 1-3 illustrates the periodic behavior in link volume count data obtained from a detector location on Interstate 10 in San Antonio, Texas. The plot depicts 30 days of peak AM (6:30 – 8:30) volume counts that were aggregated at 5-minute intervals. This type of data presents challenges for estimated model uncertainty evaluation.



**FIGURE 1-3: Periodic behavior of volume data<sup>2</sup>**

## 1.3 PROBLEM STATEMENT

### 1.3.1 Need for Uncertainty Modeling in Travel Time Prediction

A review of the literature on travel time prediction indicates the availability of several models to facilitate the prediction of mean travel times. The focus of the majority of these studies has been on the predictive accuracy of the model, which is the ability to provide an accurate point estimate of the mean travel time in comparison to travel times encountered in real time. Thus a point estimate of the prediction is given which does not provide any knowledge into the uncertainty margin that exists around the prediction. However, studies (Arnott et al. 1991; Khattak et al. 1995; Mahmassani et al. 1999) that have investigated the potential benefits of ATIS emphasize among other things, the

<sup>2</sup> Image source: Appiah et al. 2008

reliability of traffic information to greatly influence driver responses (Van Berkum and Van Mede 1993; Mahmassani et al. 1999). This may suggest that in order for the predicted mean travel time to have a positive impact on congestion and safety (through road-users being able to make smarter route decisions), it must be consistent—drivers must be able to both trust and rely on the travel time estimate.

Additionally, given the number of travel time prediction models available, engineers are faced with the challenge of selecting and implementing the most effective modeling scheme. As a general guide to selecting one of the numerous models for implementation, it would be instructive to have a means of assessing the reliability of these models. One way of doing this, is by being able to accurately quantify the uncertainties in the predictions in terms of variances or confidence intervals.

Uncertainty in the travel time prediction arises from noise inherent to the measured data and noise due to model structure (i.e., uncertainty due to the approximating function being trained on a selected random sample available from the population). The poor quality of measured data has been studied extensively and can be addressed using a number of different methods, for example, a generalized reduced gradient approach (Vanajakshi 2000) and multivariate screening methods (Park et al. 2003). There, however, is need to quantify the uncertainty due to errors in model (mis)specification. More specifically, there is need to explicitly address the confidence in the model parameters. Eisele (2001) outlined a loess non-parametric statistical procedure for estimating link and corridor travel time mean and variance using ITS data. This statistical procedure presents a method of locally-weighted smoothing that allows estimation of travel time mean and variance.

Van Lint (2003) evaluated two different methods—non-parameterized bootstrapping (Heskes 1997) and an approximate Bayesian approach (Papadopoulos et al. 2001)—for assigning confidence to the travel time prediction parameters obtained from a proposed state space neural network (Lint et al. 2002) model. Both methods exploit the bootstrap mechanism (Efron and Tibshirani 1993) and yield plausible results in terms of the number of travel times that fall within their respective confidence intervals. Van Hinsbergen (2010) evaluated a Bayesian inference framework for assigning error bars (prediction intervals) around output from traffic prediction and estimation models. A limitation of the researches is that it is based on the assumption that the data are independently and identically distributed. This is unlikely to be the case.

### **1.3.2 Need for Considering the Structure of Traffic Data in Modeling**

ITS and loop detector data (volume, speeds, densities and occupancy) are readily available for use with travel time prediction. These data have a nonstationary distribution and exhibit a general periodicity as shown previously in Figure 1-3. Additionally, the data are weakly dependent; that is, the dependence diminishes as the aggregation interval becomes large (i.e., traffic characteristics on Monday at 7:30 AM influence traffic characteristics on Monday at 7:35 AM, but do not influence traffic characteristics on the next Monday at 7:35 AM).

This type of data presents a challenge for estimated model uncertainty evaluation. Thus, when quantifying the uncertainty in the travel time prediction, there is need to consider the nonstationary distribution and dependence structure of the ITS data.

## **1.4 RESEARCH OBJECTIVES**

The primary goal of this research was to examine the uncertainty arising in travel time prediction estimates due to model structure. Specifically, this research aimed at addressing the reliability (confidence) in travel time predictions. This objective was achieved by the following specific aims:

1. Investigated the characteristics of available ITS point and interval data, such as speed, flow and travel time. Particular focus was on the periodicity and dependence of these types of data.
2. Demonstrated applications of the ordinary and blocked bootstrap methods for evaluating uncertainties in travel time prediction models.
3. Introduced and implemented a recently developed gapped bootstrap method of assessing uncertainty due to a model's structure being specified on a select sample dataset. This will help in providing an unbiased estimate of model parameters when dealing with data that has a nonstationary distribution, is dependent and exhibits a characteristic periodic behavior.
4. Made comparisons of the performances between the proposed uncertainty evaluation methods (i.e., ordinary, block and gap bootstrapping).

## **1.5 STATEMENT OF WORK**

### **Task 1: Perform a literature review**

Related research reports, journal articles, and Ph.D. dissertations were thoroughly reviewed. The primary areas of interest included a succinct knowledge of (1) travel time

data collection and analysis, (2) existing travel time prediction techniques, and (3) existing methods for quantifying uncertainty in model parameters. The purpose of this task was to ensure that no research relevant to this study was overlooked or inappropriately duplicated.

### **Task 2: Develop study design and data collection**

This task included the selection of the study corridors from which data for the various analyses in this dissertation were gathered. One of the data sources was a proposed corridor that is a section of Interstate 35 located within the TransGuide project area in San Antonio, Texas. TransGuide—San Antonio’s advanced traffic management system (ATMS)—is designed to provide information to motorists about traffic conditions such as incidents, congestion and construction. Data for this study corridor is collected using ITS equipment, such as inductive loop detectors. The data was downloaded from the TransGuide website archive ([www.transguide.dot.state.tx.us](http://www.transguide.dot.state.tx.us)).

The other proposed data source was a simulated section of Interstate 80 located between the cities of Lincoln and Omaha, Nebraska. The simulated study corridor is part of a large area micro-simulation project being modeled using VISSIM. The use of data from two study corridors was intended to validate the results from this research.

### **Task 3: Investigating characteristics of ITS traffic data**

The ITS data contained discrepancies and missing values, therefore the data were initially “cleaned” and preprocessed for quality control. Standard quality control methods were

implemented. As mentioned in the problem statement, research available to date is based on the assumption that the traffic data are independently and identically distributed. However, this is not likely to be the case. An additional goal of this task was to identify the structure of the data sets in terms of periodic behavior and trends of dependency.

#### **Task 4: Assessment of uncertainties in the model parameters**

There is limited research (Eisele 2001; Van Lint 2003) available on the provision of confidence intervals to the output from travel time prediction models. Bootstrapping is a technique that allows making probability based inferences, or compute standard errors, about a population related parameter based on a sample estimate. A number of bootstrap methods are available.

The ordinary bootstrap is a useful technique when dealing with data that is independently and identically distributed. However, for data that has a dependent structure, the block bootstrap technique is adopted. Still, “a bias correction is needed to accurately estimate uncertainties” (Lahiri 1999). In this task attention was focused on implementing a recently proposed gapped bootstrap method (Spiegelman 2008).

The gapped bootstrap method produces an estimate of standard error that is asymptotically unbiased. In the case when there is a bias, it is known to produce an estimate that, on average, is large—a conservative estimate of uncertainty is not a major disadvantage. What makes this method potentially attractive is that, unlike ordinary and block bootstraps, the gap bootstrap provides accurate estimates of the standard error for parameters when the data are dependent and have a nonstationary distribution.

The different bootstrap methods were applied to a neural network model to get a measure of uncertainty around the value of the predicted mean travel time. The comparison in performance between the three bootstrap methods was presented as a part of this task.

### **Task 5: Summary and Conclusions**

A summary of the research findings and relevant conclusions based on these findings were provided. Issues pertaining to any future research in the area were identified.

### **1.6 EXPECTED RESEARCH CONTRIBUTIONS**

Provision of time based information is a major component of ATIS. This time-based information allows road-users to make more informed route decisions (pre-trip and en-route), and that can potentially yield more stable and less congested traffic conditions. For traffic managers, this is an important index for monitoring traffic system operation. While a significant amount of research has been conducted in this area, there is still important work that needs to be done.

To date there have been numerous travel time estimation and prediction models that have been developed. The bulk of previous work has largely focused on an aggregate estimation of the mean travel time. One key contribution of this research was to identify an approach to compute an estimate of standard error for highly nonlinear models. The approach is generic and can be applied to other estimation and prediction models. In this dissertation the approach was illustrated on a travel time prediction model. It is expected

that by quantifying the uncertainty, a more reliable travel time estimate would be available for drivers and transit agencies.

In the past, it has been assumed that traffic data such as travel times, flow or speeds are independently and identically distributed. This is unlikely to be the case which produces biased uncertainty estimates. In this research, explicit consideration of the nonstationary distribution and dependence structure of multivariate ITS data sets was made. Thus, a way to identify reliability measures for traffic data which have been shown to exhibit a time dependent, periodic and nonstationary structure was presented. The application of the methods to the domain of travel time prediction is new.

It is expected that as traffic management centers continue to provide road users with textual time-based information (via phone, radio and roadside or overhead variable message signs) on typical, or even custom, routes, the proposed research could be applicable to ITS engineers as a decision making tool. It could prove useful when selecting the most appropriate estimation and forecasting technique for deployment in their respective traffic management programs.

## **1.7 ORGANIZATION OF THE DISSERTATION**

This dissertation is organized into six chapters. Chapter One is an introduction to the research and discusses the background of the problem, statement of the problem, research objectives, research methodology, contributions of the research, and the organization of the dissertation. Chapter Two presents a literature review on methods for collecting travel times, methods for estimation of link travel time from loop detectors, prediction of



link travel time, and uncertainty modeling with travel time prediction. Chapter Three presents the details of the study corridor and the data collection procedures along with standard data reduction techniques adopted in this dissertation. Chapter Three also discusses some exploratory analyses to identify characteristics in the data. Chapter Four describes the travel time estimation and prediction models adopted within this dissertation. Chapter Five details the proposed uncertainty modeling methodology and discusses the bootstrapping technique. Chapter Six provides conclusions and suggestions for further research. The references are followed by a glossary of frequently used terms.

## **CHAPTER 2**

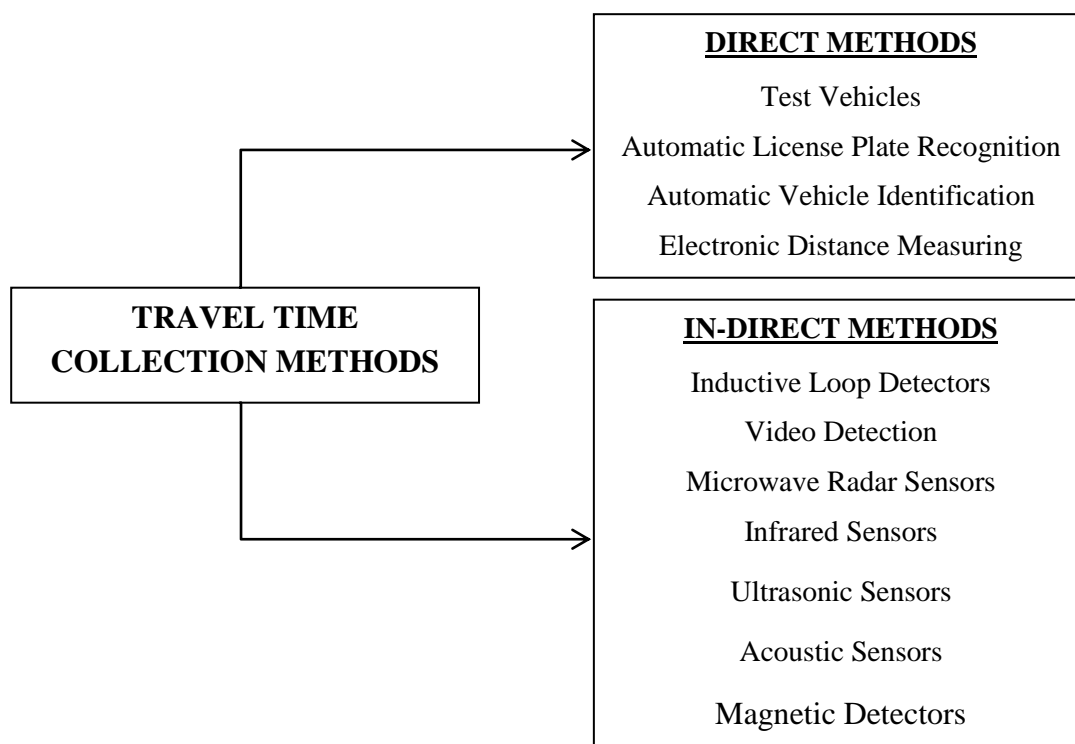
### **LITERATURE REVIEW**

#### **2.1 INTRODUCTION**

This chapter provides detail on existing literature pertaining to link travel time mean and median estimation. The chapter begins with a section on travel time collection methods focusing particularly on inductive loop detectors (ILD), their operation and installation, and the data available from ILDs. Subsequently, the relevant literature pertaining to link travel time estimation using ILD data is presented. It is followed by a discussion of work related to link travel time prediction. As well a detailed discussion on research involving link travel time prediction using neural networks is presented. The final section of this chapter discusses uncertainty modeling and the reported methods for calculating uncertainty. Also included within this final section is a discussion on uncertainty modeling related to link travel time prediction.

#### **2.2 TRAVEL TIME COLLECTION METHODS**

Traditionally, travel time has been measured using the test vehicle or floating car technique. The methodology involves driving an instrumented (with manual or automatic measuring devices) vehicle(s) within the traffic stream to specifically collect data. With the advent of Intelligent Transportation Systems, many varying techniques are available for travel time measurement. These ITS techniques can be divided broadly into direct and indirect measuring methods as illustrated in Figure 2-1.



**FIGURE 2-1: Travel time collection methods**

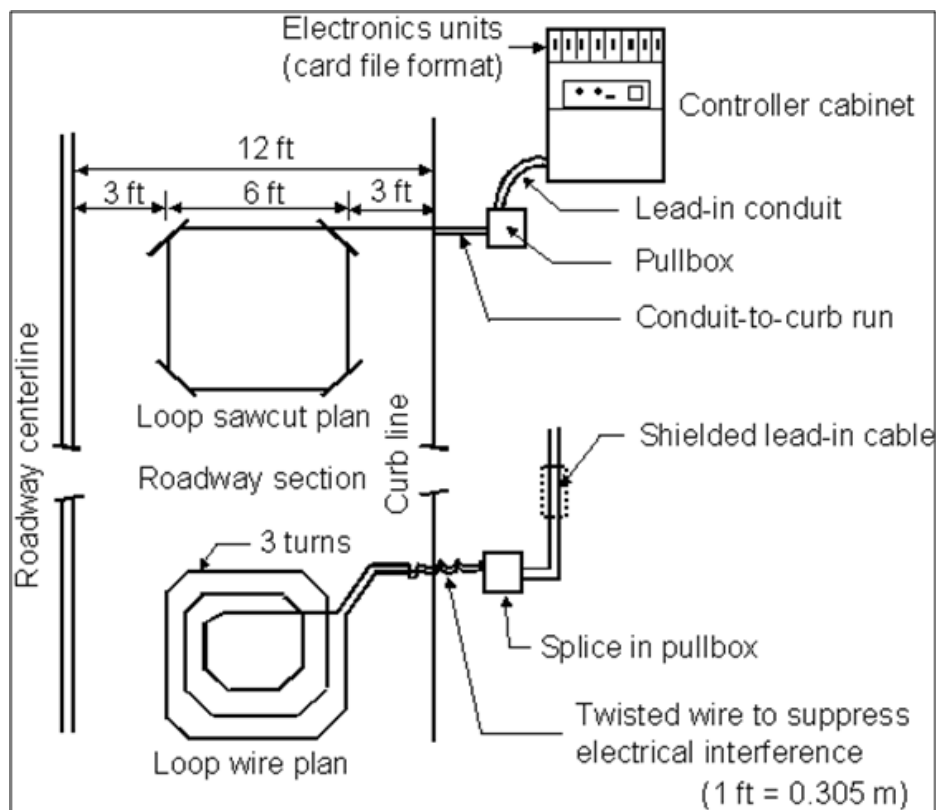
With the direct methods, travel time is collected from the field using methods that include test vehicles, automatic license plate recognition, automatic vehicle identification and electronic distance measuring devices. With the indirect measuring methods, the travel time is estimated from other measured parameters such as speed, volume and occupancy using standard formulations. Sources for indirect travel time include intrusive and non-intrusive detection sensors such as inductance loops, video detection, microwave radar, infrared, ultrasonic, passive acoustic array, and magnetic technologies (Turner 1998).

In most metropolitan cities within the United States, the freeways have already been instrumented with inductive loop detectors. These detectors are a good source of

traffic data from which travel time information can be obtained. Moreover, loop detectors are a continuous and less expensive source of data as compared to methods such as test vehicles and automatic vehicle identification. For this dissertation, the real-time raw data used is obtained from ILDs. Therefore, the next sub-sections present specific detail related to the operation, placement and data collected from inductive loop detectors.

### **2.2.1 Overview of Inductive Loop Detectors**

The National Electrical Manufacturers Association (NEMA) standards provide the definition of a vehicle detector as, “a system for indicating the presence or passage of vehicles.” The vehicle detector system is the backbone of any traffic management and data collection system (NEMA 1983). Of a variety of vehicle detection systems available on the market, the inductive loop detector is the most widely used (Raj and Rathi 1994; Klein et al. 2006). Inductive loop detector technology has been in use for the detection of vehicles since the early 1960s (Potter 2009). Inductive loop detectors consist of one or more loops of wire embedded in the pavement and connected to a control box. When a vehicle passes over or rests on the loop, the inductance of the loop is reduced, thus indicating the presence of a vehicle. The data that is typically supplied by inductive loop detectors include vehicle passage, presence, count and occupancy.



**FIGURE 2-2: Inductive loop installation<sup>3</sup>**

### 2.2.2 Principle and Theory of Operation

Loop detectors operate on the principle of inductance. The typical components of an inductive loop detector are one or more turns of insulated wire (also known as a loop), a lead in cable which runs from a roadside pull box to a controller and an electronics unit located in the controller cabinet. Figure 2-2 depicts the principal components in an inductive loop detector and their typical installation.

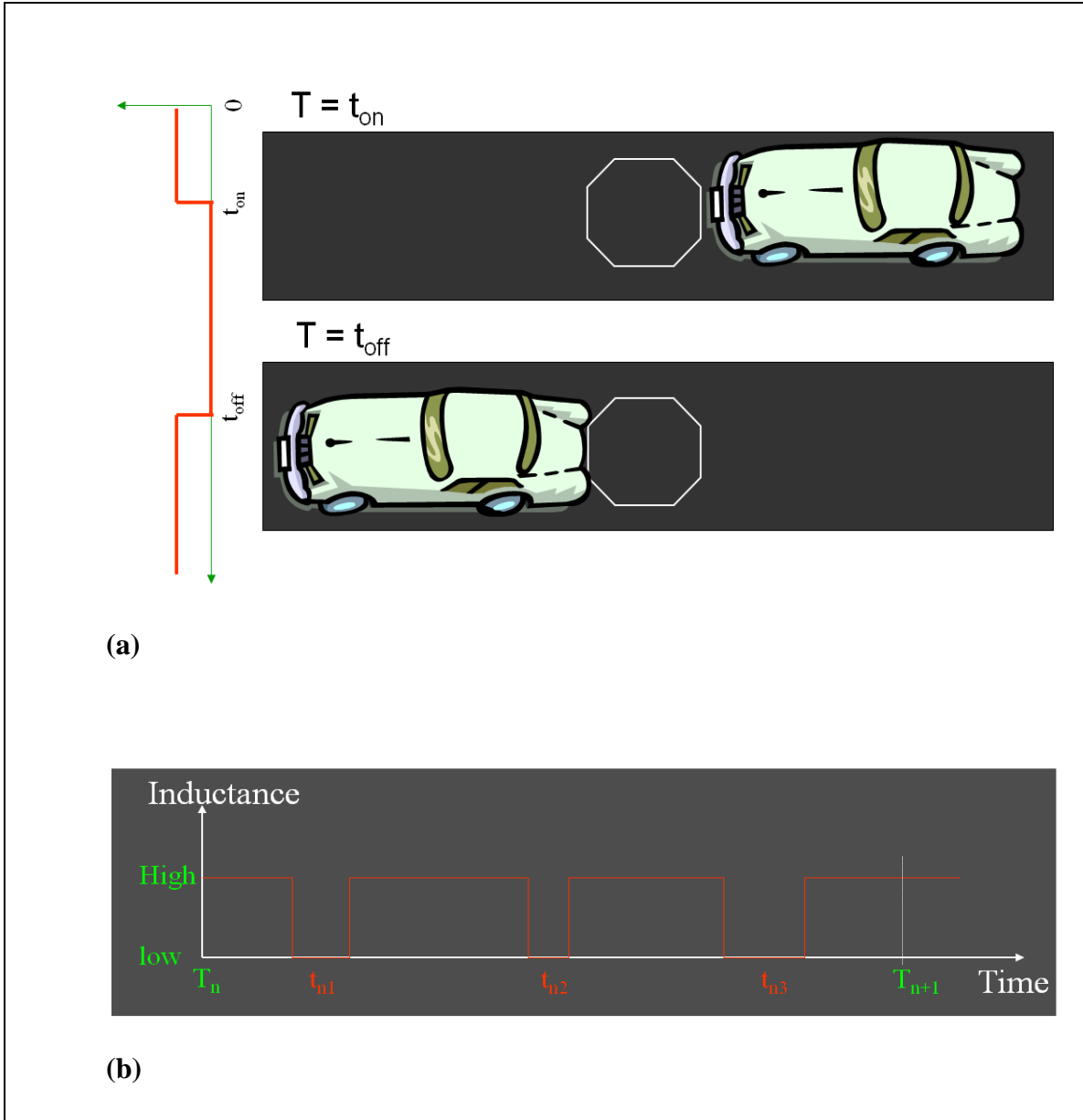
The insulated electrical wire, usually several meters to a side with several turns, is buried up to 20-inches below the road surface in a 0.15-inch wide shallow cutout. The

<sup>3</sup> Image source: Klein *et al.* 2006

pull-box is usually located adjacent to the roadway and houses the splices between the lead-in cable from the controller and the lead-in wires from the loop. The lead-in wires are shielded and twisted to eliminate disturbances from external electromagnetic fields, such as adjacent loops. Energy in the range of 10 kHz to 200 kHz is supplied to the wire loops by the electronics unit. The inductive-loop system behaves as a tuned electrical circuit in which the loop wire and lead-in cable are the inductive elements.

When a vehicle stops on or passes over the loop, its inductance is decreased as shown in Figure 2-3 (a). The decreased inductance increases the oscillation frequency and causes the electronics unit to send a pulse to the controller, indicating the presence or passage of a vehicle. Figure 2-3 (b) depicts a series of low-high pulses indicating that three vehicles passed over the loop. The differences in width, or time, of the low frequency seen in Figure 2-3 (b) indicate how long the vehicle was present on the detector. Thus, the vehicle passing during time  $t_{n3}$  was present over the detector much longer than the vehicle passing during time  $t_{n1}$ .

The size and the number of turns of a loop or combination of loops, together with the length of the lead-in cable, must produce an inductance value that is compatible with the tuning range of the electronics unit and with other requirements established by the traffic engineer. The loops are read many times a second though the data are typically reported back to the traffic management center at intervals of 20 or 30-seconds. For freeway applications, loops are often placed 0.25 to 0.50-miles apart. Inductance loop detectors on arterial streets are commonly placed at major intersections, where traffic conditions vary considerably throughout the traffic signal cycle.



**FIGURE 2-3: Loop detector inductance measurements**

**2.2.3 ILD Configurations and Data Collected**

Inductive loop detectors can be configured to work as either a single loop or a dual loop. The single-loop detector, like the name suggests, uses a single loop of wire at each location as shown in Figure 2-4. In the case of the dual-loop detector, two single

loops are placed a small distance apart at each detector location as illustrated in Figure 2-5. Both detector configurations supply data that includes vehicle passage, presence, count (volume) and occupancy. The essential difference is in the way vehicle speed is calculated using each detector configuration. Single-loops cannot measure speed directly and thus a value of speed is estimated based on a function of effective loop length, average vehicle length, time over the detector and the number of vehicles counted (May 2009). With dual loops the speed can be measured directly. Equations 2.1 and 2.2 are used for calculating the speed using single and dual loops, respectively.

$$v_n = \frac{L_n + L_d}{(t_{occ})_n} \quad (2.1)$$

where:

$L_n$  = vehicle length (feet);

$L_d$  = detection zone length (feet); and

$(t_{occ})_n$  = individual occupancy time (seconds).

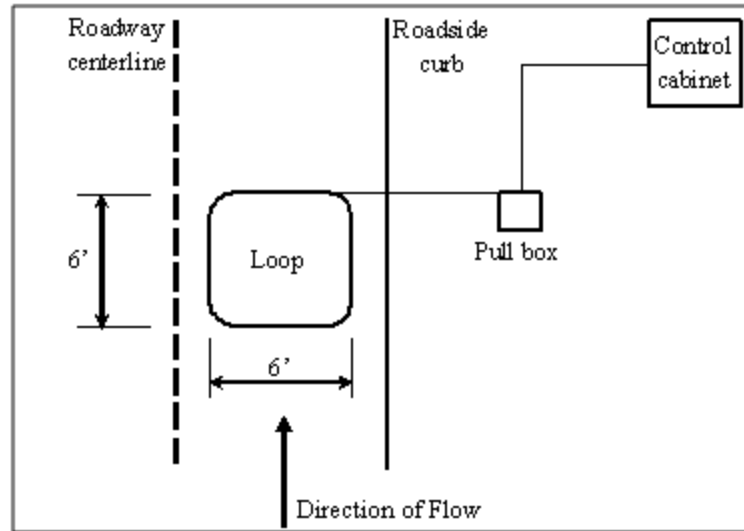
$$v_n = \frac{D}{[(t_{on})_n]_B - [(t_{on})_n]_A} \quad (2.2)$$

where:

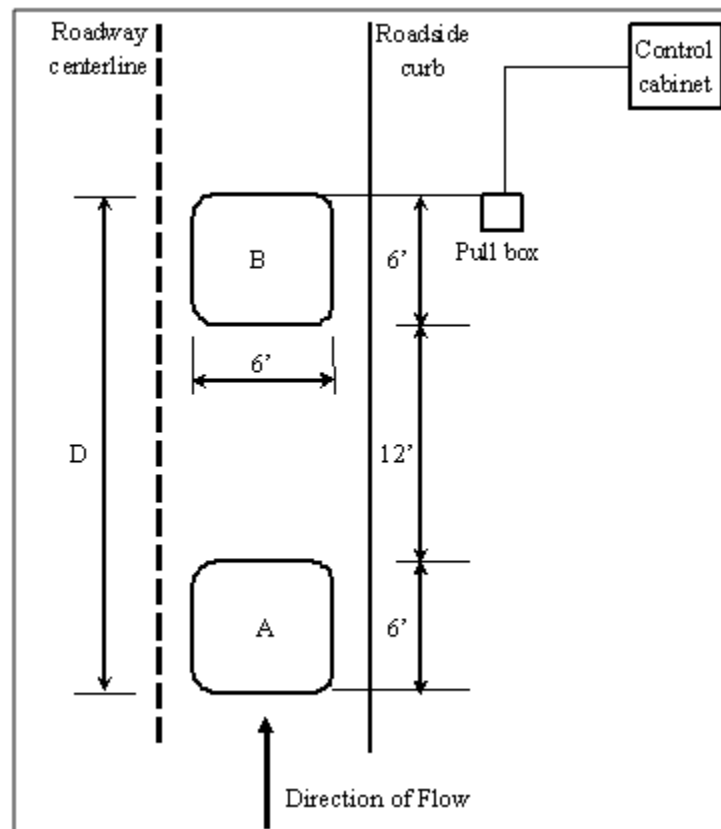
$A$  and  $B$  = first and second loops in the dual-loop detector respectively; and

$D$  = distance from upstream edge of detection zone A to downstream edge of detection zone B (feet).





**FIGURE 2-4: Single loop detector in one lane of a roadway**



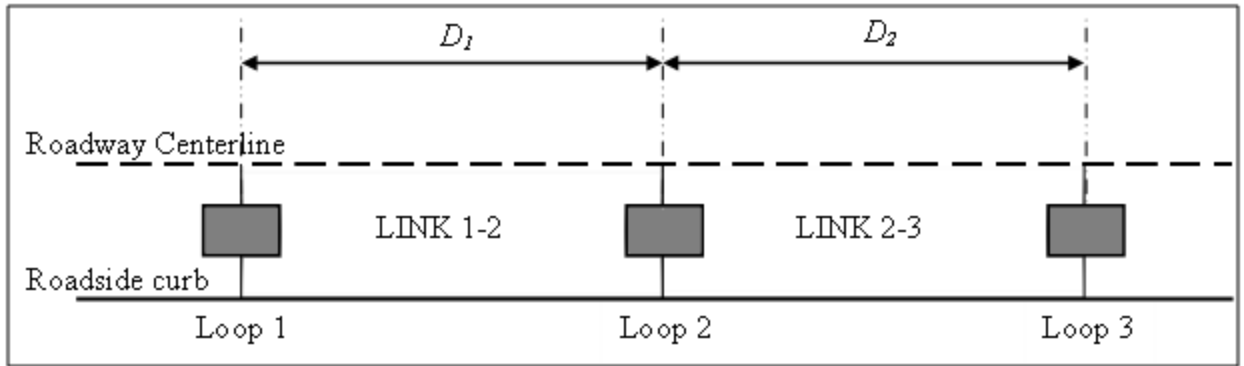
**FIGURE 2-5: Dual loop detector in one lane of a roadway**

## **2.3 LINK TRAVEL TIME ESTIMATION FROM INDUCTIVE LOOP DETECTORS**

As mentioned previously, link travel time data may be gathered directly using methods that include the use of instrumented test vehicles, license plate matching, vehicle probes (i.e., global positioning systems and automatic vehicle identification) or emerging technologies (e.g., cell phones) (Turner et al. 1996, 1998). However, these methods are costly to implement and maintain. Alternative, less costly methods to estimate or calculate travel times from directly measured parameters, such as point speeds obtained from single or dual inductive loops (as mentioned earlier), are also available.

### **2.3.1 Extrapolation Methods**

The simplest (and most widely accepted by DOTs) methods for estimating travel time from inductive loop detector data are the extrapolation methods (Turner et al. 1998). Extrapolation methods are based on the assumption that the spot speed can be assumed to be constant for the small distance between the measurement points: usually the distance between the two detector stations (approximately one-third to one-half mile). Given that the distance between the two detectors is known, the travel time is calculated as the distance divided by the spot speed (Dhulipala 2002; Cortes et al. 2002; Van Lint et al. 2003). With the aid of Figure 2-6, a brief description of each extrapolation method is given in the following sections.



**FIGURE 2-6: Diagram to illustrate extrapolation methods**

### 2.3.1.1 Average Speed Method

In this method, it is assumed that the average speed of vehicles travelling on the link from 1 to 2 is the average of the spot speeds estimated at detector locations 1 and 2. Therefore, the estimated travel time for link 1-2 would be given as:

$$\text{Travel Time Link}_{1-2} = \frac{D_1}{(v_1 + v_2)/2} \quad (2.3)$$

where:

$D_1$  = distance between loop detector locations 1 and 2; and

$v_1$  and  $v_2$  = spot speed estimated at detector locations 1 and 2, respectively.

### 2.3.1.2 Minimum Speed Method

In this method, the minimum of the spot speeds estimated at detector locations 1 and 2 is taken to be the average speed of the vehicles traveling on the link from 1 to 2. The travel time for link 1-2 is then given as:

$$\text{Travel Time Link}_{1-2} = \frac{D_1}{v_{min}} \quad (2.4)$$

where:

$D_1$  = distance between loop detector locations 1 and 2; and

$v_{min}$  = minimum of the estimated spot speeds from detector locations 1 and 2.

### 2.3.1.3 Midpoint Method

In the midpoint method each loop detector location is assigned an influence area around it based on the location of midpoints between that detector and the next station upstream or downstream. The estimated spot speed from each detector is assumed constant within its respective influence area. Thus the travel time for link 1-2 calculated using the midpoint method is given as:

$$\text{Travel Time Link}_{1-2} = \frac{1}{2} \left( \frac{D_1}{v_1} + \frac{D_1}{v_2} \right) \quad (2.5)$$

where:

$D_1$  = distance between loop detector locations 1 and 2; and

$v_1$  and  $v_2$  = spot speed estimated at detector locations 1 and 2 respectively.

Research work by Eisele (2001) compared the travel times calculated using the midpoint method to the travel times calculated using the average speed method. It was found that the percentage difference between the two travel time estimation techniques

was less than two percent. The study used data from four weekdays (AM peaks) obtained from inductive loop detectors along a section of I-35 in San Antonio, Texas.

### **2.3.2 Theoretical Methods**

Also available to estimate travel times directly from flow and occupancy data are methods based on traffic flow theory (Nam and Drew 1996, 1998, 1999; Petty et al. 1998; Coifman 2002; Oh et al. 2003). These methods are advantageous in that they are able to capture the dynamic characteristics of traffic. Theoretical models apply the principle of the conservation of vehicles and, as such, compare the inflow of a roadway section during a previous time interval with its outflow during the current time interval (Bovy and Thijs 2000). Most of the models cited provide satisfactory travel time estimates for specific conditions. Some models perform well in normal-flow conditions only (Nam and Drew 1996; Oh et al. 2003), whereas others are applicable to congested traffic conditions only (Nam and Drew 1998, 1999).

Vanajakshi (2004, 2009) proposed a model for estimating travel time directly using speed, flow and occupancy data from ILDs. The proposed model builds upon the work of Nam and Drew (1996, 1998, 1999). Several modifications are presented that take into account the varying traffic flow during the transition period from peak to off-peak or off-peak to peak conditions. Thus, a comprehensive model that can estimate travel times directly from ILD data is presented. For this dissertation, the travel times will be estimated using the methodology proposed by Vanajakshi. A detailed discussion of the model will be given in Chapter Four.

## 2.4 LINK TRAVEL TIME PREDICTION

An important role of Advanced Traveler Information Systems is to provide the public, businesses and commercial carriers with the right travel information (such as delays, next bus arrival times and alternate routes) at the right time and right place. The success of ATIS lends in the degree of accuracy and the timeliness to which travel times for “unknown” future conditions are provided. That is, accurate predictions of link travel times are more beneficial than current link travel times, especially considering that conditions on a given link may change significantly with time. A variety of models that predict the mean travel time (for a given link) are available in the literature. The next sections provide an overview of the modeling approaches common to link travel time prediction. These modeling approaches include time series analysis, Kalman filtering and the use of neural networks.

### 2.4.1 Time Series Analysis

The fundamental goal in time series analysis is to understand the underlying mechanism that generates the observed data and, in turn, forecast future values of the series (Box et al. 1994; Brockwell and Davis 2002). The measured data are generally considered and treated as a collection of observations made sequentially in time. That is, any quantity measured over time will yield a time series. A time series model for the observed data, say  $\{x_t\}$ , is a specification of the joint distributions of a sequence of random variables,  $\{X_t\}$  of which  $\{x_t\}$  is postulated to be a realization. Time series models can have many forms and represent different stochastic processes. The various forms include; the autoregressive (AR) models, the moving average (MA) models, the

autoregressive moving average (ARMA) models and the autoregressive integrated moving average (ARIMA) models.

An AR model, of order  $p$ , assumes that the value of the series  $\{X_t\}$  at time  $t$  depends on its previous value and a random noise. If the dependence of  $\{X_t\}$  is linear then the  $\{X_t\}$  can be represented as:

$$X_t = \varphi_1 X_{t-1} + \varphi_2 X_{t-2} + \dots + \varphi_p X_{t-p} + Z_t \quad (2.6)$$

where:

$\varphi = (\varphi_1, \varphi_2, \dots, \varphi_p)$  are the AR model coefficients; and

$Z_t$  is the disturbance at time  $t$ .

The process  $Z_t$  is modeled as an independent and identically distributed white noise with zero mean and variance  $\sigma^2$ . The time series is said to be a MA process, of order  $q$ , if  $\{X_t\}$  can be written as:

$$X_t = Z_t + \theta_1 Z_{t-1} + \theta_2 Z_{t-2} + \dots + \theta_q Z_{t-q} \quad (2.7)$$

where:

$\theta = (\theta_1, \theta_2, \dots, \theta_q)$  are the moving average coefficients.

A combination of the AR and MA models results in an autoregressive moving average process of order  $(p, q)$ . That is:

$$\begin{aligned}
X_t - \varphi_1 X_{t-1} - \varphi_2 X_{t-2} - \dots - \varphi_p X_{t-p} \\
= Z_t + \theta_1 Z_{t-1} + \theta_2 Z_{t-2} + \dots + \theta_q Z_{t-q}
\end{aligned} \tag{2.8}$$

By introducing a back shift operator  $D$ , i.e.,  $D^i X_t = X_{t-i}$ , then the ARMA ( $p, q$ ) model can be re-written as:

$$\varphi(D)X_t = \theta(D)Z_t \tag{2.9}$$

where:

$$\varphi(D) = 1 - \varphi_1 D - \varphi_2 D^2 - \dots - \varphi_p D^p, \text{ and}$$

$$\theta(D) = 1 - \theta_1 D - \theta_2 D^2 - \dots - \theta_q D^q.$$

In most time series analyses, the data are taken to be stationary. That is, the properties of one section of the data are much like those of any other section (e.g., no systematic changes in mean and variance). However, in practice, data are non-stationary. To incorporate the non-stationary effect, ARMA time series' are differenced by substituting  $(1-D)^d X_t$  for  $X_t$ . The ARMA model then becomes an ARIMA ( $p, d, q$ ) model represented as:

$$(1 - D)^d \varphi(D)X_t = \theta(D)Z_t \tag{2.10}$$

The ARIMA model thus constitutes an autoregressive (AR) part, a differencing (I) part and a moving average (MA) part. The differencing part is used to convert the non-stationary series to a stationary series thus, removing any trends in the data.



#### *2.4.1.1 Applications of Time Series Analysis to Link Travel Time Prediction*

Oda (1990) proposed an approach for the prediction of travel times that incorporates an AR model and a statistical presumption of vehicle length. The AR model was developed to predict vehicle sensor data (volume and occupancy) for future conditions. Mean vehicle lengths during a given period of time were observed and used to calculate the link travel times. To evaluate the validity of the proposed approach, vehicle sensor data from national road Route 16, in Chiba Prefecture, Japan was used. The results indicated that the AR model adequately predicted the volume and occupancy though it was the vehicle length that affected the travel time prediction. When using varying vehicle lengths, the difference between predicted and measured travel times averaged five to six percent whereas the prediction deteriorated when a constant vehicle length was used.

Yang (2005) modeled arterial link travel times using time series analyses on travel time data obtained from GPS equipped vehicles. In this research, specific ARIMA models were developed for each link of a 3.7 mile corridor on the Minnesota State Highway 194. The residuals were examined and found to be essentially white noise (i.e., random and close to zero) so it was suggested that the ARIMA models developed were appropriate. Billings and Yang (2006) conducted a similar research with the same dataset from the Minnesota State Highway 194. The results indicate that, for most of the road sections, the ARIMA models produce predicted values that are within range of the observed values. As well, the prediction error seemed relatively large on the shorter road sections. The prediction performance could have been affected due to the lower speed limit and shorter distance together with the relatively high cross-street traffic.

Guin (2006) investigated the possibility of extending the usual time series analysis to develop seasonal ARIMA prediction models for travel times on freeways. Video detection data (15-minute average speeds) from a 7.2 mile corridor on Interstate 285 in Atlanta, Georgia were used. To fit the time series model, the section travel times were first converted to zero-mean values and plotted against time. The zero-mean time plots indicated non-stationary characteristics that required differencing. Varying differencing levels were analyzed and it was the weekly differencing that yielded a stationary time series. Correlogram plots of the differenced (weekly) data were then plotted to select the most appropriate ARIMA model for the process. The  $ARIMA(3,0,2)(0,1,1)_{480}$  model was found to be the most optimal. This model was found to provide reasonable prediction results in comparison to a one-step ahead random walk model.

#### *2.4.1.2 Comments on Time Series Applications to Link Travel Time Prediction*

The research cited above indicates the potential and effectiveness of using time series analyses in the prediction of link travel times. However, an issue to consider in time series analysis is the assumption that historic patterns will remain the same in the future. The accuracy of these models is a function of the similarity between the real-time and historic patterns. Variations in historical data or changes in the relationship between historical data and real time data could cause significant inaccuracy in the prediction results.

### 2.4.2 Kalman Filtering

Originally developed for signal processing, the Kalman filter (Kalman 1960) is essentially an optimal recursive data processing algorithm. It is optimal in the sense that it minimizes the estimated error variance when some presumed conditions are met (Gelb 1974). The filter combines available measured data, regardless of their accuracy with prior knowledge about the system and measuring devices, to estimate a desired variable of interest in such a manner that the error is minimized. The two main features of the Kalman formulation and solution to the problem are: (i) vector modeling of the random processes under consideration, and (ii) recursive processing of the noisy measurement (input) data. The model is essentially a set of recursive mathematical equations (or sub models) that when used together will model and accurately estimate the movement of a dynamic system.

The equations of the Kalman filter fall into two groups: state update (or predictor equations) and measurement update (or corrector) equations (Welch and Bishop 1995). The state update Equations 2.11 and 2.12 are responsible for projecting forward (in time) the current state and error covariance estimates to obtain *a priori* estimates for the next time step.

$$\hat{X}_k^- = A\hat{X}_{k-1} + Bu_k \quad (2.11)$$

$$P_k^- = AP_{k-1}A^T + Q \quad (2.12)$$

where:

$\hat{X}_k^-$  and  $P_k^-$  = *a priori estimate* of state and covariance for time step  $k$ , respectively;

$\hat{X}_{k-1}$  and  $P_{k-1}$  = state and covariance estimates from time step  $k-1$ , respectively;

$u_k$  = random variable representing the system noise;

$A = n \times n$  matrix relating the state at previous time step  $k - 1$  to the current step  $k$ ;

$B = l \times n$  matrix relating the optional control input to the state  $x$ ; and

$Q$  = process noise covariance.

The measurement update equations are responsible for incorporating a new measurement into the *a priori* estimate to obtain an improved *a posteriori* estimate. The measurement update is executed as three tasks given by Equations 2.13, 2.14 and 2.15.

$$K_k = P_k^- H^T (H P_k^- H^T + R)^{-1} \quad (2.13)$$

$$\hat{X}_k = \hat{X}_k^- + K_k (z_k - H \hat{X}_k^-) \quad (2.14)$$

$$P_k = (1 - K_k H) P_k^- \quad (2.15)$$

where:

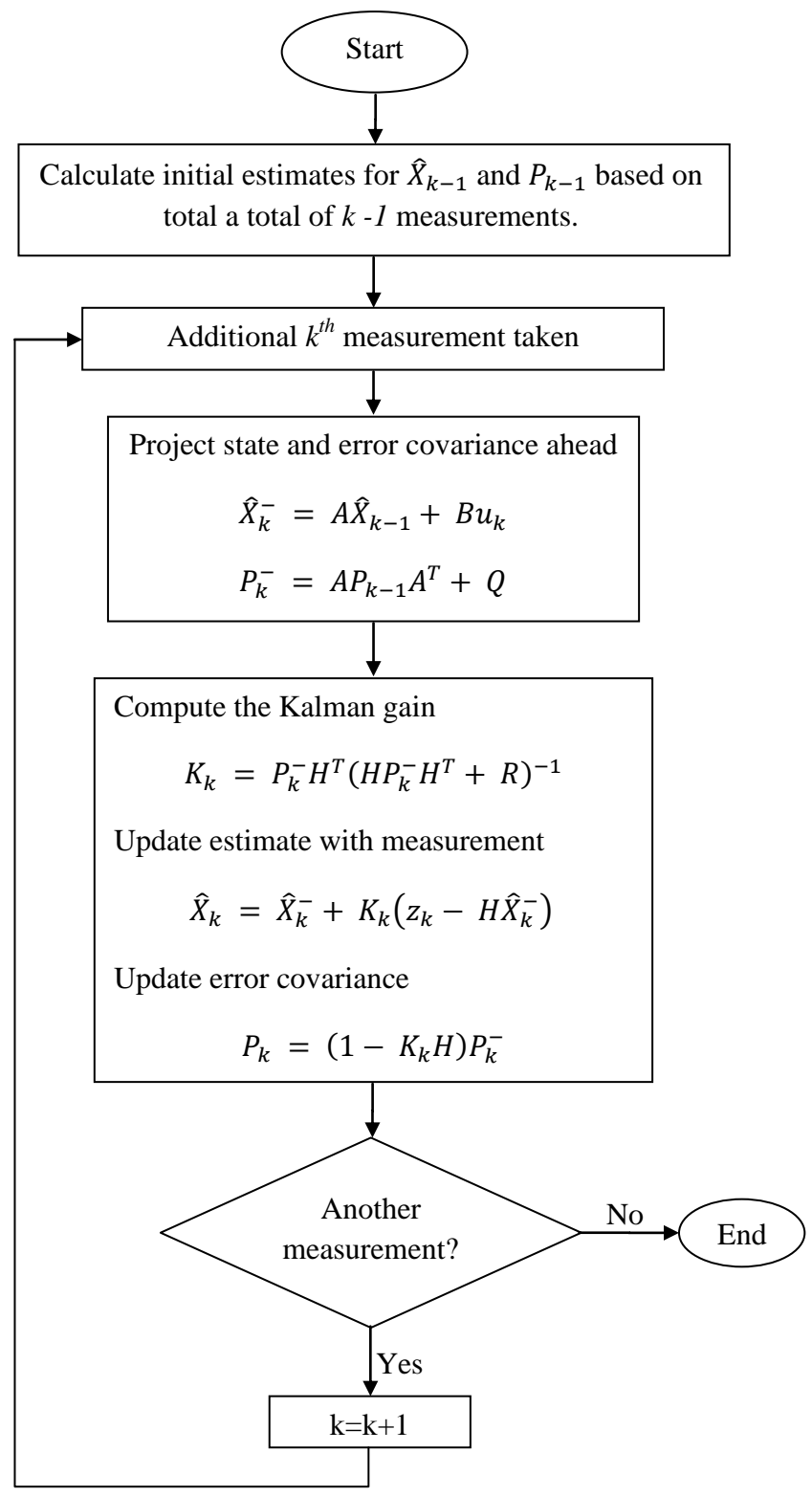
$K_k$  = the Kalman gain;

$\hat{X}_k$  and  $P_k$  = state and covariance estimates at time step  $k$ , respectively;

$R$  = measurement noise covariance.

After each state and measurement update pair is executed, the process is repeated with the previous *a posteriori* estimates used to predict the new *a priori* estimates.

Figure 2-7 shows a flow diagram of the Kalman filter process.



**FIGURE 2-7: Flow chart of the Kalman filtering process**

#### *2.4.2.1 Applications of Kalman Filtering to Link Travel Time Prediction*

Suzuki et al. (2000) modified the conventional Kalman filtering (KF) model to simultaneously predict dynamic origin-destination travel times and traffic flow on an expressway corridor in Bangkok, Thailand. In order to enable non-linear formulations of the state and measurement equations the KF model was integrated with an artificial neural network model, called the Neural Kalman filter (NKF) model. Numerical analysis under free flow and congested conditions showed that the NKF model was fairly accurate in predicting dynamic travel time and flow.

Chen and Chien (2002) compared the prediction accuracy of path-based travel times versus link-based travel times. The study showed that under recurrent traffic conditions, path-based prediction is more accurate than link-based prediction. The KF technique was used to carry out the dynamic travel time prediction with average travel times from probe vehicles as the input data. The results revealed that during peak hours, the historic path-based data used for prediction are better than the link-based data due to smaller travel time variance and larger sample size.

The KF model proposed by Chen and Chien was further investigated using different datasets in research work by Chien and Kuchipudi (2003); Chien et al. (2003) and Yang (2005). The latter research utilized probe vehicle information from a simulated section of I-80 in New Jersey whereas the other two studies used real-time and historic data collected on the New York State Thruway. The results indicated that the proposed model provided accurate predictions of travel time.

Nanthawichit et al (2003) developed a method to estimate and predict traffic variables such as flow, density and travel time by integrating probe vehicle data with conventional fixed detector data. The data collected by probe vehicles were integrated into the measurement equation of the KF model. Estimated travel times were updated with information from both fixed detectors and probe vehicles. The proposed model was tested using three-hour data from a freeway simulated using INTEGRATION. As well the proposed method was tested using real time data from the A92 Motorway close to Munich, Germany (Wang et al. 2006, 2007). The results show that the proposed method was able to provide reasonably comparable travel time estimates.

Oh et al. (2003) proposed a methodology to estimate link travel time using the traffic density on a given link. For this study, the process model of the KF was based on the macroscopic hydrodynamic traffic flow theory developed by Lighthill, Whitham and Richards (LWR). Further research by Chu et al. (2005) proposed an improvement to the model by applying an Adaptive Kalman Filter that fused both point detection data and probe vehicle data. In addition a set of unknown time-varying statistical parameters of noises were estimated simultaneously with the system state and error covariance. The model was tested and compared with other existing travel time prediction models along a stretch of freeway using simulated data from a microscopic simulation model, PARAMICS.

Xiaobo (2004) incorporated the KF model into both an exponential smoothing model and a moving average and as such developed three dynamic recursive models. The models developed include; a dynamic exponential smoothing model (DESM), an improved dynamic exponential smoothing model (IDESM) and a dynamic moving

average model (DMAM). The models were tested on data from a selected highway in southern New Jersey that was simulated using CORSIM. The results showed that incorporating the KF into the base exponential smoothing model and a moving average model improved the stability in the predictions.

#### *2.4.2.2 Comments on Kalman Filtering Applications to Link Travel Time*

##### *Prediction*

The research cited above indicates the potential and effectiveness of using Kalman filtering for the prediction of travel time (mean) for links on a freeway corridor. Unlike in time series analyses where historic data are used for prediction, the Kalman method uses adaptive parameters responsive to dynamic conditions. Therefore the Kalman method provides a prediction of travel time that quickly reflects the traffic fluctuations. Kalman filtering also finds applicability in fusing data from multiple sources in order to improve the prediction estimate. Although the Kalman filtering technique has superior prediction capabilities, it has been criticized for doing so only to a limited time interval (Park et al. 1998; Rilett and Park 2001).

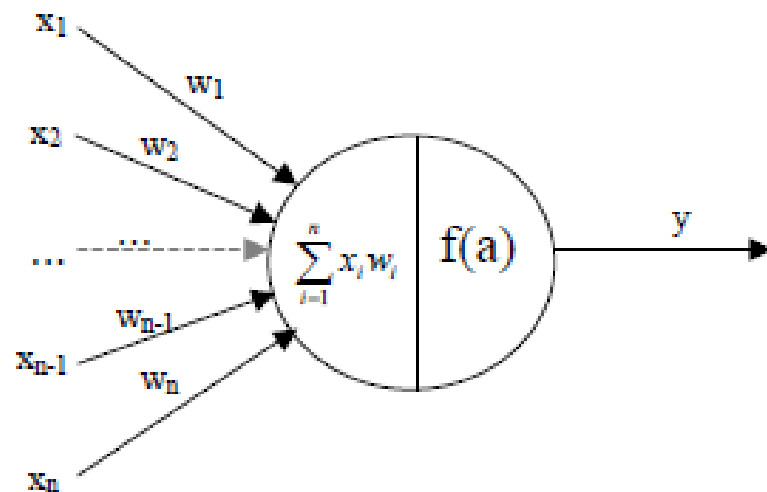
### **2.4.3 Neural Networks**

Neural networks are a familiar technique in the area of artificial intelligence—a discipline that seeks to understand natural intelligence and to build intelligent systems (Pfeifer and Scheier 1999). Neural networks are essentially statistical models that are able to capture and represent complex input/output relationships (NeuroSolutions 2008). In their most general form, NNs aim at mimicking the human brain in performing a



particular task or function of interest. NNs thus resemble the brain in two particular respects: (i) they acquire knowledge through training, and (ii) weights are used to store the acquired knowledge (Haykin 1999).

A NN model is comprised of several building blocks called neurons. Each neuron is composed of two units, as shown in Figure 2-8. The first unit sums the products of weight coefficients and inputs. The second unit is a nonlinear function known also as an activation function. The summed (and weighted) input is put through the activation function to produce an output. If the output is not the same as the desired output, then an apparent error will be present.



**FIGURE 2-8: Nonlinear model of a neuron<sup>4</sup>**

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<sup>4</sup> Image source: Jacobs 2003

This error is fed back to the model and the weights are re-adjusted. This process is called training and is repeated until the model performance is acceptable. Once the model has been trained, the model parameters (weights) are set and the model can be used for the prediction task. The NN model can now produce answers for input values that were not a part of the training dataset. The major capacity of NNs includes Pattern Recognition, Classification, Detection, Adaptive Filtering, Data Inversion, Target Tracking, estimation, and prediction. The neural network has become a major application to help improve transport problems (Kirby and Parker 1994; Dougherty 1995).

#### *2.4.3.1 Applications of Neural Network Analysis to Link Travel Time Prediction*

Smith and Demetsky (1994) developed a back-propagation artificial neural network (ANN) model and a time series model to forecast short-term traffic flow. The prediction results showed that in comparison to the time series model, the back-propagation ANN was more responsive to dynamic traffic conditions and held considerable potential application in real-time intelligent transportation systems applications.

Bae (1995, 1997) applied the ANN to interpret auto travel time directly from bus travel times. A regression model was used to identify directly the correlation between bus and auto travel times on a link with dynamic traffic flow. Both dynamic and static field data that affected the travel times of bus and auto were collected and used to validate the travel time prediction model. The ANN outperformed the regression model when dealing with the non-linear system.

Park and Rilett (1998) developed a two step methodology to forecast multiple period freeway link travel times. First, the historic link travel times were classified based on an unsupervised clustering technique. Second, a modular ANN is calibrated for each class and then used to predict link travel times. It was found that the modular ANN outperformed a conventional singular ANN. In a further study, Park and Rilett (1999) developed a multilayer feed-forward neural network for freeway link travel times where the travel time patterns of neighboring links were incorporated as input variables to reflect the correlation between links. It was found that when predicting one or two periods into the future, the ANN model that gave the best results was the one that only considered previous travel times from the target link. However, when predicting three to five time periods into the future, the ANN model that employed travel times from upstream and downstream links in addition to the target link gave superior results. The data used were link travel times from Houston that were collected as part of the AVI system of the Transtar project.

Using the same data as their previous studies above, Park et al. (1999) examined how real-time information gathered as part of intelligent transportation systems can be used to predict link travel times for one through five time periods. A spectral basis neural network (SNN) that utilizes a sinusoidal transformation technique to increase the linear separability of the input features was developed. The results indicated that the SNN outperformed a conventional neural network and gave similar results to that of modular neural networks. When compared to other link travel time prediction techniques such as Kalman filtering and exponential smoothing, the SNN was found to give relatively better results. Rilett and Park (2001) further develop a SNN to predict corridor travel time.

Huisken and Berkum (2003) developed an ANN model that predicted spot measurements of flow and speed collected from inductive loop detectors on a section of the A13 motorway from The Hague to Rotterdam, Netherlands. The link travel time was then estimated from the predicted flow and speed. Five algorithms to estimate the travel times were assessed using data from actually measured travel times through license plate recognition. The proposed neural network was compared to two naive methods that are currently in operation. The results indicated that the ANN method significantly outperformed the other two prediction methods.

Van Lint et al. (2002) developed an ANN for freeway travel time prediction. The recurrent neural network topology presented was derived from a state-space formulation of the travel time prediction problem which is in line with traffic flow theory. The performance of several versions of the state space neural network was tested on synthetic data from a densely used highway stretch in the Netherlands. Results indicated that the model could accurately predict travel time and produce approximately zero mean normally distributed residuals.

Kisgyorgy and Rilett (2002) applied an ANN with two different approaches to predict travel time for a freeway corridor in San Antonio, Texas. The first approach used the ANN to predict speed from its measured value and then calculate the future travel time using a standard formulation. In the second approach, the travel time was predicted directly with the ANN. The best results were obtained while the travel times were estimated directly. On the other hand, the results indicated that the expected travel time prediction error with ANN is seven seconds or approximately four percent of the practical travel time.

Ishak and Alecsandru (2003) used multiple ANN topologies for short-term traffic prediction on freeways under different network and traffic conditions. Using a mix of traditional and modern ANN topologies, the prediction performance was evaluated under different settings (e.g., traffic situation or type of networks) and prediction horizons (e.g., from five to twenty-minutes). Results showed that the developed ANNs resulted in better performance. The study implied that identifying appropriate traffic situations, types of networks and traffic settings could improve the prediction accuracy.

#### *2.4.3.2 Comments on Neural Network Applications to Link Travel Time*

##### *Prediction*

The research cited above indicates that, over the years, neural networks have proven to be a very powerful method in the area of travel time forecasting. Whereas neural networks can perform highly nonlinear mappings between input and output spaces, the neural network approach is nonparametric. Therefore, one need not make any assumptions about the functional form of the underlying distribution of the data. Neural networks can be applied to forecast multiple period mean travel times more accurately than competing approaches, such as time series and Kalman filtering. It should be noted that in the available research, the focus has been on forecasting mean travel times and not median travel times. In the case where the travel times are skewed, the mean becomes influenced and may not describe the data correctly. In that case, the median becomes a more robust measure as it is not heavily influenced by outliers and skewed data.

## 2.5 UNCERTAINTY MODELING

The literature on travel time forecasting suggests that the travel time mean has become an established measure of interest from which the performance of transport systems could be measured. The value of the forecasted travel time mean is monitored and expressed in precise numerical terms using sophisticated modeling approaches, as explained earlier. The modeling approaches could provide complete information about the measure, the population, but, more commonly, only information on a sample of the measure is possible. Inference about the behavior of the population is then made from the sample. However, samples are subject to variation and therefore some account of the variability around a forecasted travel time mean is necessary. That is, a quantification (uncertainty) of how far the estimated statistic is from the “true value” of the population. Uncertainty is generally presented in the form of measures, such as confidence intervals and prediction intervals.

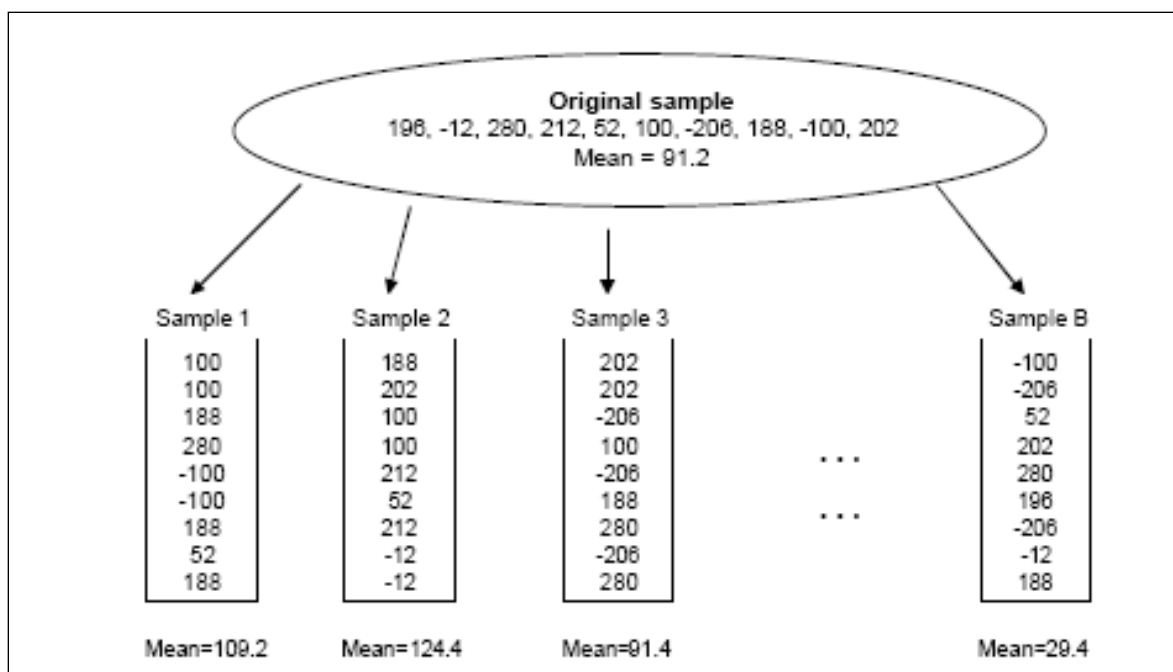
The uncertainty in travel time prediction modeling propagates from noise inherent to the measured data and noise due to model structure—imperfect data and imperfect model parameters, respectively. The former expresses confidence in the model performance and is given by constructing confidence intervals. The uncertainty due to noise inherent in the data can be modeled separately by constructing prediction intervals. This dissertation confines itself to evaluating confidence intervals, and the next section discusses a common re-sampling technique that is adopted for quantifying model uncertainty.

### 2.5.1 Bootstrapping

The technique of bootstrap estimation falls within the family of re-sampling techniques (Efron 1982; Efron and Tibshirani 1993). It is a computationally intensive, nonparametric technique that can produce probability based inferences (standard errors and confidence intervals) about a population related parameter based on a sample estimate. The process essentially involves taking repeated subsamples from a larger sample (with replacement) and calculating the statistic of importance based on this subsample. The distribution of these subsample statistics is then used to infer information about the population as a whole. The most common implementations of the bootstrap are the ordinary bootstrap and the block bootstrap methods.

#### *2.5.1.1 The Ordinary Bootstrap*

The ordinary bootstrap is the simpler and more general version of bootstrapping that is most commonly applicable to independently and identically-distributed data. The methodology involves starting with an original sample, then creating a new sample (bootstrap sample) by randomly sampling with replacement from the original. The process is repeated a number of times (generally 1000) to generate a series of bootstrapped samples, and the statistic of interest (such as the mean) is computed for each bootstrapped sample. Figure 2-9 illustrates this process. Note that because the re-sampling is done randomly with replacement, bootstrap samples can duplicate observations from the original sample. The standard error (of the mean) is then calculated by finding the standard deviation of the bootstrapped means.



**FIGURE 2-9: Illustration of the ordinary bootstrap method<sup>5</sup>**

### 2.5.1.2 The Block Bootstrap

The block bootstrap is the best known method for implementing the bootstrap with time-series (dependent) data. The general concept of the block bootstrap is similar to that of the ordinary bootstrap discussed earlier. Both methods are based on sampling observations with replacement. For time series data, however, the situation is more complicated and the re-sampling must be carried out in a way that suitably captures the dependence structure in the data generation process (Hardle et al. 2003). Therefore, in the block bootstrap, the data are divided into contiguous (overlapping or non-overlapping) blocks that are randomly sampled in order to construct the bootstrap samples. With this given, the data consists of observations  $\{X_i : i = 1, \dots, n\}$  and block

<sup>5</sup> Image source: Barker (2005)



length  $l$ . Then with overlapping blocks, block 1 would be observations  $\{X_j : j = 1, \dots, l\}$ ; block 2 would be  $\{X_{j+l} : j = 1, \dots, l\}$ ; and onwards (Hall 1985; Kunsch 1989; Politis and Romano 1993). With non-overlapping blocks, block 1 would be  $\{X_j : j = 1, \dots, l\}$ ; block 2 would be  $\{X_{l+j} : j = 1, \dots, l\}$ ; and so forth (Hall 1985; Carlstein 1986). The bootstrap sample is obtained by sampling blocks randomly with replacement and laying them end-to-end in the order sampled.

### *2.5.1.3 Uncertainty Modeling Applications*

In the area of transportation, uncertainty modeling has been applied to the problem of how a given transport model can not only produce a central estimate of traffic—such as volume, revenue or availability—but also confidence bounds around these. Many of the studies adopt methods such as the Jackknife, repeated model runs from simulated inputs and parameters, and repeated estimation on simulated datasets (De Jong et al. 2005, 2007). Methods that involve bootstrapping have also been used. Brundell-Freij (2000) studied the model uncertainty associated with the value of time parameter. A bootstrap analysis was used to calculate the standard errors around the in-vehicle value of time. Research by Hugosson (2004, 2005) uses the ordinary bootstrap method to study the uncertainty in the total and origin-destination demand by mode. The uncertainty in the estimates was expressed in terms of 95-percent confidence intervals.

Specific literature on quantifying the uncertainties in travel time forecasts with the bootstrapping method is fairly limited. Van Lint (2003) modeled the uncertainty associated with a state-space neural network model. The research evaluated the performance of a non-parameterized bootstrapping method for assigning confidence in

the travel time prediction parameters. The performance was measured in terms of the number of observed travel times that fell within the computed confidence intervals. The results were plausible, however, it should be noted that it is based on the assumption that the data are independently and identically distributed—this is unlikely to be the case.

## **2.6 CONCLUDING REMARKS**

A variety of methods are available to measure travel time. Because freeways in most metropolitan areas in North America are instrumented with inductive loop detectors, they are a good source for traffic data. This dissertation uses data obtained from loop detectors, therefore a discussion on inductive loop detectors was presented within this chapter. This chapter also presented some of the significant literature related to the task of travel time estimation and forecasting. One observation that can be made from this review is that all the methods perform well. For the case where travel time is to be forecast for multiple periods, the literature suggests the neural network technique to be the most popular. This was the technique adopted within this dissertation. Details of this will be elaborated in Chapter Four.

This chapter also reviewed the idea of uncertainty modeling and described a re-sampling method, bootstrapping, that can be used to quantify the uncertainty in parameter estimates. One observation that can be made is that there is fairly limited literature on uncertainty modeling, especially that pertaining to travel time forecasting. An objective of this dissertation is to present a methodology to quantify the uncertainty around travel time forecasts in terms of standard errors or confidence interval using a newly proposed bootstrapping technique. Details of this new bootstrapping technique—the gapped

bootstrap—will be presented in Chapter Five. In the next chapter, a description of the study corridor, data collection and data quality control will be presented.

## CHAPTER 3

### DATA COLLECTION AND PRELIMINARY DATA ANALYSES

#### 3.1 INTRODUCTION

The data used in this dissertation consists of an empirical dataset and a simulated dataset. The empirical dataset is part of a large database of inductive loop detector data. These ILDs are placed at approximately one-half mile spacing and cover 26-miles of downtown freeway in San Antonio, Texas as an essential component of TransGuide<sup>®</sup>. San Antonio's advanced traffic management system, TransGuide<sup>®</sup> is designed to provide information to motorists about traffic conditions such as incidents, congestion and construction.

This chapter presents a description of the specific study corridor in San Antonio, Texas from which the empirical dataset was obtained. In Chapter Two a general description on the principle of operation and configuration of ILDs and the data collected was provided. This chapter will discuss in detail the ILD data from San Antonio as well as the preliminary quality control and the error correction procedures applied to this data. As well, a section of this chapter presents a discussion on the analyses conducted to identify any periodic behavior and trends of dependency and nonstationarity in the ILD data from the field.

The simulated dataset is used in this dissertation to validate the results from the various analyses. This simulated dataset is obtained from a traffic micro-simulation

model of Interstate 80 (I-80) located between the cities of Lincoln and Omaha, Nebraska. A section of this chapter will also present details on the simulated dataset.

## **3.2 EMPIRICAL DATA**

### **3.2.1 Study Corridor**

The study corridor is located northeast of downtown San Antonio, Texas along Interstate 35 (I-35). The specific area of San Antonio where the study corridor is located is indicated within the box shown in Figure 3-1. This corridor section is part of the busiest interstate in Texas. I-35 merges into I-10, the north leg of the San Antonio downtown loop, and connects the cities of San Antonio and Austin, Texas. After a preliminary analysis on the raw data, a test bed that is approximately 1.39 miles long was adopted for analyses in this dissertation. Figure 3-2 shows a schematic map of the selected test bed that consists of three links. The corridor is a three-lane freeway cross section in the northbound direction. There are four main lane dual loop detectors (stations 159.500 to 160.892) including two on-ramps and one off-ramp on this test bed. Because ramp traffic (merging and diverging) causes disturbances to traffic on a multi-lane facility and also affects the travel times on the basic freeway segment, the volume data from the on/ off ramps were added to the appropriate main lane data. Thus, the entering traffic at location A would affect conditions on the basic freeway segment around the main lane detector 159.998, as shown in Figure 3-2. The traffic data from detector EN2 159.960 were therefore added to data from detector 159.998. Similarly, at location B, the traffic data from detector EX1 160.625 were added to the data from detector 160.504.

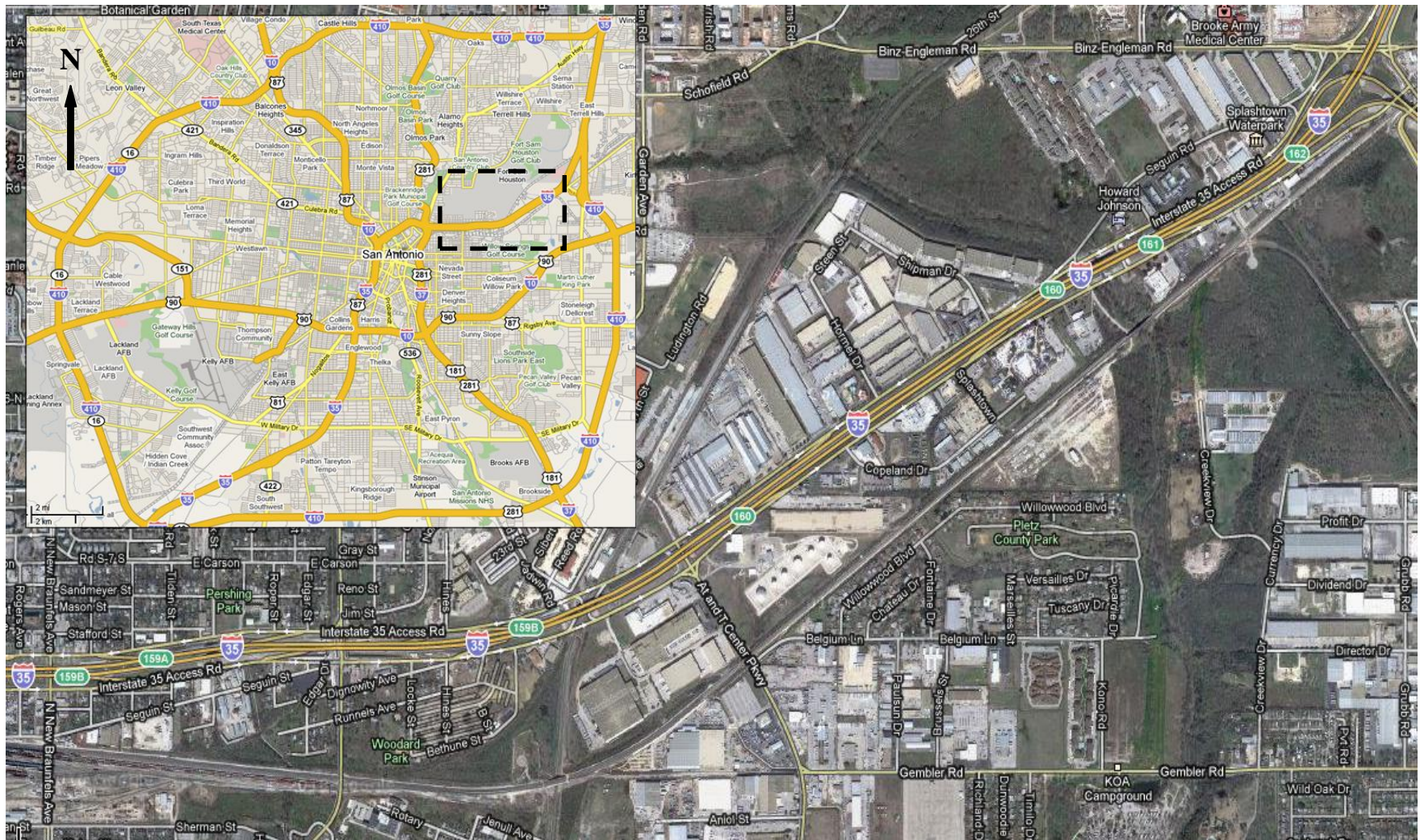


FIGURE 3-1: Regional map of San Antonio, Texas<sup>6</sup>

<sup>6</sup> Image source: <http://www.maps.google.com>

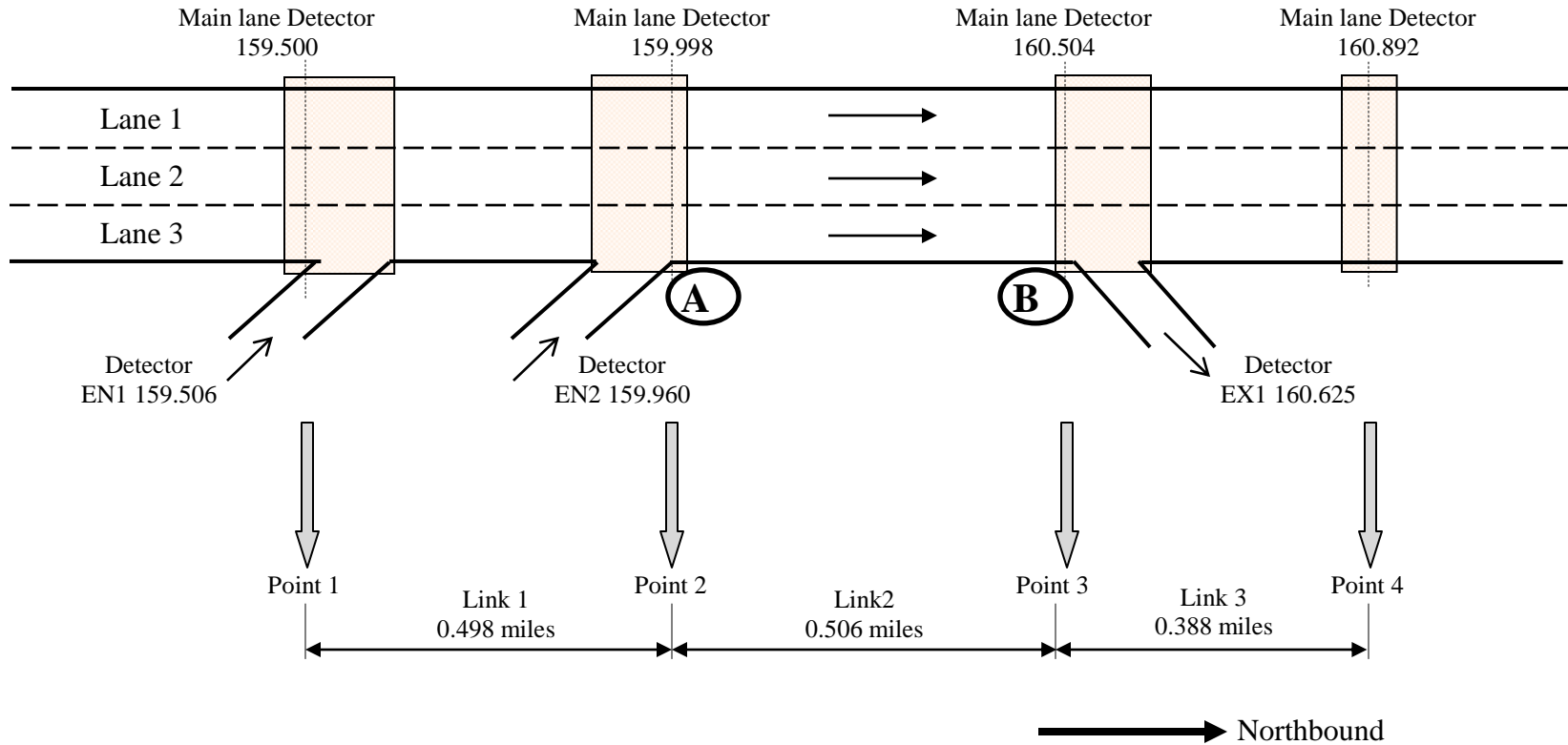


Figure not to scale

**FIGURE 3-2: Schematic diagram of the test bed from I-35N corridor, San Antonio, Texas**

The data used in this dissertation are for the morning peak period from 7:00 AM to 9:00 AM for 130 weekdays during the period between April 1, 2007 and September 30, 2007. Although lane-by-lane data were available, these were aggregated for each detector location. Hence, throughout this dissertation, the main lane data at a single location are the average of the detector data from three lanes.

### **3.2.2. Inductive Loop Detector Data**

The ILDs within the TransGuide<sup>®</sup> system are configured as dual (trap) inductance loops at approximately one-half mile spacing. The loops, which are centered in each lane, are six feet by six feet (1.83 m by 1.83 m) and buried an inch (2.54 cm) below the road surface. As shown in Figure 2-5 the two loops in the dual (trap) are installed 12-feet (3.66 m) apart longitudinally. Data are collected at twenty second intervals and sent to any one of nine servers at the TransGuide<sup>®</sup> traffic management center where they are archived and available for download at the TransGuide website ([www.transguide.dot.state.tx.us](http://www.transguide.dot.state.tx.us)).

The raw data collected at each of the servers are in the format given in Figure 3-3. The date and time are given in columns one and two, respectively. The third column provides detail on whether the data are from an exit (EX) or entry (EN) ramp or from the main lane by indicating the specific lane, numbered from the median to the curbside, as L1, L2 or L3. The interstate name and mile marker are also given in column three. The speed, volume and occupancy values are indicated in columns four, five and six, respectively, for each twenty-second period.



08/25/2007	00:00:27	L1-0410W-015.633	Speed=57	Vol=001	Occ=001
08/25/2007	00:00:27	L2-0410E-015.455	Speed=62	Vol=002	Occ=002
08/25/2007	00:00:27	L2-0410W-015.633	Speed=60	Vol=002	Occ=002
08/25/2007	00:00:27	L3-0410E-015.455	Speed=64	Vol=001	Occ=001
08/25/2007	00:00:27	L3-0410W-015.633	Speed=62	Vol=002	Occ=002
08/25/2007	00:00:27	L4-0410E-015.455	Speed=64	Vol=004	Occ=004
08/25/2007	00:00:27	L4-0410W-015.633	Speed=64	Vol=002	Occ=001
08/25/2007	00:00:27	L5-0410W-015.633	Speed=64	Vol=005	Occ=005
08/25/2007	00:00:28	L3-0410W-019.865	Speed=73	Vol=002	Occ=002
08/25/2007	00:00:29	EN1-1604E-028.572	Speed=-1	Vol=000	Occ=000
08/25/2007	00:00:29	EX1-1604W-028.564	Speed=-1	Vol=001	Occ=001
08/25/2007	00:00:29	L1-1604E-028.549	Speed=68	Vol=001	Occ=001
08/25/2007	00:00:29	L1-1604W-028.549	Speed=68	Vol=001	Occ=001
08/25/2007	00:00:29	L2-1604E-028.549	Speed=69	Vol=002	Occ=002
08/25/2007	00:00:29	L2-1604W-028.549	Speed=57	Vol=001	Occ=001
08/25/2007	00:00:30	L1-1604E-029.042	Speed=71	Vol=001	Occ=001
08/25/2007	00:00:30	L1-1604W-029.042	Speed=71	Vol=001	Occ=001
08/25/2007	00:00:30	L2-1604E-029.042	Speed=65	Vol=003	Occ=003
08/25/2007	00:00:30	L2-1604W-029.042	Speed=63	Vol=006	Occ=005
08/25/2007	00:00:31	L1-1604E-030.034	Speed=65	Vol=003	Occ=003
08/25/2007	00:00:31	L1-1604W-030.034	Speed=71	Vol=001	Occ=001
08/25/2007	00:00:31	L2-1604E-030.034	Speed=68	Vol=001	Occ=001
08/25/2007	00:00:31	L2-1604W-030.034	Speed=71	Vol=002	Occ=002
08/25/2007	00:00:32	EN1-1604W-029.460	Speed=-1	Vol=000	Occ=000
08/25/2007	00:00:32	EX1-1604E-029.361	Speed=-1	Vol=000	Occ=000
08/25/2007	00:00:32	L1-1604E-029.532	Speed=69	Vol=002	Occ=002

**FIGURE 3-3: Raw ILD data format**

The calculations for speed are made when the vehicle passes the second ILD in the dual loop. These speed calculations are based on the known distance between the two ILDs and the time taken to travel between the first and second ILDs (Sreedevi and Black 2001). The speed calculation is given in Equation 3.1.

$$v_n = \frac{D}{[(t_{on})_n]_B - [(t_{on})_n]_A} \quad (3.1)$$

where:

$A$  and  $B$  = first and second loops in the dual-loop detector respectively; and

$D$  = distance from upstream edge of detection zone A to downstream edge of detection zone B (feet).

The volume (or flow) and occupancy are reported as the vehicle crosses the first ILD in the dual loop. The volume is the number of vehicles that crossed the detector during a specified time period. The percent occupancy is a surrogate of density and is obtained by determining the percent of time the detector is occupied (May 1990). Therefore, percent occupancy is computed as:

$$O = \frac{\sum_{n=1}^N (t_{occ})_n}{\Delta t} \times 100 \quad (3.2)$$

where:

$O$  = percent occupancy time;

$N$  = number of vehicles detected in time period;

$\Delta t$  = selected time period (seconds); and

$(t_{occ})_n$  = individual occupancy time (seconds).

Density is calculated from the present occupancy as:

$$k = \frac{52.8}{L_V + L_d} \times O \quad (3.3)$$

where:

$k$  = density (vehicles per lane mile);

$\bar{L}_V$  = average vehicle length (feet); and

$L_d$  = length of detection zone (feet).

### **3.2.3 Data Extraction, Reduction and Quality Control**

#### *3.2.3.1 Data Extraction*

At the TransGuide® center, there are nine servers that are dedicated to archiving and processing the ILD data. Throughout each day, data from the field are sent for storage to any one server (of the nine) that is available during a given 20-second polling cycle. Therefore, there are nine data files with raw data available for a single day. A computer program written in the PERL programming language was developed for extracting the data in the following steps:

1. Download the raw data for the required analysis period from the Transguide website. For this dissertation, data for all weekdays from April 2007 to September 2007 was downloaded.
2. Search the entire raw dataset for data corresponding to the specific detectors along the test corridor. This data was downloaded on a lane-by-lane basis at each detector location. Thus, for the three lane roadway, each detector station will have three files containing data for each roadway lane.

#### *3.2.3.2 Data Reduction and Quality Control*

3.2.3.2.1 Individual Threshold Checks: The individual threshold checks examined the values of the speed, volume and occupancy in each individual record of the data set. For

each variable, a feasible region was identified and if an observed value was not within this region, then it was discarded and replaced by a value that equaled the average of the previous and next time step values. Table 3.2 presents the number of occurrences of these individual threshold errors at each main lane detector location. The threshold values as established in previous studies (Park et al. 2003; Eisele 2001; Turner et al. 2000; Turochy 2000) are:

- i) Occupancy— a maximum of 90 percent,
- ii) Volume— a maximum of 3000 vehicles per hour per lane (approx. 17 vpl per polling cycle), and
- iii) Speed— a maximum value of 100 miles per hour (160 km/h).

3.2.3.2.2 Combination Checks: A series of checks on the three variables—speed, volume and occupancy—in combination were conducted. These checks are presented in Table 3.1. These checks were established previously by Brydia et al. (1998) and Turner et al. (1997).

**TABLE 3.1 Data Screening Rules**

Check Type	Action taken IF condition satisfied
1. speed = 0, volume = 0, occupancy = 0	Remove from dataset
2. speed = 0 - 100, volume = 0 - 17, occupancy 0 - 90	Accept the data point
3. speed = 0, volume = 0, occupancy > 0	Replace speed and volume values
4. speed = 0, volume > 0, occupancy > 0	Replace speed values
5. speed = 0, volume > 0, occupancy = 0	Replace speed and occupancy values
6. speed > 0, volume = 0, occupancy = 0	Replace volume and occupancy values
7. speed > 0, volume > 0, occupancy = 0	Replace occupancy values
8. speed > 0, volume = 0, occupancy = 0	Replace volume and occupancy values

NOTE: speed (mph); volume per 20 second; occupancy (%).

The first combination check examined the situation when all three traffic parameter values are equal to zero. That is the speed, volume and occupancy values in each row of data equals zero. In practice, this occurs when vehicles are either stopped over the detector or if there are no vehicles present. These data were removed from the data set so that they would not improperly affect the average speeds when taking the two-minute average and, subsequently, the estimated travel times. The second combination check ensures that only observations for which the speed, volume and occupancy values are within their acceptable ranges are kept in the dataset.

Screening checks three through eight are used to identify unreasonable combinations of speed, volume and occupancy. That is, all combinations of one of the three traffic variables—speed, volume, and occupancy—being zero, was examined in congruence with the other two being non-zero. Similarly, combinations with one being non-zero with the other two being zero were also checked. The cause of such unreasonable combinations is unknown. Any occurrence of the unreasonable combinations was replaced by an average of the previous and next value. The numbers of occurrences of these combination errors at each main lane detector location are presented in Table 3.2.

3.2.3.2.3 Missing Data Imputation: The polling cycle for the San Antonio data was 20-seconds, but the cycle occasionally skips to 60 and 120-seconds. This seems to suggest occurrences of missing data; however, this is not the case. Instead, it is a situation that occurs when the ILD polling cycle is less than two minutes, in which the current observation contains the sum of the traffic characteristics between the previous and current observation (Gold et al. 2001). This means that the volume and occupancy values

indicated by the current observation are the sums of the volumes and occupancies since the previous observation, respectively, and the speed is the average speed since the previous observation. In this case, the missing speed observation was imputed with a value whose magnitude was an average of the previous and next intervals. Missing volume and occupancy observations were imputed with values obtained when the next interval value was split into 20-second intervals, respectively. These imputations can be given mathematically as:

$$\text{Imputed volume} = \frac{20 \times \text{volume}(t)}{(t) - (t - 1)} \quad (3.4)$$

$$\text{Imputed occupancy} = \frac{20 \times \text{occupancy}(t)}{(t) - (t - 1)} \quad (3.5)$$

$$\text{Imputed speed} = \frac{[\text{speed}(t) + \text{speed}(t - 1)] \times 20}{(t) - (t - 1)} \quad (3.6)$$

where:

$\text{volume}(t), \text{occupancy}(t)$  or  $\text{speed}(t)$  = current volume, occupancy or speed observation;

$\text{speed}(t - 1)$  = previous observation of speed;

$(t)$  = current time period; and

$(t - 1)$  = previous time period.

**TABLE 3.2 Summary of Data Screening**

Detector	Check Type	Lane Number 1	Lane Number 2	Lane Number 3	Total
159.500	Spd = 0, Vol = 0, Occ = 0	6	0	0	6
	Occupancy > 90%	129	181	172	482
	Volume > 17 vphpl	590	14	1	605
	Speed > 100 mph	101	38	63	202
	Percent Missing	21.6	8.0	12.2	13.9
159.998	Spd = 0, Vol = 0, Occ = 0	2	0	0	2
	Occupancy > 90%	110	69	49	228
	Volume > 17 vphpl	550	27	5	582
	Speed > 100 mph	61	46	66	173
	Percent Missing	19.9	7.0	11.2	12.7
160.504	Spd = 0, Vol = 0, Occ = 0	10	15	0	25
	Occupancy > 90%	249	318	74	641
	Volume > 17 vphpl	854	38	75	967
	Speed > 100 mph	81	28	36	145
	Percent Missing	19.3	6.6	10.2	12.0
160.892	Spd = 0, Vol = 0, Occ = 0	1	0	0	1
	Occupancy > 90%	70	33	66	169
	Volume > 17 vphpl	519	8	0	527
	Speed > 100 mph	85	47	52	184
	Percent Missing	19.3	7.9	12.3	13.2

The percent of missing observations by detector location for the entire empirical dataset are given in Table 3.2. This missing percent is computed relative to the total number of possible observations which is calculated, as shown in Equation 3.7.

*Theoretical number of observations*

$$\begin{aligned}
 &= (24 \text{ hrs of data}) \times \left(\frac{60 \text{ mins}}{\text{hour}}\right) \times \left(\frac{3 \text{ observations}}{\text{minute}}\right) \times (130 \text{ days}) \\
 &= 561,600 \text{ observations/lane}
 \end{aligned}
 \tag{3.7}$$

The data screening process was automated using programs developed in the PERL programming language. Once the data were “cleaned,” they were aggregated into two minute intervals. Thus, the 4320 records for a single day would be reduced to 720 records after aggregation. Finally, the two minute lane-by-lane data were aggregated across the lanes at each loop detector location. That is, the two-minute volume would be the sum for the three lanes, whereas the occupancy and speed were averages across the three lanes. As well, the entry-exit ramp volume data were added to the appropriate main lane detector data.

Note that the above approach can identify and correct for obvious errors in the data. However, systematic errors are not caught by this approach. An example would be that ILDs might consistently undercount or overcount traffic volumes. To address these systematic errors, other techniques that are based on the conservation of vehicles principle (Vanajakshi, 2004) were adopted as will be described in Chapter Four.

### **3.3 SIMULATED DATA USING VISSIM**

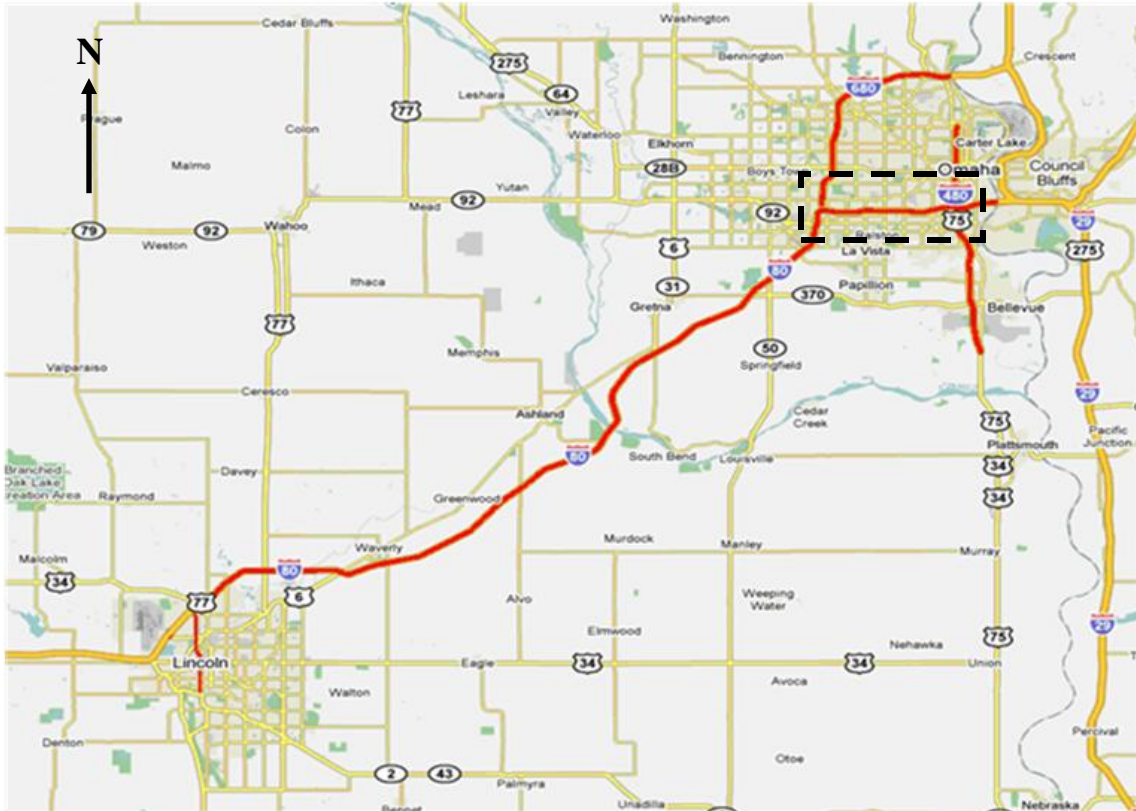
The simulated dataset was generated from a wide-area traffic micro-simulation model of Interstate 80 (I-80) in Nebraska. The model was built using the VISSIM simulation software. VISSIM is a traffic micro-simulation software developed by Planung Transport



Verkehr—PTV AG, Germany (VISSIM User Manual 2004)—and is based on the microscopic traffic model suggested by Wiedemann (1974, 1991). VISSIM comprises two components that communicate through an internal interface. The first component is a traffic model that simulates the movement of vehicles by modeling driver behavior at the individual vehicle level. The model classifies the driver's reaction (i.e., free driving, approaching, following or braking) in response to the perceived relative speed and distance with respect to the preceding vehicle. The lane changing decisions are made based on either a routing requirement, or are made by the driver in order to access a faster-moving lane. The second component is a signal state generator (SSG) that simulates and updates at every time step the status of traffic signals within the model. The inputs in VISSIM include lane assignments, geometries, travel demand, distributions of vehicle speeds, accelerations and decelerations. VISSIM can be used to model an existing field network, and traffic data such as flow, speed, occupancy and travel time can be collected. Further descriptions of the VISSIM software can be found in the VISSIM user manual (2004).

### **3.3.1 Study Corridor**

As mentioned above, the simulated corridor is part of a large area traffic micro-simulation project being modeled using VISSIM. The large area traffic micro-simulation project, as shown in Figure 3-4, involves modeling the traffic on Interstate 80 between the cities of Lincoln and Omaha, Nebraska. To save on computational time, a small network within the larger simulation model (as indicated in the box shown in Figure 3-4) was simulated. Specifically, the small network section is between the I-80/I-680



**FIGURE 3-4: Location map of simulation corridor**

interchange to the I-80/I-480 interchange. Detectors were placed 0.5 miles apart along this network. Traffic volumes were input into the network based on observed empirical values. The traffic micro-simulation model was calibrated to replicate empirical (observed) speeds and travel times. For details on the calibration and validation processes refer to Naik et al. (2009).

### 3.3.2 Data

The simulated data collected from the detectors included speed, volume, occupancy rate and travel time. The simulation model was run using 130 random seed

numbers with each run being representative of a different day. During each simulation run, data were generated for a two hour period replicating the peak AM traffic conditions. A 15-minute initializing period was given for the system to be in a steady state—that is, there were no sudden changes in traffic volumes over time. The detector output is given in two separate files. The travel times are output as a .RSZ file and the speed, volume and occupancy data are given in a .MES file. The data were aggregated at two minute intervals within VISSIM.

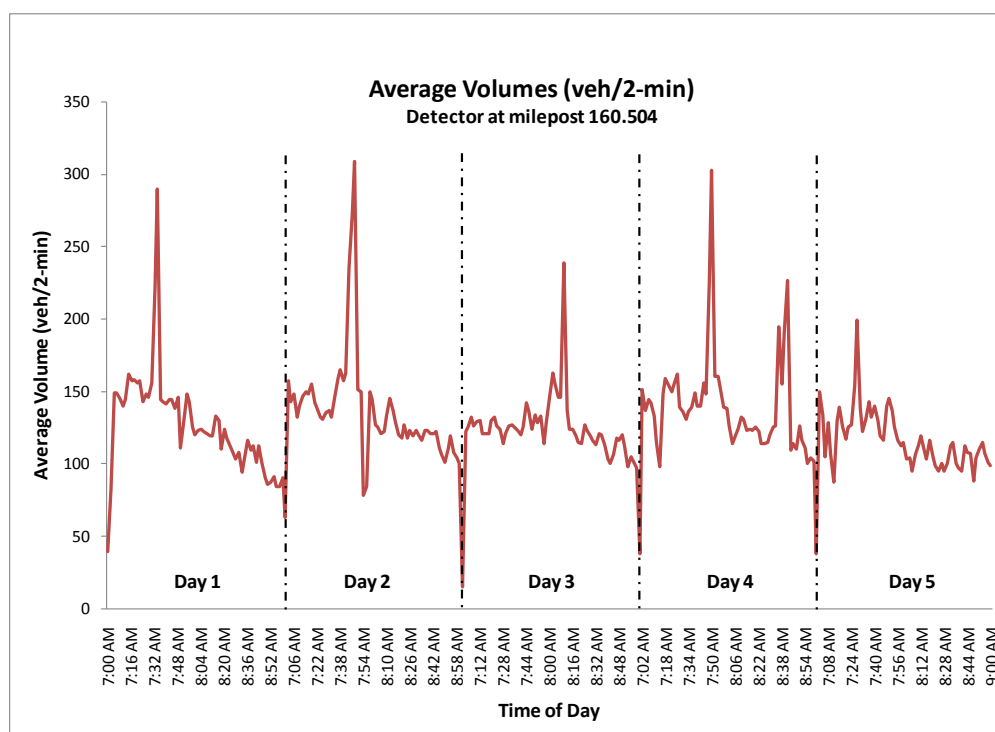
### **3.4 EXPLORATORY DATA ANALYSES**

#### **3.4.1 Empirical Data from San Antonio, Texas**

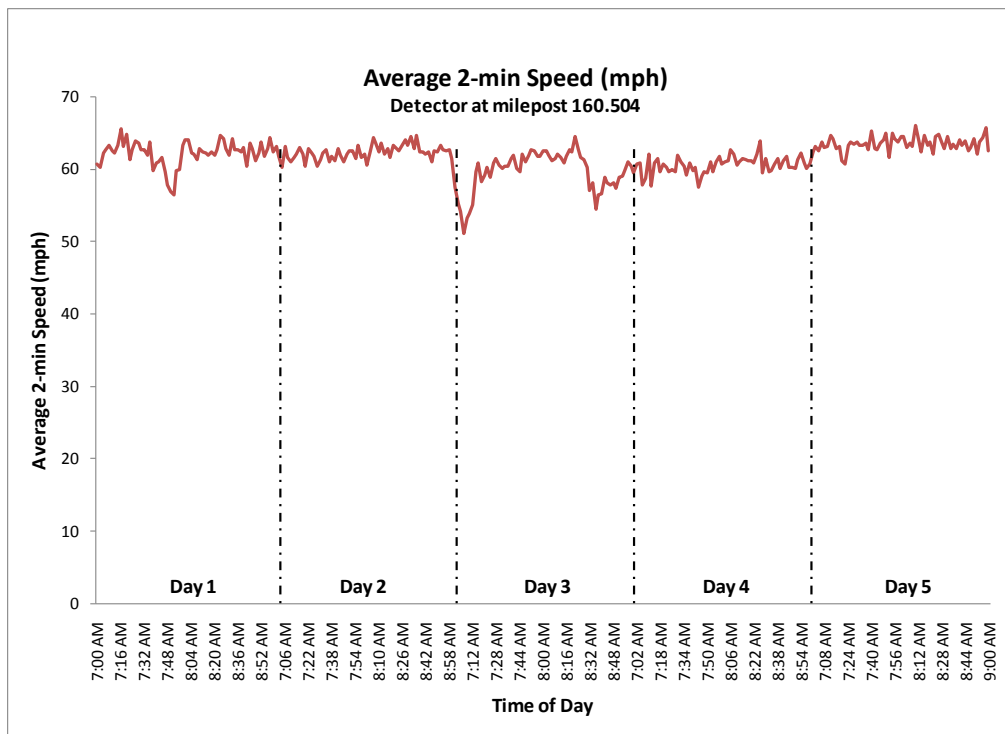
It was necessary to explore the characteristics of the data—temporally and spatially—in order to choose the most appropriate estimating and prediction models, both for the mean as well as the confidence interval measures. It has been shown that point data such as that from loop detectors have a nonstationary distribution and exhibit a general periodicity (May 1990). Namely, the traffic flow on each day exhibits a repeating pattern such as a huge peak at 8:00 AM, a smaller peak at around 4:00 PM and an absolute minimum around 2:00 PM. Additionally, the data are also weakly dependent. That is, the dependence diminishes as the aggregation interval becomes large (i.e., traffic characteristics on Monday at 7:30 AM influence traffic characteristics on Monday at 7:35 AM, but do not influence traffic characteristics on the next Monday at 7:35AM). This section presents exploratory analyses conducted on the speed, volume and occupancy data (empirical and simulated). The characteristics of travel times estimated as a function

of the speed, volume and occupancy are also presented within this chapter. The travel times are estimated using a methodology that is presented in Chapter Four.

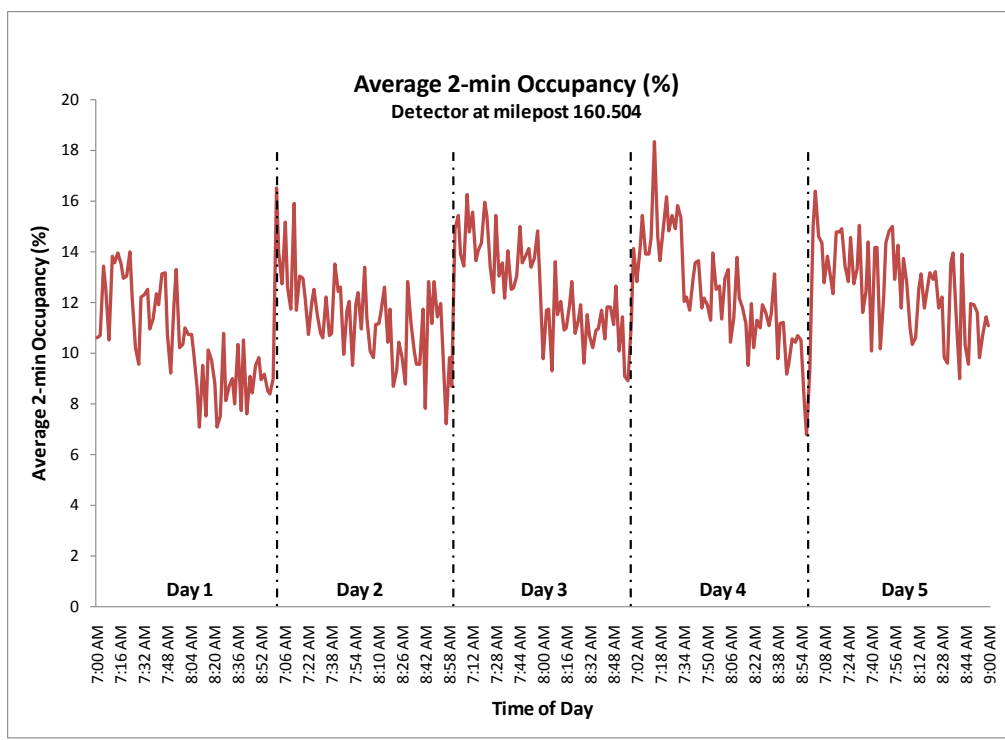
A periodic behavior (repeating pattern) can be observed by plotting each day's data side-by-side. Figures 3-5 to 3-8 show the data for the morning peak period (7 AM – 9 AM) as a function of time of day. A noticeable pattern can be observed in each of the plots. The volume, occupancy and travel times exhibit a distinct repeating pattern as seen in Figures 3-5, 3-7 and 3-8, respectively. However, Figure 3-6 shows that a defined pattern is not observable for the speed because they do not vary much during the 7-9 AM period. It should be noted that it was difficult to view the entire data (130 days) when plotted at once, therefore only data for five days (305 data points) were plotted. As an example, data from the main lane detectors located at milepost 160.504 are presented. Also, the estimated travel times on the link are illustrated.



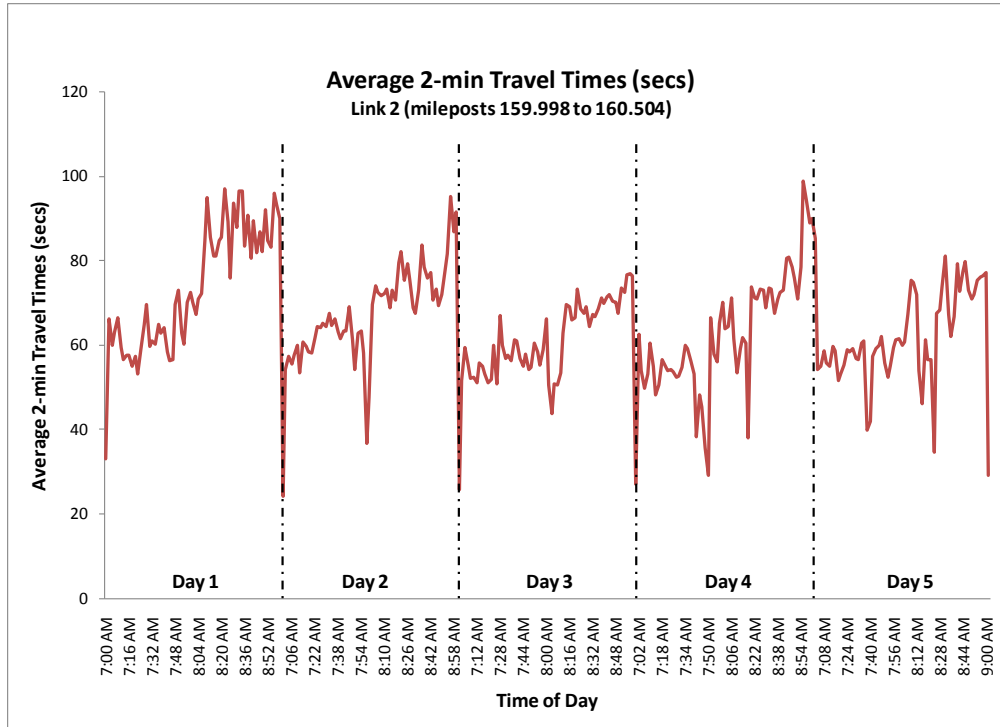
**FIGURE 3-5: Peak hour traffic volume data at milepost 160.504**



**FIGURE 3-6: Peak hour traffic speed data at milepost 160.504**



**FIGURE 3-7: Peak hour traffic occupancy data at milepost 160.504**



**FIGURE 3-8: Peak hour travel time between milepost 159.998 and 160.504**

Autocorrelation functions (correlograms) were also plotted to further explore the characteristics of the data. A correlogram is a plot of the autocorrelation coefficients against the time lags. The autocorrelation coefficients measure the correlation between observations at different lags or distances apart (Chatfield 1996). The autocorrelation coefficient  $r_k$  at time lag  $k$  is computed as:

$$r_k = \frac{\sum_{t=1}^{N-k} (x_t - \bar{x})(x_{t+k} - \bar{x})}{\sum_{t=1}^N (x_t - \bar{x})^2} \quad (3.8)$$

where:

$$\bar{x} = \frac{\sum_{t=1}^N x_t}{N} = \text{mean}$$

$r_k$  = correlation coefficient at lag  $k$ ;

$x_t$  = observation at current time;

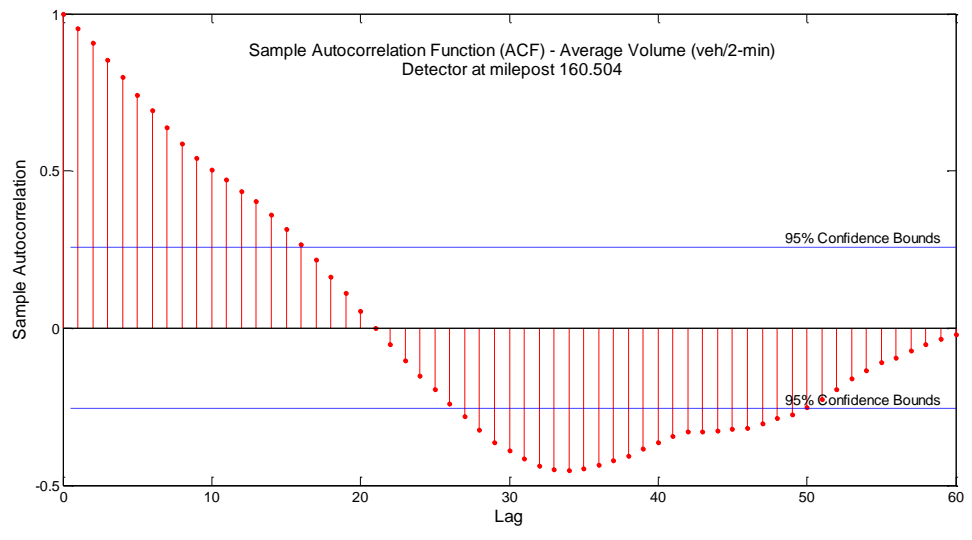
$x_{t+k}$  = observation at one lag ahead and

$N$  = size of series.

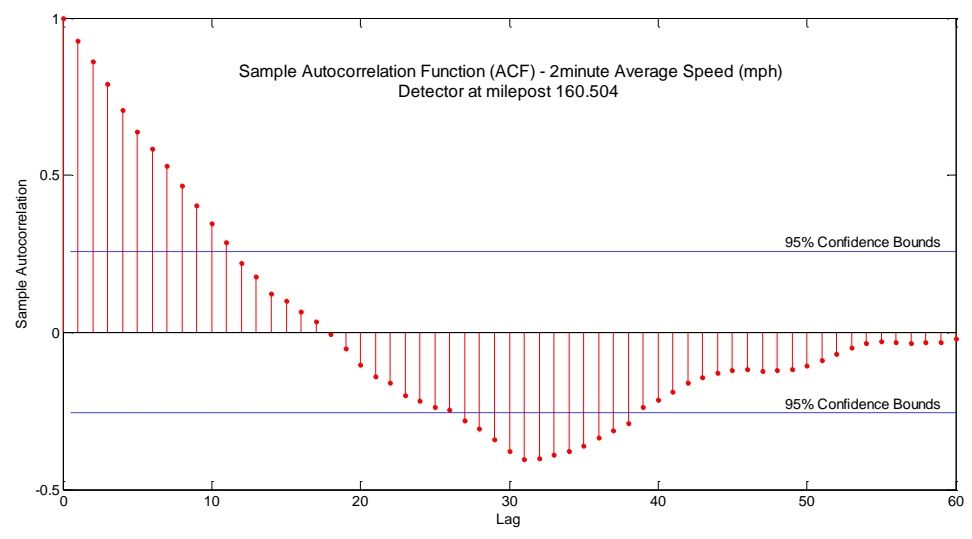
Figures 3-9 to 3-12 illustrate the correlograms for the volume, speed, occupancy and travel time, respectively. The dashed horizontal lines are the confidence bounds:  $\pm 1.96\sqrt{n}$  (1.96 is the .975 quantile of the standard normal distribution). The 60-lags represent the 7-9 AM time period with each lag denoting a 2-minute interval.

The correlograms illustrate that more than 95% of the autocorrelation coefficients are outside the confidence bounds. This indicates that there is time dependence in the data (Brockwell and Davis 2003). That is, data from the current time step is dependent on the data from the previous time step. As an example, travel time at 7:12 AM is dependent on travel time at 7:10 AM. As well, the correlation coefficients tend to decay slowly as the lag increases. This is indicative of the data being nonstationary. That is, the statistical characteristics, the mean and variance, of the data change over time.

It can be concluded that point data (volume, speed and occupancy) and interval data (travel time) all exhibit a periodic behavior and are time dependent as defined by common statistical tests. Additionally, the data also have a nonstationary distribution.

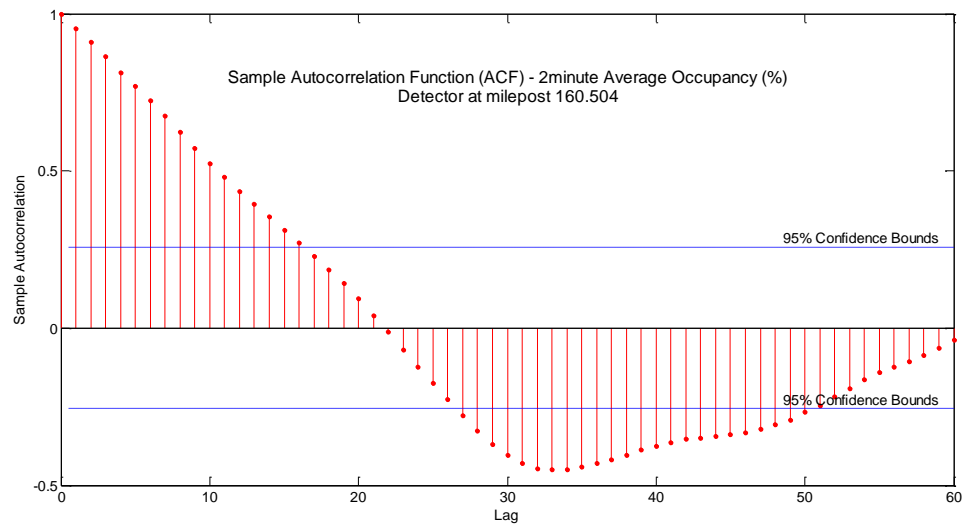


**FIGURE 3-9: Autocorrelation plot for traffic volume data**

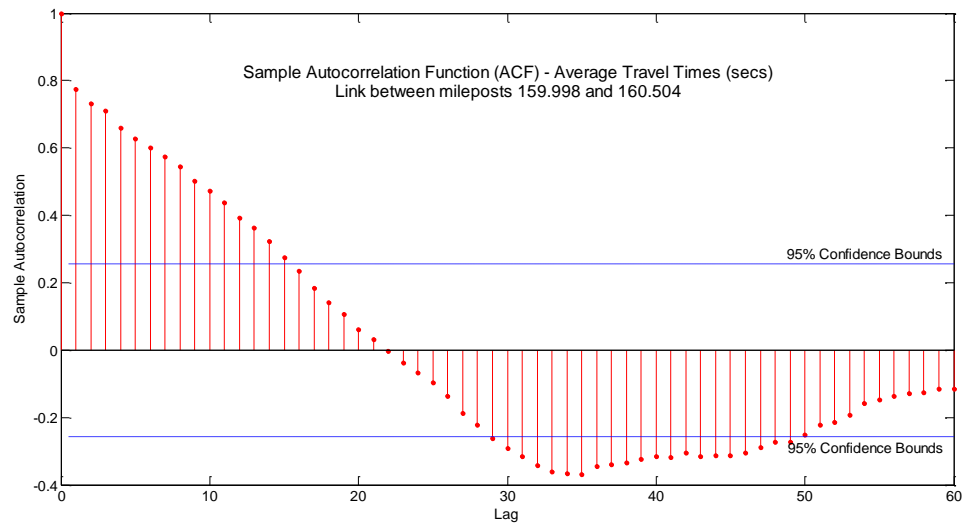


**FIGURE 3-10: Autocorrelation plot for traffic speed data**





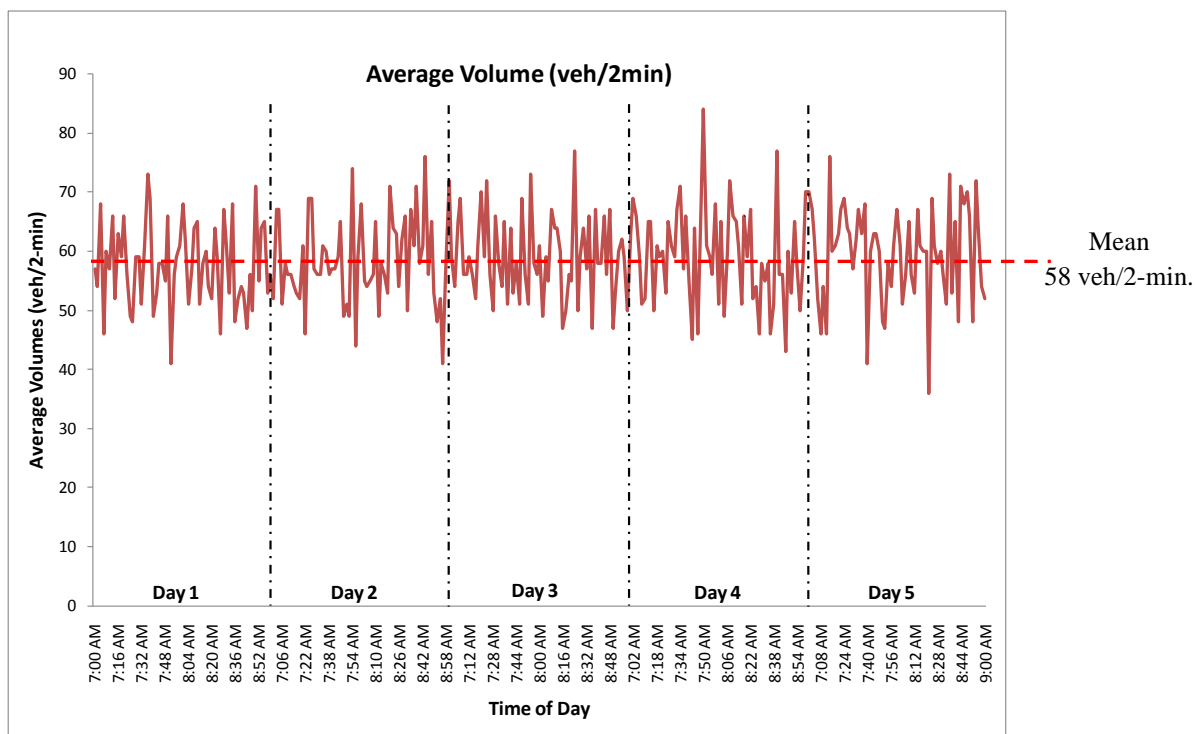
**FIGURE 3-11: Autocorrelation plot for traffic occupancy data**



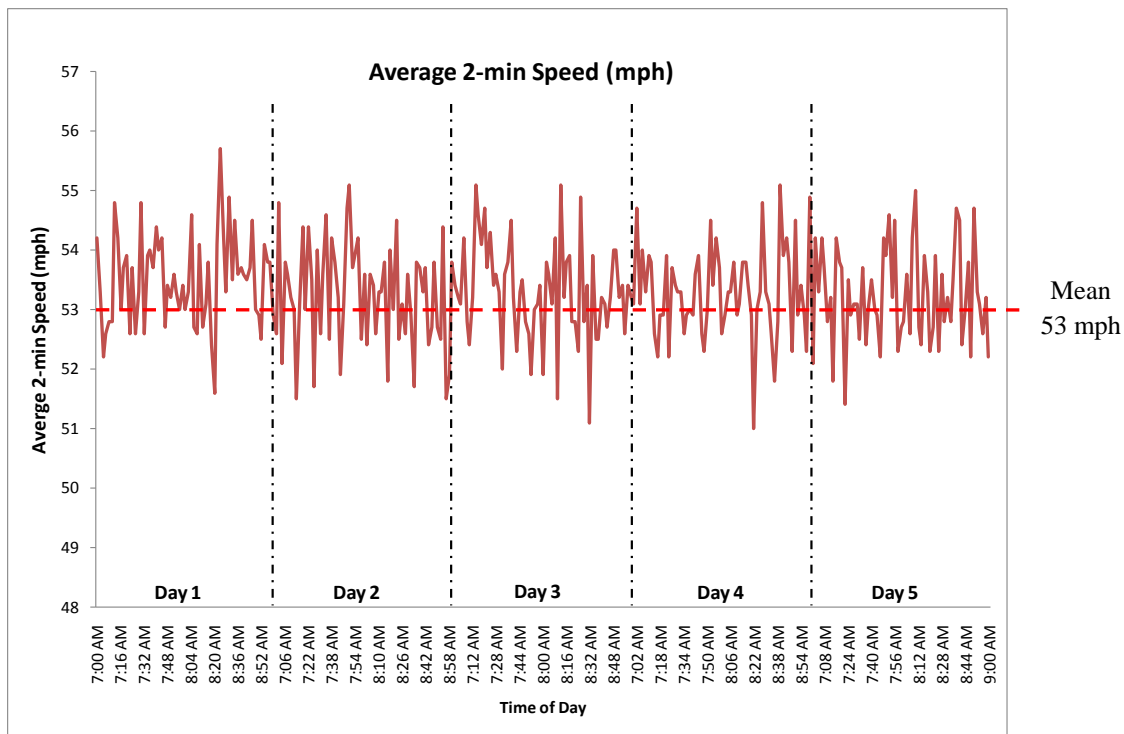
**FIGURE 3-12: Autocorrelation plot for travel time**

### 3.4.2 Simulated Data From Omaha, Nebraska

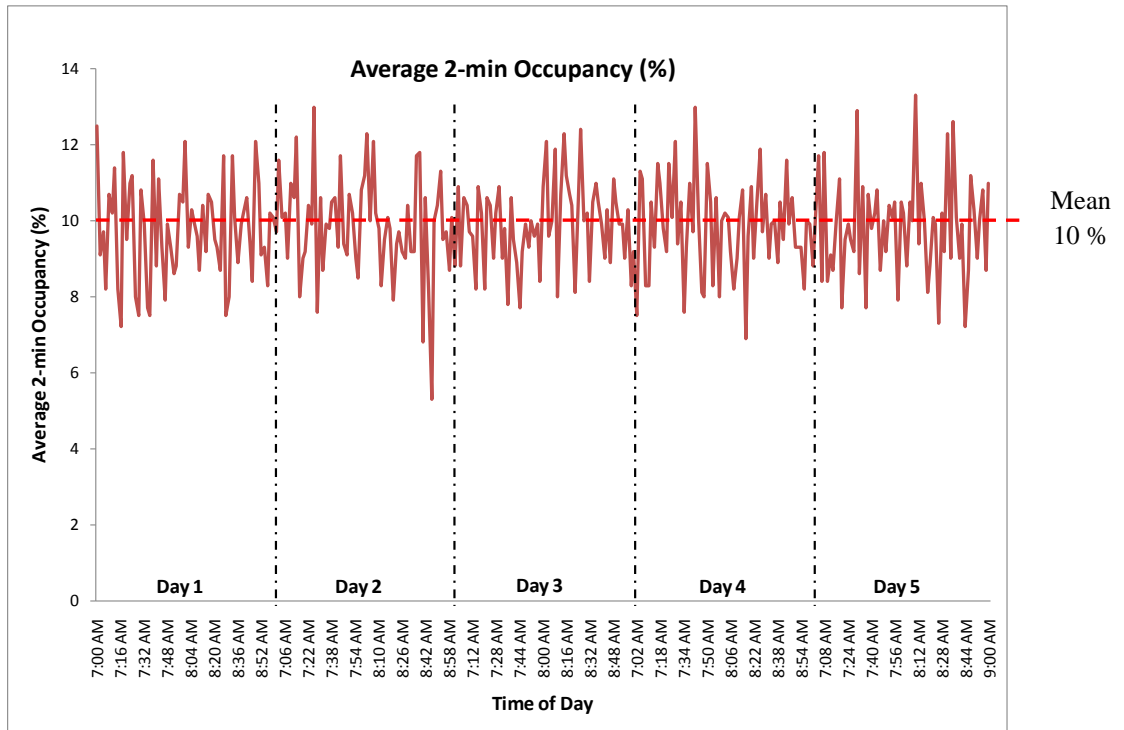
The data set from the I-80 simulation corridor was also explored to investigate for any characteristics of periodicity, non-stationarity and time dependence in its structure. Figures 3-13 to 3-16 illustrate plots for each data type as a function of the time of day. A clearly visible repeating pattern is not present in the plots. Instead, it can be observed that the data fluctuate in a random pattern around an expected mean value. The mean value around which the data fluctuate is 58veh/2-min, 53mph, 10% and 35 secs for the volume, speed occupancy and travel time, respectively. It can be concluded that the data are not periodic and have a nonstationary distribution.



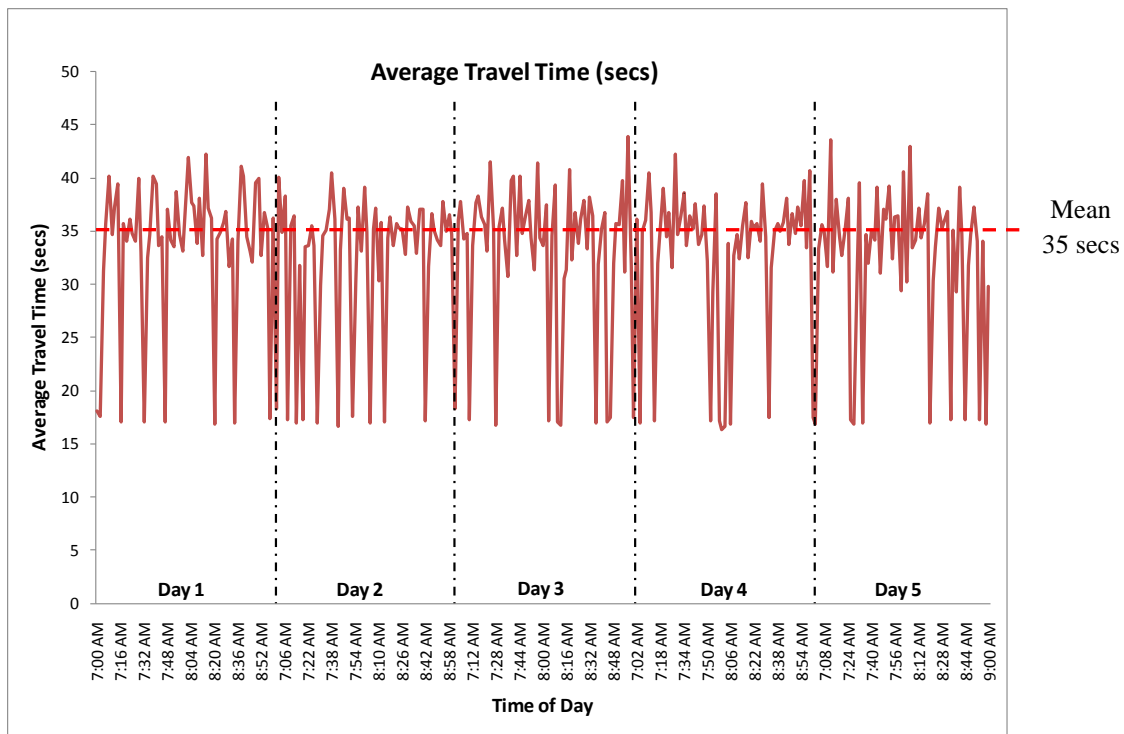
**FIGURE 3-13: Peak hour traffic volume data**



**FIGURE 3-14: Peak hour traffic speed data**

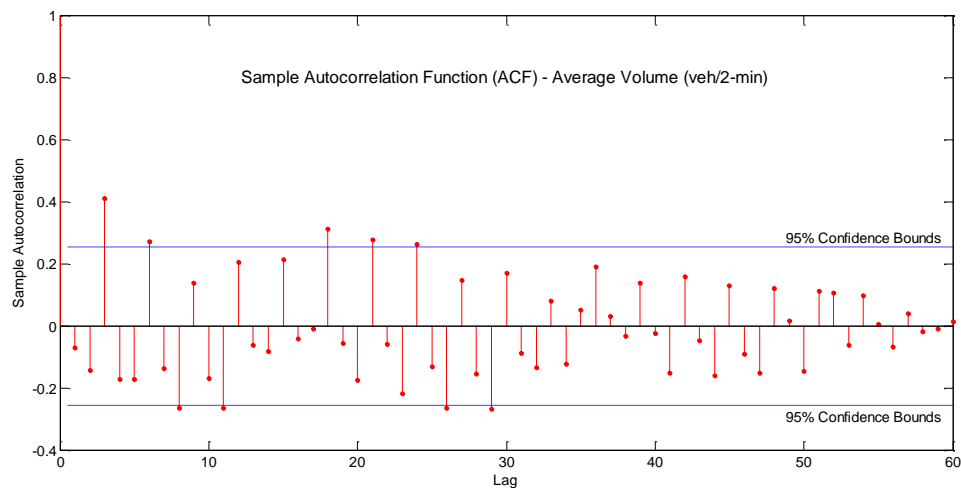


**FIGURE 3-15: Peak hour traffic occupancy data**

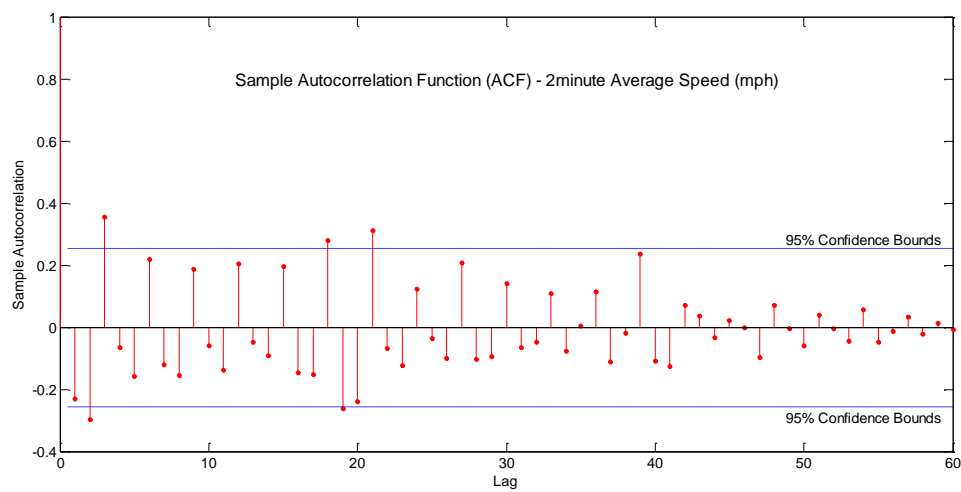


**FIGURE 3-16: Peak hour estimated travel time data**

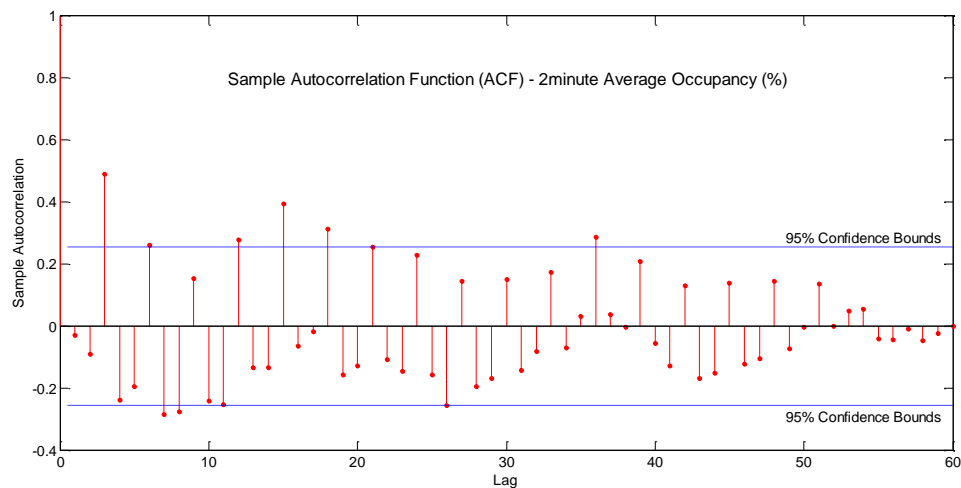
Figures 3-17 to 3-20 illustrate the correlograms for the volume, speed, occupancy and travel time data, respectively. In all the correlograms, it can be seen that the autocorrelation coefficients are inside the 95% confidence bounds. This suggests that there is no time dependence in the dataset. As such, data from the current time step is not dependent on the data from the time step ahead.



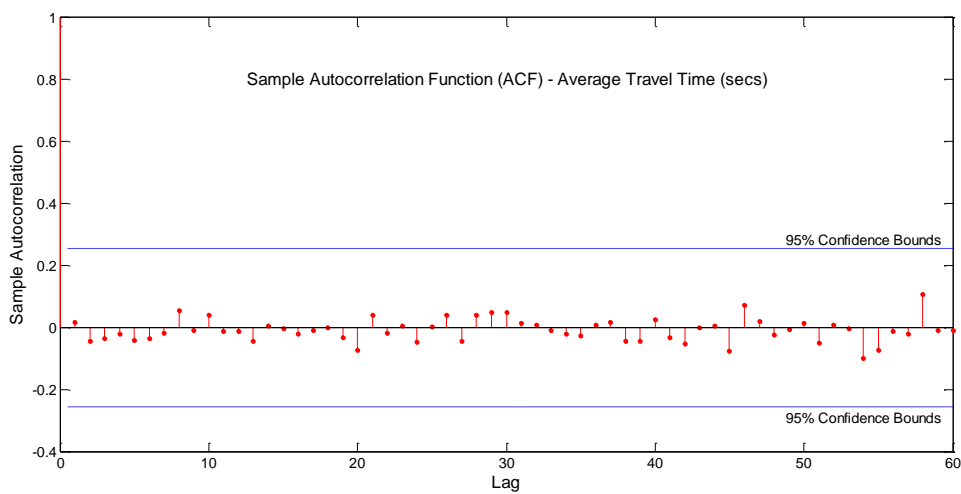
**FIGURE 3-17: Autocorrelation plot for 2-minute average traffic volume data**



**FIGURE 3-18: Autocorrelation plot for 2-minute average traffic speed data**



**FIGURE 3-19: Autocorrelation plot for 2-minute average traffic occupancy data**



**FIGURE 3-20: Autocorrelation plot for 2-minute average estimated travel time data**

### **3.5 CONCLUDING REMARKS**

This chapter has described the data collection and study corridors used in this study. It described the empirical dataset obtained from a freeway corridor in San Antonio, Texas. Archived inductive loop detector data were extracted for a section of Interstate 35 for a period starting April 1, 2007 and ending September 30, 2007. The chapter also describes the simulated dataset obtained from a calibrated and validated traffic micro-simulation model of Interstate 80 in Nebraska.

This chapter also presented the steps taken to ensure that the data was ‘cleaned’ and of quality. The techniques employed to perform the quality control on the empirical dataset were based upon proven methods adopted for cleaning similar data sets in previous research. Finally, the chapter also described some exploratory data analyses conducted to identify certain characteristics in the empirical and simulated datasets. Specifically, the datasets were investigated for characteristics of periodicity (exhibiting a periodic behavior), being dependent and having a nonstationary distribution. It was found that the empirical data (point and interval) exhibits a periodic behavior, are time dependent and also nonstationary. A clearly identifiable repeating pattern could not be observed for the simulated dataset. The simulated data were also found to have a nonstationary distribution and no time dependence exists.

## CHAPTER 4

### ESTIMATION AND PREDICTION OF TRAVEL TIME

#### 4.1 INTRODUCTION

The ability to predict future link travel time is critical for many Intelligent Transportation Systems' applications such as route guidance systems and traffic management systems. As presented in Chapter Two, a variety of modeling approaches to compute future link travel time are available in the literature. Of these modeling approaches, neural networks have proven to perform better than competing approaches especially for multiple period forecasting. Moreover, neural networks can perform nonlinear mappings and are nonparametric. The latter part of this chapter discusses a neural network model that was developed to obtain predicted values of link travel time for this dissertation.

An essential step in developing a neural network is the training process. During training, the model weights (or parameters) are adjusted iteratively such that the difference between the network output (predicted travel time) and its corresponding target travel time is minimized. In general, the target travel times are directly measured, such as with AVI data. However, for this dissertation, the target travel times were not available.

In the absence of directly measured travel times, an indirect method developed by Vanajakshi was used. This approach has been shown to provide accurate estimates of travel time (Vanajakshi 2004; Vanajakshi and Rilett 2006; Vanajakshi et al. 2009). First,

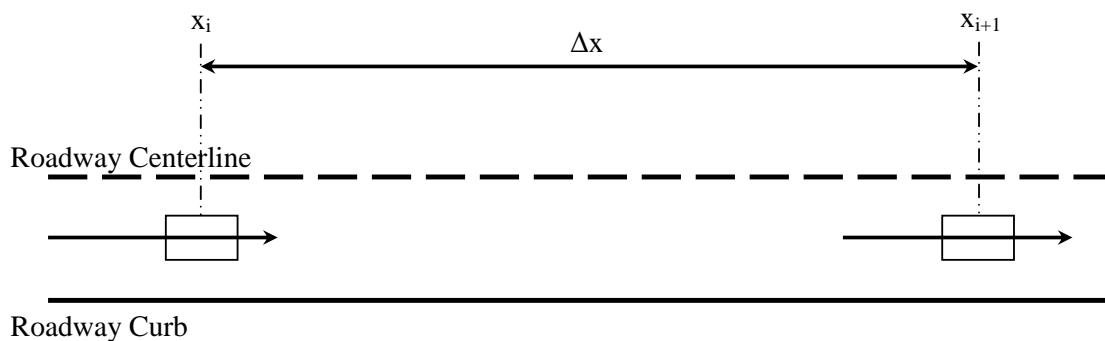


a brief background into the Vanajakshi estimation method is presented within this chapter. Next, the Vanajakshi method, its application to an empirical dataset in this dissertation and the results are presented.

## 4.2 TRAVEL TIME ESTIMATION

### 4.2.1 Background

Nam and Drew developed a traffic dynamics model for indirectly estimating link travel time. The model is based on the characteristics of the stochastic vehicle counting process and the principle of conservation of vehicles. An inductive modeling approach was adopted along with geometric interpretations of cumulative arrival-departure diagrams. The link travel time was computed as the area between the cumulative volume curves from loop detectors at either end of the link. For specific details on the model refer to Nam and Drew (1996, 1998, 1999).



**FIGURE 4-1: Illustration of roadway section**

Given a one lane roadway with detectors located at each end, as shown in Figure 4-1, the Nam and Drew model consists of two separate models: one that estimates travel times under “normal” flow conditions and the other that provides travel time estimates under “congested” flow conditions. The travel time  $tt(t_n)$  for vehicles entering and exiting the link during the same interval is estimated using the following.

*For Normal Flow Conditions:*

$$tt(t_n) = \frac{\Delta x}{2} \frac{[q(x_i, t_n)k(t_{n-1}) + q(x_{i+1}, t_n)k(t_n)]}{[q(x_i, t_n)q(x_{i+1}, t_n)]} \quad (4.1)$$

*For Congested Flow Conditions:*

$$tt(t_n) = \frac{\Delta x}{2} \frac{[k(t_{n-1}) + k(t_n)]}{[q(x_{i+1}, t_n)]} \quad (4.2)$$

where:

$tt(t_n)$  = the estimated travel time for link  $i$  to  $i + 1$  for time interval  $t_{n-1}$  to  $t_n$ ;

$\Delta x$  = distance between detector locations;

$q(x_i, t_n)$  = flow at location  $i$  from time interval  $t_{n-1}$  to  $t_n$ ; and

$k(t_n)$  = density in the link between location  $i$  to  $i + 1$  at time  $t_n$  that is calculated as;

$$k(t_n) = \frac{n(t_n)}{\Delta x} = \frac{[Q(x_i, t_n) - Q(x_{i+1}, t_n)]}{\Delta x} \quad (4.3)$$

where

$Q(x_i, t_n)$  = the cumulative flow at location  $i$  from time interval  $t_{n-1}$  to  $t_n$ ; and

$Q(x_{i+1}, t_n)$  = the cumulative flow at location  $i$  from time interval  $t_{n-1}$  to  $t_n$ .

Nam and Drew made the distinction between the normal and congested regions using a dynamic link performance measure:  $m(t_n)$ . That is the number of vehicles that enter the link during the interval  $t_{n-1}, t_n$  and that exit the link during the same interval. Under the first-in/ first-out condition  $m(t_n)$  is expressed as:

$$m(t_n) = Q(x_{i+1}, t_n) - Q(x_i, t_{n-1}) \quad (4.4)$$

A traffic condition where the value of  $m(t_n) \leq 0$  would indicate congested flow. Under congested conditions, none of the vehicles that enter the link during the interval  $t_{n-1}, t_n$  exit the link during the same interval. In the case of normal flow conditions, all vehicles entering the link will exit the link.

Different studies have identified drawbacks in the Nam and Drew model (Son 1997; Dhulipala 2002; Oh et al. 2003). These drawbacks include:

1. The model only accounts for vehicles that traveled the entire link during the given time interval (no violation of the conservation of vehicles principle). However, there are always some vehicles that enter a link during one time period and leave during the next period. During congestion, there will be even more of such vehicles in the link.
2. The distinction between normal and congested flow was based on whether a vehicle that entered the link at a specific time step was able to exit the link in the

same time step. This classification does not consider the transition period between normal and congested flow (Son 1997).

3. The accuracy of the method is solely dependent on the accuracy of the flow values. In an ideal situation (detectors work perfectly) this would be an efficient method for computing the section density. However, in reality, detectors may not be working perfectly and are known for over- and under-counting vehicles (May 1990; Petty et al. 1998; Oh et al. 2003).
4. The travel time estimates from the model were questionable because they are computed as a function of the measured flow (Vanajakshi 2004). However, Sisiopiku et al. (1994) conclude that under low flow traffic conditions, travel time is independent of both flow and occupancy.

To address all the above concerns, Vanajakshi (2004) proposed modifications that are presented in the next section.

#### **4.2.2 “Vanajakshi” Travel Time Estimation Model**

Research work by Vanajakshi (2004) proposed modifications to address the drawbacks identified in the original work suggested by Nam and Drew. The problem of the data violating the conservation of vehicles principle was dealt with by using a generalized nonlinear optimization method—namely, the Generalized Reduced Gradient (GRG) method. The GRG method enforces the conservation of vehicles principle in the following ways:

(1) By making the cumulative flow at successive detectors smaller or equal to the previous point, and the difference, if any, should equal the number of vehicles on the link between them; and

(2) By keeping the difference in the cumulative flows between successive detectors less than the capacity of the link between.

For specific details on the formulation, the performance evaluation and the validation of the GRG method refer to Vanajakshi and Rilett (2006).

A modified “congested” flow model was adopted for use under all traffic flow conditions so that it considers the flow state transition. Thus, the new proposed model was given as:

$$\begin{aligned}
 tt(t_n) = m_p(t_n) \frac{\Delta x}{2} \frac{[q(x_i, t_n)k(t_{n-1}) + q(x_{i+1}, t_n)k(t_n)]}{[q(x_i, t_n)q(x_{i+1}, t_n)]} \\
 + (1 - m_p(t_n)) \frac{\Delta x}{2} \frac{[k(t_{n-1}) + k(t_n)]}{[q(x_{i+1}, t_n)]}
 \end{aligned} \tag{4.5}$$

where

$$m_p(t_n) = \frac{m(t_n)}{q(x_i, t_n)} \tag{4.6}$$

To account for the effect of detector malfunctions, the density was computed using Equation 4.7. As stated earlier, this is because detector malfunctions have a lesser impact on speed and occupancy in comparison to flow data.

$$k = 52.8 \times \frac{O}{(\bar{L}_v + L_d)} \quad (4.7)$$

where

$k$  = density (vehicles per mile);

$\bar{L}_v$  = average vehicle length (feet);

$L_d$  = detection zone length (feet); and

$O$  = vehicle occupancy (percent).

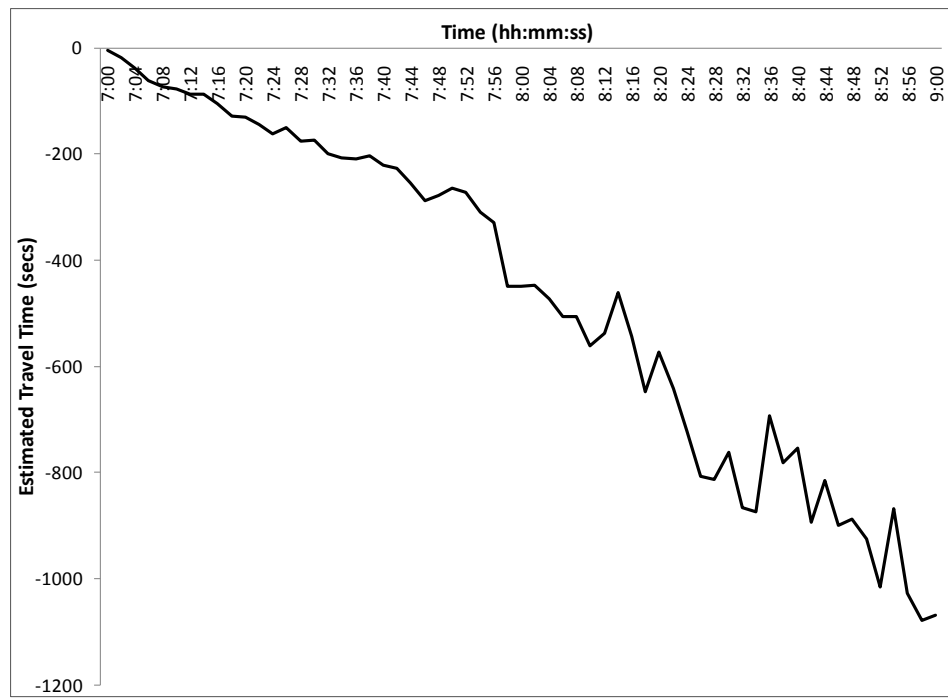
A final modification that was incorporated by Vanajakshi (2004) was to apply an extrapolation method (Equation 2.3) during low volume conditions. This is because under low traffic conditions, speed-based travel time estimation methods are better suited than flow based methods. The extrapolation method was used when the flow, over the three lanes, was less than 50 vehicles per 2-minute interval.

Vanajakshi tested and validated the proposed model and modifications using empirical and simulated data (using actual travel time obtained from AVI). The mean absolute percent errors (for the proposed model with respect to AVI data) were computed as 4.5 percent and 8.9 percent using simulated and empirical data, respectively. The results indicated that the proposed model is a promising tool for the estimation of link travel time from ILD data under a full spectrum of traffic flow conditions (Vanajakshi 2004, 2009). The next section presents results that were obtained when the Vanajakshi model is applied to the data in this dissertation.

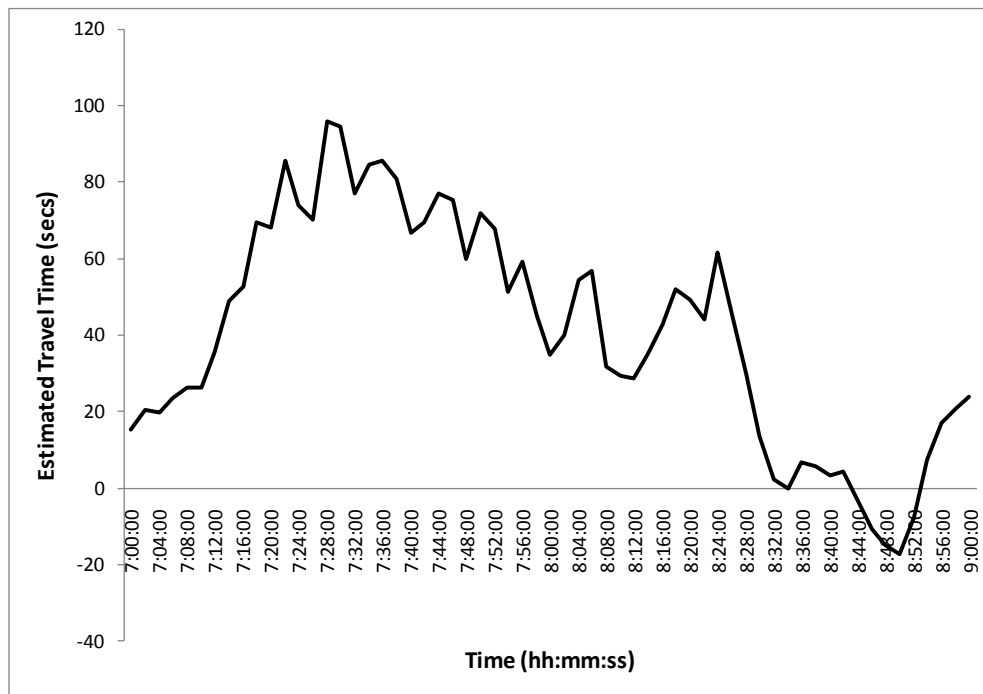
### 4.2.3 Results of Travel Time Estimation using Empirical Data

The Vanajakshi travel time estimation model described in section 4.2.2 was implemented using the MATLAB programming environment. The data collected from link 2 (between milepost 159.998 and 160.504, shown in Figure 3-2) of the test bed in San Antonio, Texas are used here to illustrate the travel time estimation process. Specifically, the results of analyses on ILD data for the peak 7-9 AM period on two days (April 2<sup>nd</sup>, 2007 and September 3<sup>rd</sup>, 2007) are presented. The effects of the modifications suggested by Vanajakshi are illustrated as well. Due to data limitations, a validation of the results with direct measures of travel time was not possible with the empirical dataset. A validation of the travel time estimation algorithm is therefore conducted using the simulated dataset. The results of this validation are presented in section 4.2.4.

Figures 4-2 and 4-3 show sample plots of travel times estimated using the Nam and Drew model with traffic flows that are not optimized (i.e., not corrected for breach of the conservation of vehicles principle). It can be observed from Figure 4-2 that for the morning peak period (7-9 AM) on April 2<sup>nd</sup> the estimated travel times are all negative. On September 3<sup>rd</sup>, the estimated travel times varied between 20 and 100-seconds, and for instances between 8:42 AM and 8:52 AM the travel times were negative, as seen in Figure 4-3. These estimated travel time values are not realistic and indicate the need for optimizing the detector volumes. That is, the need to check and correct for breach of the conservation of vehicles principle.



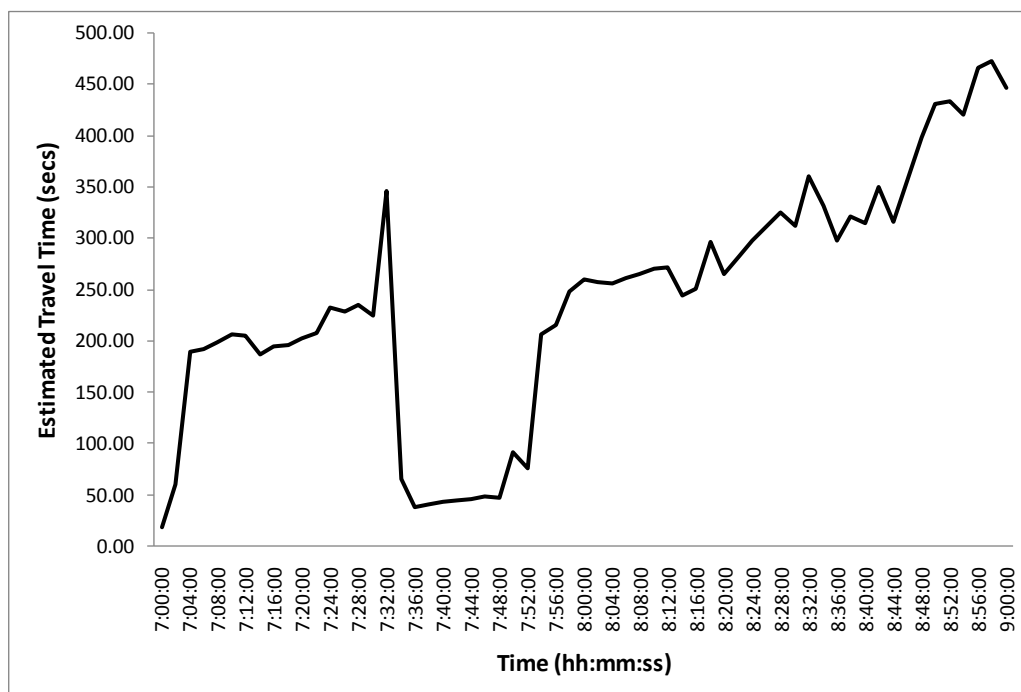
**FIGURE 4-2: Estimated travel time using Nam and Drew model with actual data on April 2nd, 2007**



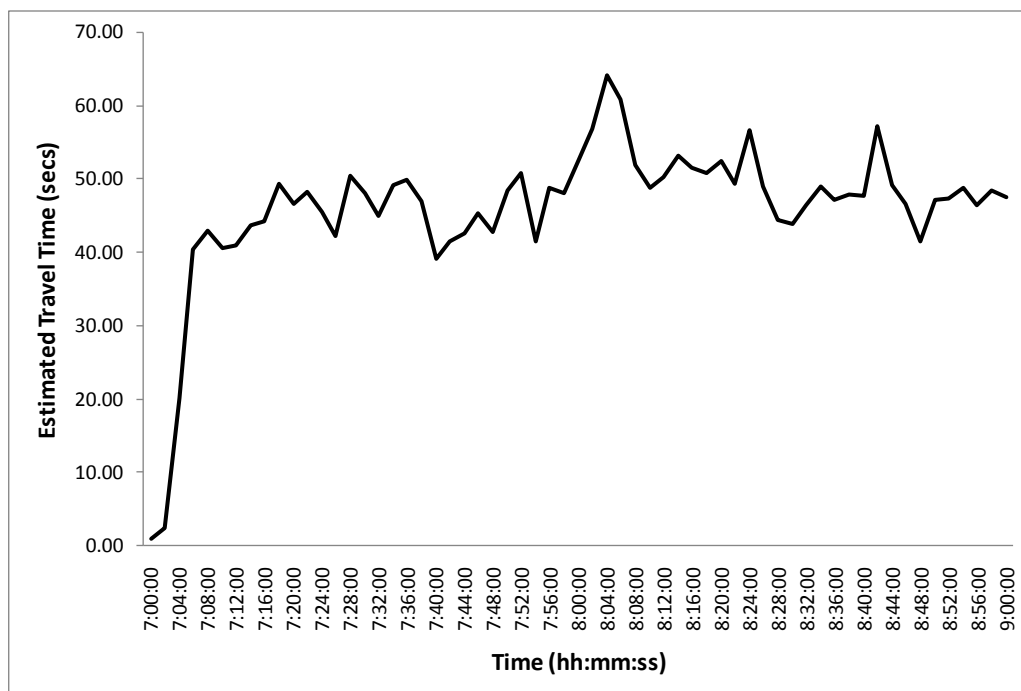
**FIGURE 4-3: Estimated travel time using Nam and Drew model with actual data on September 3rd, 2007**



In Figures 4-4 and 4-5 the travel times estimated after correcting the traffic flows for the conservation of vehicles are presented. It can be observed that the estimated travel times are physically realistic (there are no longer any negative values). However, the values are unreasonably high and not representative of actual traffic conditions. A consideration of the speed data indicates that speeds range between 53 mph to 80 mph and 60 mph to 85 mph. The corresponding estimated travel times must therefore range between 23 seconds to 34 seconds and 20 seconds to 31 seconds on April 2<sup>nd</sup> and September 3<sup>rd</sup>, respectively. These results suggest that a further improvement in the estimated travel times was necessary. The Vanajakshi model (Equation 4.5) was implemented to improve the travel time estimates while also calculating the density using Equation 4.7.



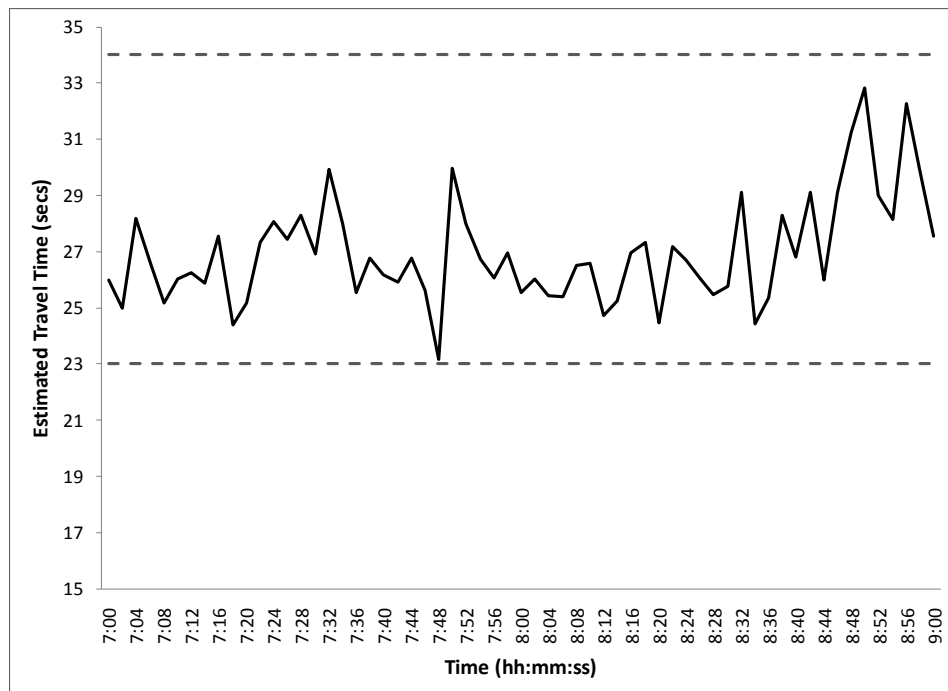
**FIGURE 4-4: Estimated travel time using Nam and Drew model with optimized data on April 2nd, 2007**



**FIGURE 4-5: Estimated travel time using Nam and Drew model with optimized data on September 3rd, 2007**

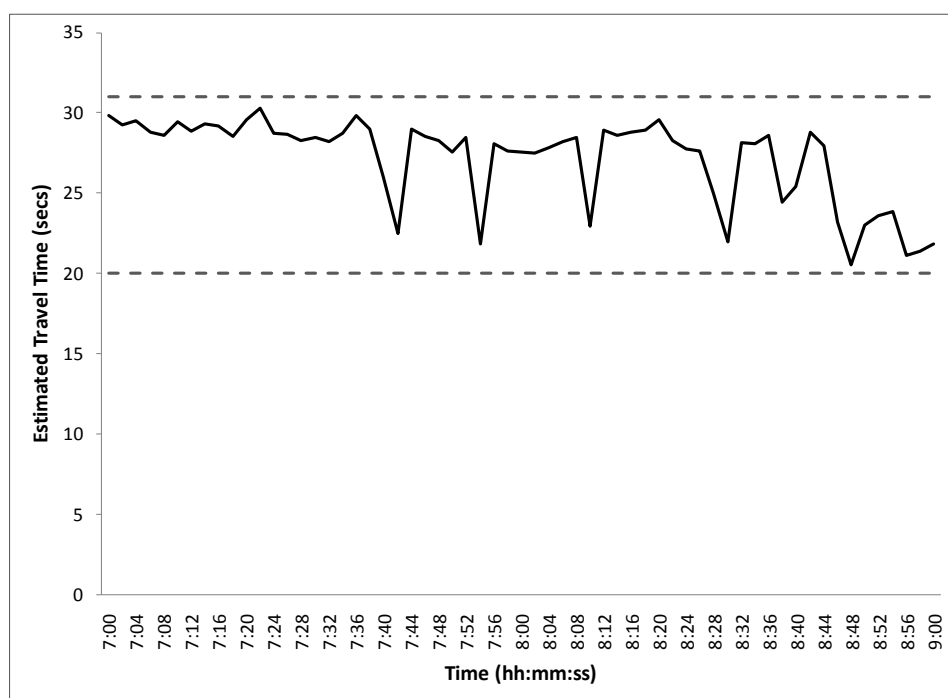
The resulting travel times on the link on April 2<sup>nd</sup> and September 3<sup>rd</sup> after implementing the Vanajakshi model are depicted in Figures 4-6 and 4-7, respectively. It can be observed that the travel times are within reasonable limits (23 seconds to 34 seconds and 20 seconds to 31 seconds on April 2<sup>nd</sup> and September 3<sup>rd</sup>, respectively) and match the speed patterns in the empirical data.

Directly measured travel times (e.g., AVI) were not available from the I-35 corridor in San Antonio, Texas. Therefore, a comparison between estimated and observed travel times was not possible. A model validation was instead conducted using the simulated dataset obtained from a traffic micro-simulation model. The results of the validation are presented in the next sub section.



\*Dashed lines indicate travel time limits when considering observed speed data

**FIGURE 4-6: Estimated travel time using Vanajakshi model on April 2nd, 2007**



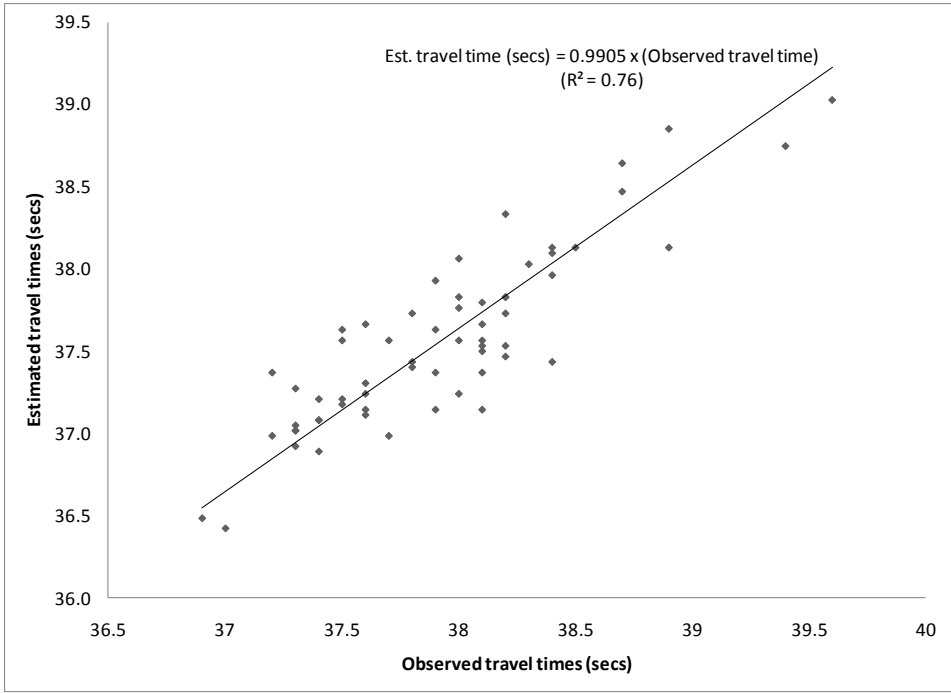
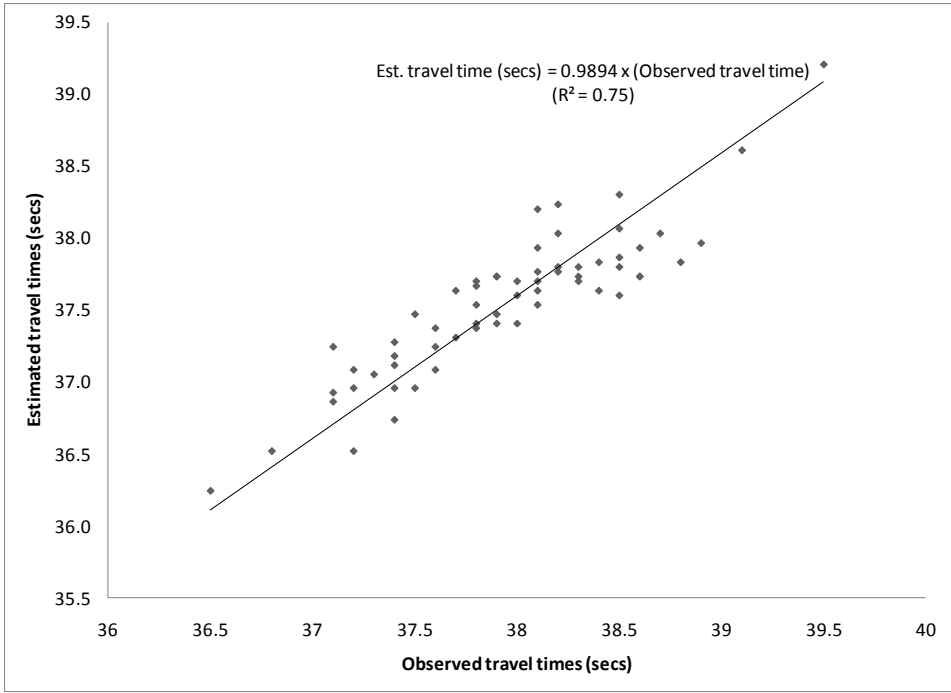
\*Dashed lines indicate travel time limits when considering observed speed data

**FIGURE 4-7: Estimated travel time using Vanajakshi model on September 3rd, 2007**

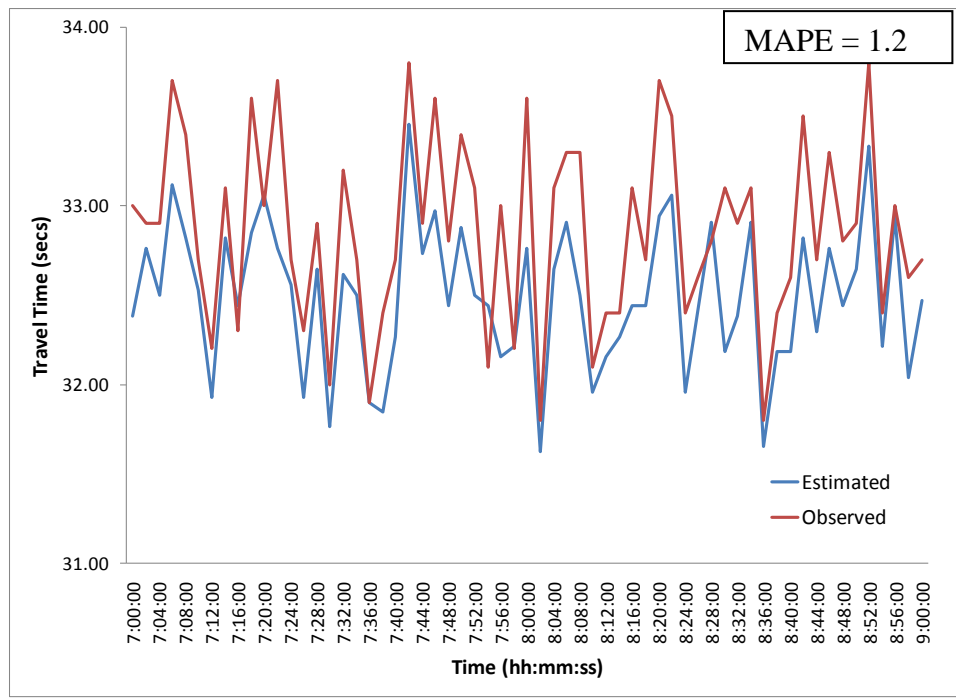
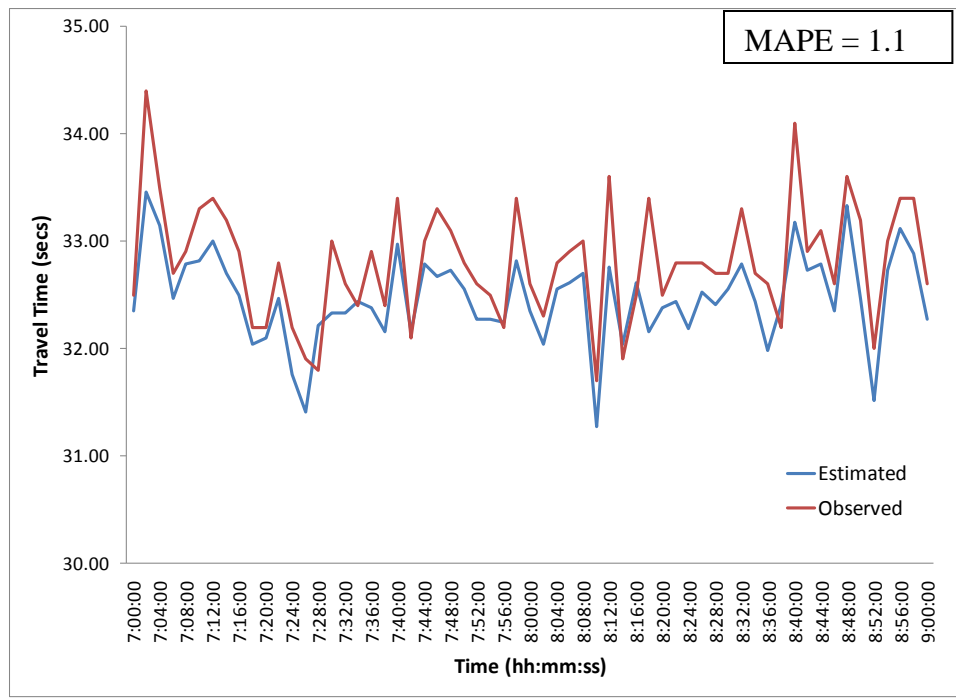
#### 4.2.4 Results from Validation using Simulated Data

A large scale traffic micro-simulation model of the Interstate 80 (I-80) freeway system between the cities of Omaha and Lincoln, Nebraska is the source of the simulated dataset used in this dissertation. The traffic micro-simulation model was built in VISSIM and calibrated to replicate field (observed) speeds and travel times. Traffic volumes were input into the network based on values obtained from the field. A small freeway section within the larger simulation model was equipped with detectors placed at every 0.5 miles apart. The detectors collected speed, volume, occupancy rate and travel time data. The data were generated for a 2-hour period and aggregated at 2-minute intervals. Details of the traffic micro-simulation model and the simulated dataset are given in Chapter Three.

Using occupancy rate, volume and speed values from a given simulated link as input into the Vanajakshi model, travel times were computed. These estimated travel times were then compared to directly measured travel times that were collected from the micro-simulation model. Figures 4-8 and 4-9 illustrate the performance of the Vanajakshi model on simulated data that represent two different days. Figure 4-8 illustrates scatter plots of the estimated travel times versus the observed travel times. The slope of the linear line for both days is approximately equal to one (i.e., 0.989 and 0.990) indicating that there is a strong correlation and the estimated travel times are similar to the observed times.



**FIGURE 4-8: Comparison of observed and estimated travel time for two separate days using simulated data**



**FIGURE 4-9: Comparison of observed and estimated travel time for two separate days using simulated data**

Figure 4-9 shows that the trend in the travel times estimated using the Vanajakshi model follows closely the trend in the travel times directly measured from the VISSIM simulation model. The mean absolute percent error (MAPE) calculated for the two days of data was 1.1% and 1.2% respectively. These results support the validation results obtained by Vanajakshi (2004) and Vanajakshi et al. (2009).

Given these validation results and in the absence of empirical AVI data, it could be reasonable to use the estimated travel times as target data for the neural network model that is to be developed.

## **4.3 TRAVEL TIME PREDICTION USING NEURAL NETWORKS**

### **4.3.1 Background**

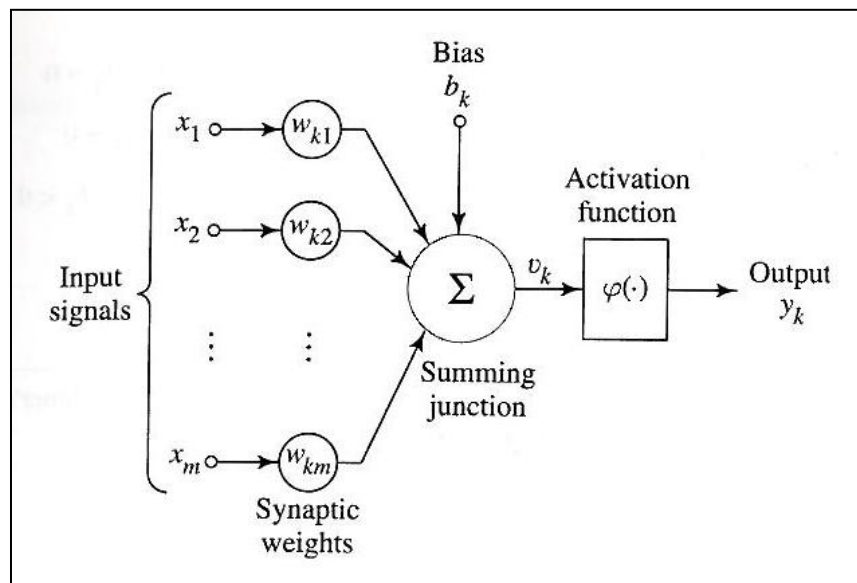
Over the past 60 years, neural networks have been used prominently for pattern recognition and classification and to model nonlinear relationships. In the field of traffic engineering, neural networks have become widespread for over 16 years. A neural network is essentially a statistical model capable of learning the complex relations between its input features and its output simply from seeing examples of the input factors and corresponding output. Typical neural network applications include; sensor processing, pattern recognition, and data analysis and control. Another major application area of neural networks is in forecasting. In transportation studies, neural networks have been used to forecast traffic variables such as speed, flow, occupancy and travel times. Literature specific to the use of neural networks for travel time prediction is reviewed in detail in Chapter Two.

### 4.3.2 Concept of a Neural Network

A neural network is built of several simple elements called neurons that form the basis for their design (Haykin 1999). Figure 4-10 shows the model of a typical neuron.

The neuron (or node) consists of three basic elements:

1. A set of connecting links that is each characterized by a weight ( $w$ ) and through which the input parameter ( $x$ ) makes its entry.
2. A summing junction where the input signals (multiplied by their weights) are added.
3. An activation function where the neuron's output is produced. A variety of activation functions that include threshold, piecewise-linear and sigmoid are available in the literature.



**FIGURE 4-10: A neuron model<sup>7</sup>**

<sup>7</sup> Image source: Haykin 1999



Mathematically, an input vector  $\mathbf{p}$  consisting of inputs  $x_1, x_2, x_3, \dots, x_m$  is transformed to an intermediate vector of hidden variables  $\mathbf{v}_k$  using an activation function  $f$ . Therefore, the output from the hidden layer of the  $k^{th}$  neuron is given as:

$$v_k = \left( \sum_{j=1}^m w_{kj} x_j + b_k \right) \quad (4.8)$$

where:

$(w_{kj})$  = weights for neuron  $k$  and input  $j$ ; and

$(b_k)$  = externally applied bias.

The final output from the neuron is given as:

$$y_k = \varphi(v_k) \quad (4.9)$$

where:

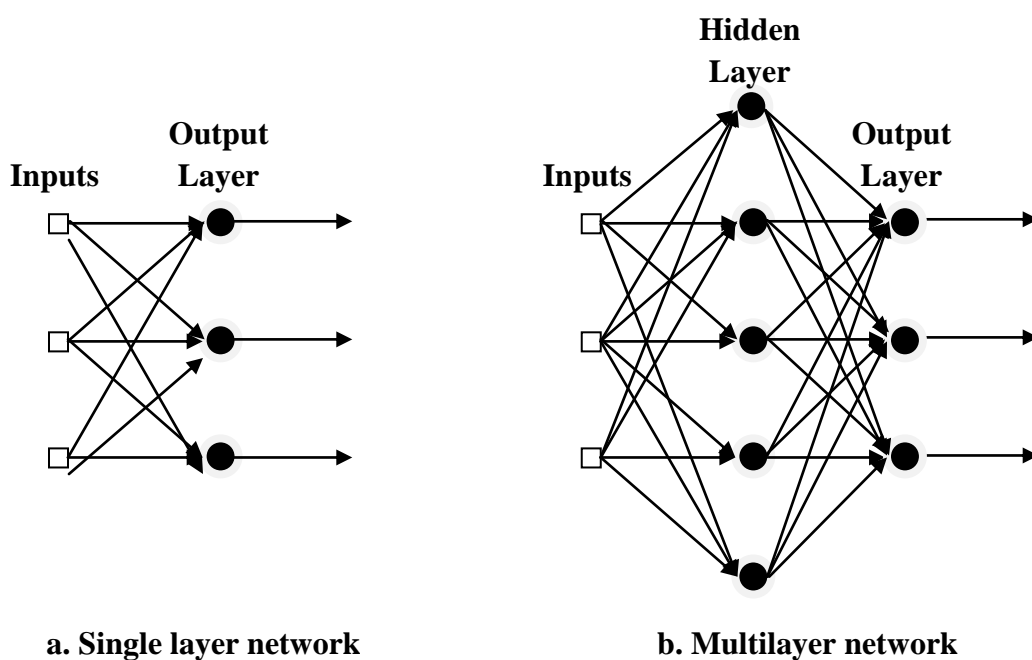
$\varphi(.)$  = the activation function (i.e., threshold, piecewise-linear or sigmoid).

### 4.3.3 Network Topology

The neurons are generally organized in the form of layers. Each neuron has  $(m)$  inputs and only one output. Two fundamentally different classes of network topologies are available: feedforward and recurrent networks (Haykin 1999).

### 4.3.3.1 Feedforward Networks

In its simplest form, a feedforward network consists of a layer of inputs that project onto a layer of neurons that produce an output as seen in Figure 4-11a. This type of network is called a single-layer feedforward network. A multilayer feedforward network has one or more hidden layers between the input and the output units. This hidden layer of neurons enables the network to extract higher-order statistics (Haykin 1999). An example of a multilayer network is shown in Figure 4-11b. This dissertation utilizes a multilayer feedforward topology the details of which are presented in section 4.3.5.



**FIGURE 4-11: Feedforward neural networks**

#### *4.3.3.2 Recurrent Networks*

Recurrent networks distinguish themselves from feedforward networks in that they have feedback loops. This loop feeds the output signal back to the input of the neuron.

#### **4.3.4 Training a Network**

A neural network is able to learn complex relationships between its input and output through a process known as training. Training can be done by either of two ways: supervised or unsupervised learning. For this dissertation, supervised learning, which is commonly used for transportation models, was adopted. Supervised learning algorithms adjust the weights in a network such that the error between the actual network output and the corresponding target output in the training dataset is minimized. Therefore, in each step, the network output is compared with the desired output and a global error is computed. The weights are then adjusted to reduce the error. This process is iterated on the same set of data many times as the weights are refined.

##### *4.3.4.1 Back propagation*

Back propagation is the most successful and widely used supervised learning algorithm (Rumelhart et al. 1986). Back propagation is an extension of the least mean square algorithm. The algorithm has a learning rate parameter  $\eta$  that controls the step size when weights are iteratively adjusted. The algorithm initializes by assigning randomly generated values (in the range  $[-0.5, 0.5]$ ) to the weights. The first step is then for the algorithm to select an input/output pair from the training dataset. The input is propagated forward into the network and an output  $y_k$  calculated. In the second step,  $y_k$  is compared

to the desired output  $d_k$  and an error  $\delta_k$  is computed. An update of the weights by small displacements of the output towards the desired output is then performed. This update starts at the output and is propagated back to adapt the weights using Equation 4.10.

$$w_{ij}(t+1) = w_{ij}(t) + \eta \delta_k y_k \quad (4.10)$$

where:

$w_{ij}(t)$  = weights for node  $i$  to  $j$  at time  $t$ ;

$\eta$  = is the error gain term; and

$\delta_k$  = error term for node  $k$  and depending on whether node  $k$  is an output or hidden neuron is calculated using Equations 4.11 and 4.12, respectively.

For output units

$$\delta_k = y_k(1 - y_k)(d_k - y_k) \quad (4.11)$$

For hidden units

$$\delta_k = y_k(1 - y_k) \sum_k \delta_k w_{jk} \quad (4.12)$$

where the sum is over all the  $k$  nodes in the layer above node  $j$  (Beale 1990).

### **4.3.5 Design of Proposed Neural Network**

Past research indicates that multilayer feedforward neural networks that adopt the back propagation algorithm have been applied successfully to forecast link travel times (Park and Rilett 1999; Kigyorgy and Rilett 2003; Huisken and Berkum 2003). Because neural networks are not transferrable, the network models developed in earlier studies cannot be used in this study and so there is need to develop a model for the specific roadway section used in this work. An approach similar to the cited research was adopted for this dissertation. The next sub-sections describe the neural network model developed for predicting link travel times using the empirical data.

#### *4.3.5.1 Input Data*

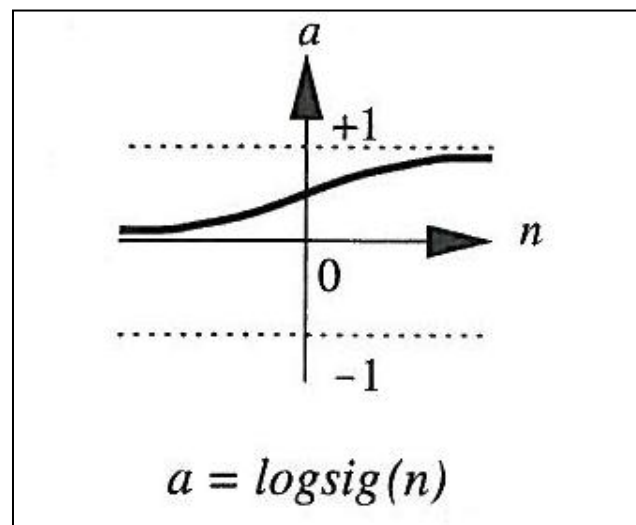
The travel times estimated using the methodology described in section 4.2.2 were used as input for the neural network to be developed. Given that prior knowledge of travel times are used to forecast future times, then the input would consist of lagged 2-minute travel times for the peak 7-9 AM period for 130 days. The data set was split into training and test data consisting 127-days and 3-days of data, respectively. Additionally, the inputs were normalized before being used in the neural network. The normalizing was done to avoid higher values driving the training process and thus masking the contribution of lower valued inputs (De Sa 2001).

#### *4.3.5.2 Selection of Training and Activation Functions*

The back propagation algorithm was developed for training neural networks with the objective of minimizing the errors between the actual and desired output. A shortcoming

of the back propagation algorithm is in its slow convergence rate (Hagan et al. 1995; Haykin 1999). Several nonlinear minimization algorithms that address this shortcoming are available. These include the steepest-gradient, quasi-Newton, conjugate gradient and the Levenberg-Marquardt (LM) algorithms. In this dissertation, the MATLAB programming environment was used to develop the neural networks. Therefore, the LM algorithm, which is a built-in function within MATLAB, was used to train the neural networks.

A variety of activation functions are available and have been used in previous studies. In this dissertation, two activation functions: (1) a log-sigmoid and (2) a linear function were used. The log-sigmoid function, as shown in Figure 4-12, was used as the neuron activation function for the hidden layer.



**FIGURE 4-12: Log-sigmoid activation function<sup>8</sup>**

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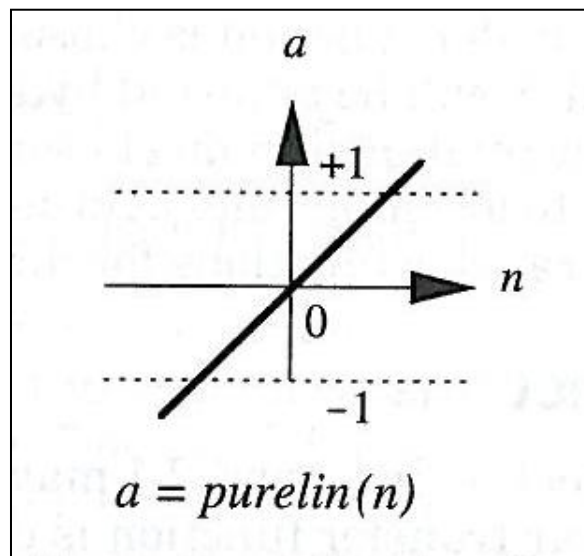
<sup>8</sup> Image source: Hagan et al. 1995

This function takes the input, which may have any value between plus and minus infinity, and transforms the output into the range 0 to 1 according to the expression:

$$a = \frac{1}{1 + e^{-n}} \quad (4.13)$$

The linear function, as shown in Figure 4-13, was used in neurons of the output layer. The output of the linear transfer function is equal to its input:

$$a = n \quad (4.14)$$



**FIGURE 4-13: Linear activation function<sup>9</sup>**

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<sup>9</sup> Image source: Hagan et al. 1995

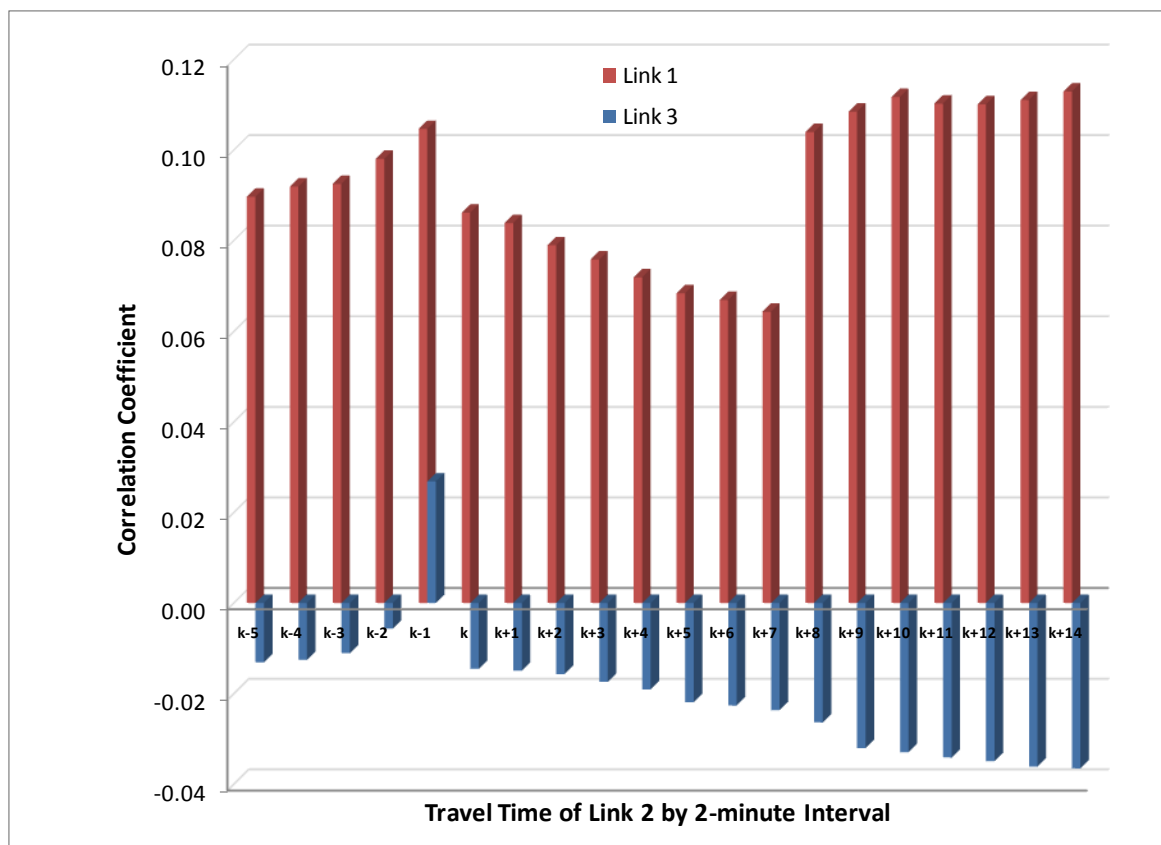
#### 4.3.5.3 Input and Output Design

A target link (on the proposed corridor) for which travel times would be predicted needed to be identified. Previous research found that a neural network model based on the travel times from the upstream, downstream and target links gave the best results when predicting 15-minutes to 25-minutes ahead (Park and Rilett 1999; Fulin 2000). For this reason, the middle link (between detectors 159.998 and 160.504 in Figure 3-2) of the study corridor in San Antonio, Texas was selected as the target link. This would also allow for the consideration of an upstream and downstream link in the model development.

A correlation analysis was conducted to investigate the relationship between the travel times on the target link and the travel times on the upstream and downstream links. Specifically, to examine the potential for including the travel times on upstream and downstream links as additional input for the neural network. The correlation coefficient,  $\rho$ , which indicates the degree of linear relationship between two random variables, was used to represent the relationship between the link travel times. The coefficient between random variables  $X$  and  $Y$  is calculated as:

$$\rho_{XY} = \frac{cov(X, Y)}{\sqrt{(varX)(varY)}} = \frac{E[(X - \mu_X)(Y - \mu_Y)]}{\sqrt{(varX)(varY)}} \quad (4.15)$$

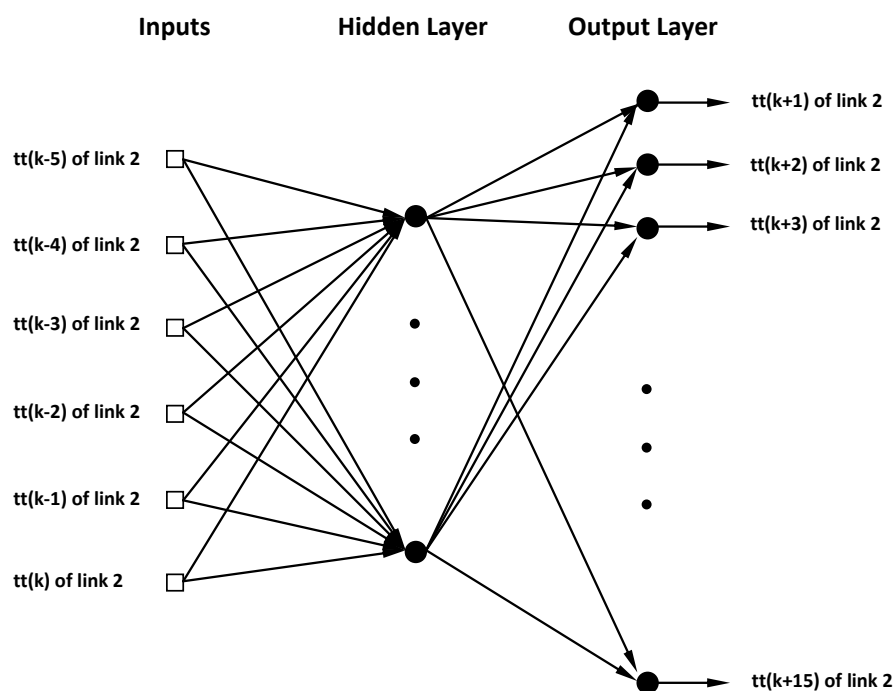




**FIGURE 4-14: Correlation coefficient of travel times between link 2 and neighboring links**

Figure 4-14 shows the correlation coefficients between the travel times on the target link and the travel times on upstream and downstream links at time steps  $k-5$  to  $k+14$ . In general, it can be observed that the travel times on the upstream link (link 1) are positively correlated, and for the downstream link (link 3) negatively correlated. The correlation coefficients, for both the upstream and downstream link were less than 0.10 and indicated that no strong correlation exists with the travel times on the target link. The results suggest that a neural network model that uses travel times from only the target link as input could be considered for design and testing.

The input travel times were lagged for a fixed number of periods as in any time series forecasting problem. A lag of five time periods was selected based on previous studies (Vanajakshi 2004; Park and Rilett 1999). A multi step forecasting of up to 30-minutes ahead was conducted for this dissertation. Therefore, the proposed neural network model will have 15 output neurons. The input-output structure for the neural network model is illustrated in Figure 4-15.



**FIGURE 4-15: Input-Output structure for neural network model**

#### *4.3.5.4 Selection of Neurons in Hidden Layer*

A multilayer feedforward neural network with one hidden layer (i.e., three layers for input, hidden and output, respectively) was assumed as being appropriate for the purposes of this dissertation. The literature indicates that this architecture is suitable for travel time prediction (Dougherty et al. 1995; Faghri and Hua 1992). A definitive rule to compute the number of neurons in the hidden layer is not available though several suggestions are available (Kanellopoulos and Wilkinson 1997; Foody and Arora 1997; Baum and Haussler 1998). A trial-and-error process was undertaken to identify the most appropriate number of neurons for the hidden layer. Eight hidden neuron configurations (i.e., 1, 3, 5, 7, 9, 11, 13, and 15) were explored.

The mean absolute percentage error (MAPE) values of travel time forecasts (up to 15-time steps ahead) obtained using the different numbers of hidden neurons in the model are presented in Table 4.1. In general, for each hidden layer structure, it can be observed that the MAPE increases as the prediction horizon increases. For example, with five neurons in the hidden layer the MAPE at time step  $k+1$  is 13.9% and at time step  $k+15$  the MAPE is 16.5%. In practice, this would mean that the accuracy of the travel time forecast decreases as the prediction horizon increases.

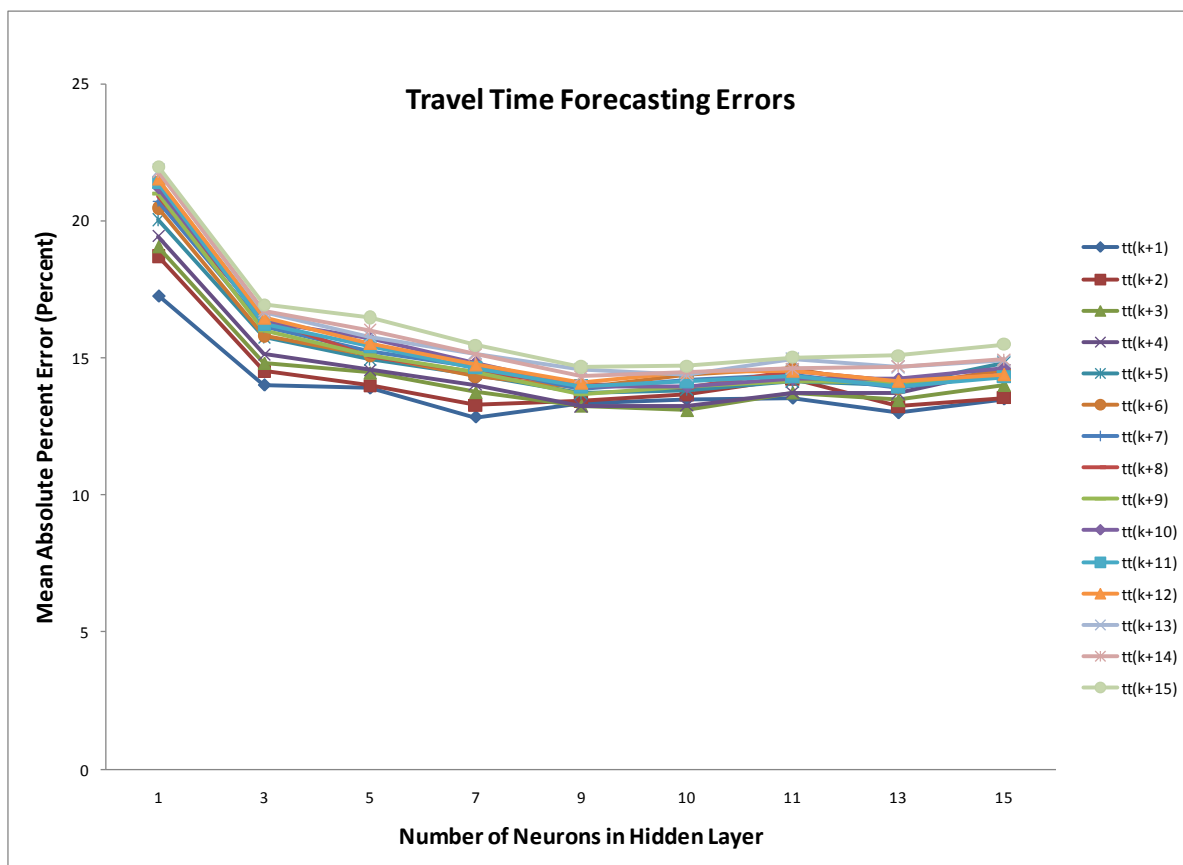
**TABLE 4.1 MAPE for Model With Different Numbers of Hidden Neurons**

Prediction Horizon	Number of Hidden Neurons							
	1	3	5	7	9	11	13	15
tt(k+1)	17.3	14.0	13.9	<u>12.8</u>	13.3	13.5	13.0	13.5
tt(k+2)	18.7	14.5	14.0	13.3	13.4	14.2	<u>13.2</u>	13.6
tt(k+3)	19.0	14.8	14.5	13.8	<u>13.3</u>	13.7	13.5	14.0
tt(k+4)	19.4	15.1	14.6	14.0	<u>13.2</u>	13.7	13.7	14.6
tt(k+5)	20.0	15.7	14.9	14.4	<u>13.7</u>	14.1	14.0	14.8
tt(k+6)	20.5	15.8	15.1	14.3	<u>13.9</u>	14.6	<u>13.9</u>	14.6
tt(k+7)	20.7	16.1	15.2	14.7	<u>13.9</u>	14.4	13.9	14.4
tt(k+8)	20.9	16.4	15.1	14.5	<u>14.0</u>	14.5	14.1	14.4
tt(k+9)	21.0	16.0	15.1	14.5	<u>13.7</u>	14.2	14.1	14.4
tt(k+10)	21.2	16.3	15.7	14.8	<u>14.0</u>	14.2	14.2	14.6
tt(k+11)	21.4	16.2	15.4	14.6	<u>13.9</u>	14.3	<u>13.9</u>	14.3
tt(k+12)	21.5	16.5	15.5	14.8	<u>14.1</u>	14.5	14.2	14.4
tt(k+13)	21.8	16.7	15.8	15.2	<u>14.6</u>	15.0	14.7	14.9
tt(k+14)	21.8	16.7	16.0	15.1	<u>14.3</u>	14.6	14.7	14.9
tt(k+15)	22.0	16.9	16.5	15.5	<u>14.7</u>	15.0	15.1	15.49
Overall Average MAPE	20.5	15.9	15.1	14.4	13.9	14.3	14.0	14.4

**Note:** The best model results are underlined for each prediction horizon

Figure 4-16 illustrates an apparent improvement in the MAPE as the number of neurons was increased from one to seven (for any prediction horizon). There was an improvement of 6.1% in the overall average MAPE (mean of all MAPE values for a given number of neurons), as seen in Table 4.1. Beyond seven neurons in the hidden layer, there are no marked improvements in the overall average MAPE as it “levels off.”

The results indicate that a hidden layer with nine neurons provides the most reasonable results.



**FIGURE 4-16: Travel time forecasting error with model**

#### 4.4 CONCLUDING REMARKS

This chapter presented a methodology for estimating travel times from inductive loop detector data. The chapter started by presenting a methodology that was originally proposed by Nam and Drew and forms its basis around the stochastic vehicle counting process and the conservation of vehicles principle (1996, 1998, 1999). However, a

number of drawbacks have been identified in the original model formulation. This chapter then presented a recent travel time estimation methodology proposed by Vanajakshi (2004) that incorporates modifications to the original Nam and Drew model.

The results of the estimation and the effects of modifications suggested by Vanajakshi are presented for two days: April 2, 2007 and September 3, 2007. The results of an optimization procedure indicate that when the flows are optimized (i.e., checked and corrected for the conservation of vehicles principle), then the travel time estimates are non-negative and physically realistic. Results of further suggested modifications show that the estimated travel times are within reasonable limits and match the patterns in the field data more closely. A validation of the estimation algorithm using a simulated dataset that was obtained from a traffic micro-simulation model of Interstate 80 in Nebraska were also presented within this chapter. The validation results indicated that the estimated travel times are similar to the measured travel times.

As part of this chapter a procedure for developing a multi-layer feedforward neural network model to forecast multiple period link travel times was presented. A network model that utilizes prior travel times with nine neurons in the hidden layer was found to provide the “best” forecasts for periods ranging from 2-minutes ahead up to 30-minutes into the future.

## CHAPTER 5

### UNCERTAINTY MODELING

#### 5.1 INTRODUCTION

The field of transportation engineering has benefited from a large number of innovative traffic forecasting methods that have been developed in the past decade. An essential feature for researchers and users of predicted traveler information has been the quality of the estimate, or prediction. In particular, this entails the ability to provide a forecasted point estimate of a traffic variable (for this dissertation, this would be mean travel time) in close comparison to values encountered in real time. Then again, the traffic forecasting systems could be improved even more by quantifying the uncertainty margin that exists around this predicted point estimate in terms of error bars or statistical intervals. The provision of intervals could not only increase the user comfort by reducing the error risk associated with the traffic information, it could also be used to assess the predicted values for model selection.

This chapter addresses the uncertainty around a predicted point estimate. The underlying assumption is that the data are time dependent, periodic and have a non-stationary distribution. The neural network model developed in Chapter Four will be used in this chapter for modeling uncertainty, however the methodology is considered generic. Therefore, the approach to estimate uncertainties is not a function of the travel time estimation or prediction model. The approach could also be readily used for other traffic parameters such as speed and flow.

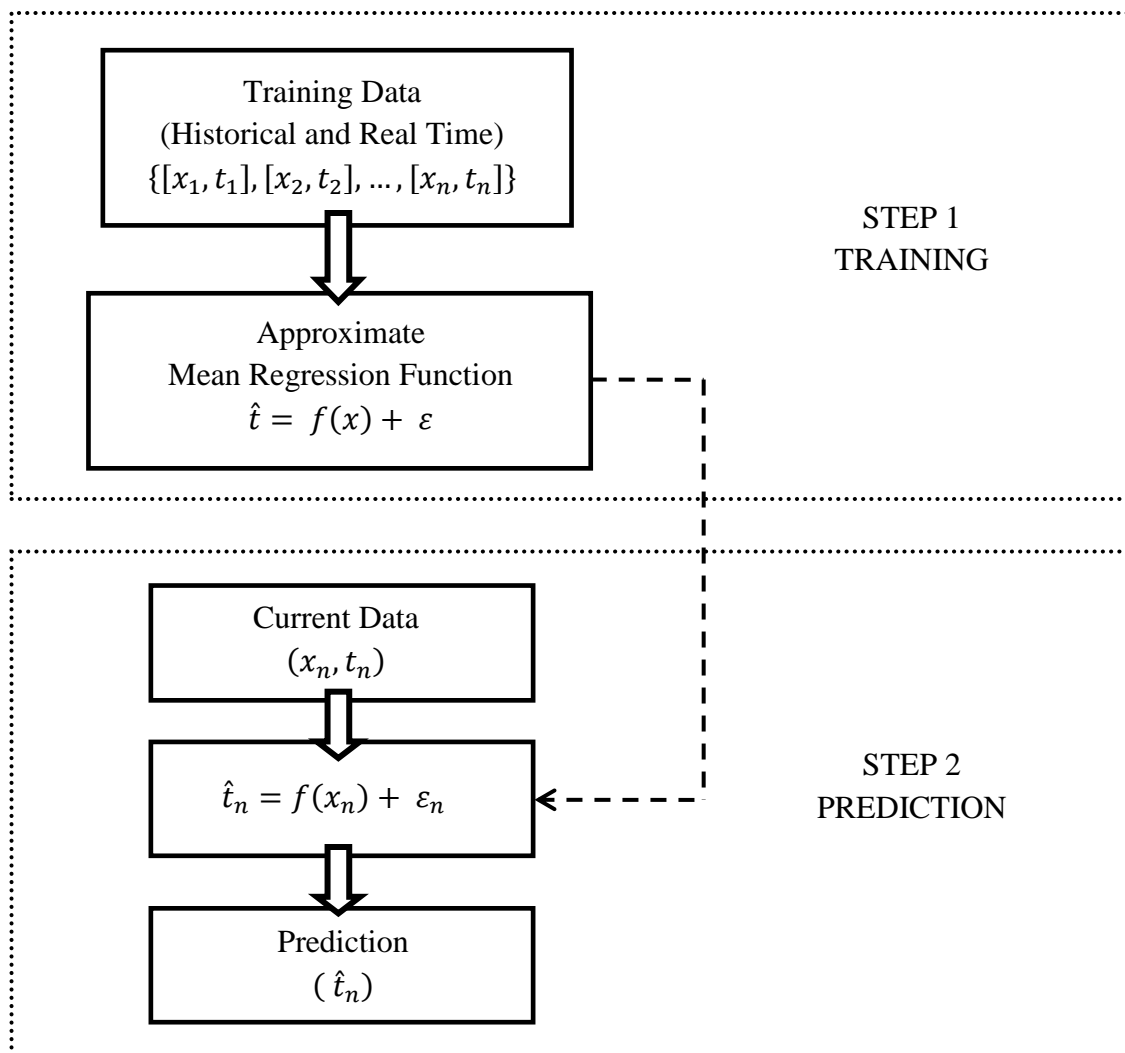
## 5.2 PROBLEM DEFINITION AND BACKGROUND INFORMATION

Predicted (or future) travel times are an integral component within freeway based Advanced Traveler Information Systems such as variable message signage and the *511* traveler information system. Several methods that provide a predicted value of travel time were presented in Chapter Two. The focus for these methods is two-fold: (i) using available traffic data to compute a prediction of the mean travel time for a given time period; and (ii) ensuring the difference between the predicted time and its real time value for the same time period is as small as possible. However, information on the quality (distributional properties) of this forecasted point value is unavailable. That is, information on the reliability of the predicted point value is not available.

A measure of the reliability is an important parameter because “drivers claim this influences their decisions that are based on the available travel time information” (Berkum and Mede 1993; Mahmassani and Liu 1999). In effect, drivers are unlikely to follow the information if they do not believe in its validity (Yang et al. 1992). To the traffic engineer, a measure of the reliability would provide a means of assessing different models for implementation. In statistical terms, this would mean quantifying the uncertainty associated with a given travel time prediction.

The typical model approximation task for a statistic  $\hat{\theta}$  (such as the mean of a sample data) can be expressed in two steps, as illustrated in Figure 5-1. Step one involves developing an initial model using a set of training data (historical and/or real-time). This developed model (essentially a mean regression function) defines the





**FIGURE 5-1: Two-step function approximation process**

relationship between inputs (data at one or more time instants) and the output (data at future time instants with respect to the inputs). The model could be parametric (e.g., linear regression, auto-regressive) or non-parametric (e.g., neural network). In the second step, the model that was developed in step one is used to compute future values, or predictions, of interest relative to current input. The predicted sample mean is reflective of the “true” population mean—however, unlikely to be exact. The “true”

value of the population parameter is unknown and it is important that predictions are accompanied by a statement about their corresponding uncertainty (Ellison et al. 2000).

In terms of travel time, this can be stated mathematically as:

$$t = \hat{t} \pm \sigma_t^2 \quad (5.1)$$

where:

$t$  = “true” travel time mean;

$\hat{t}$  = sample travel time mean; and

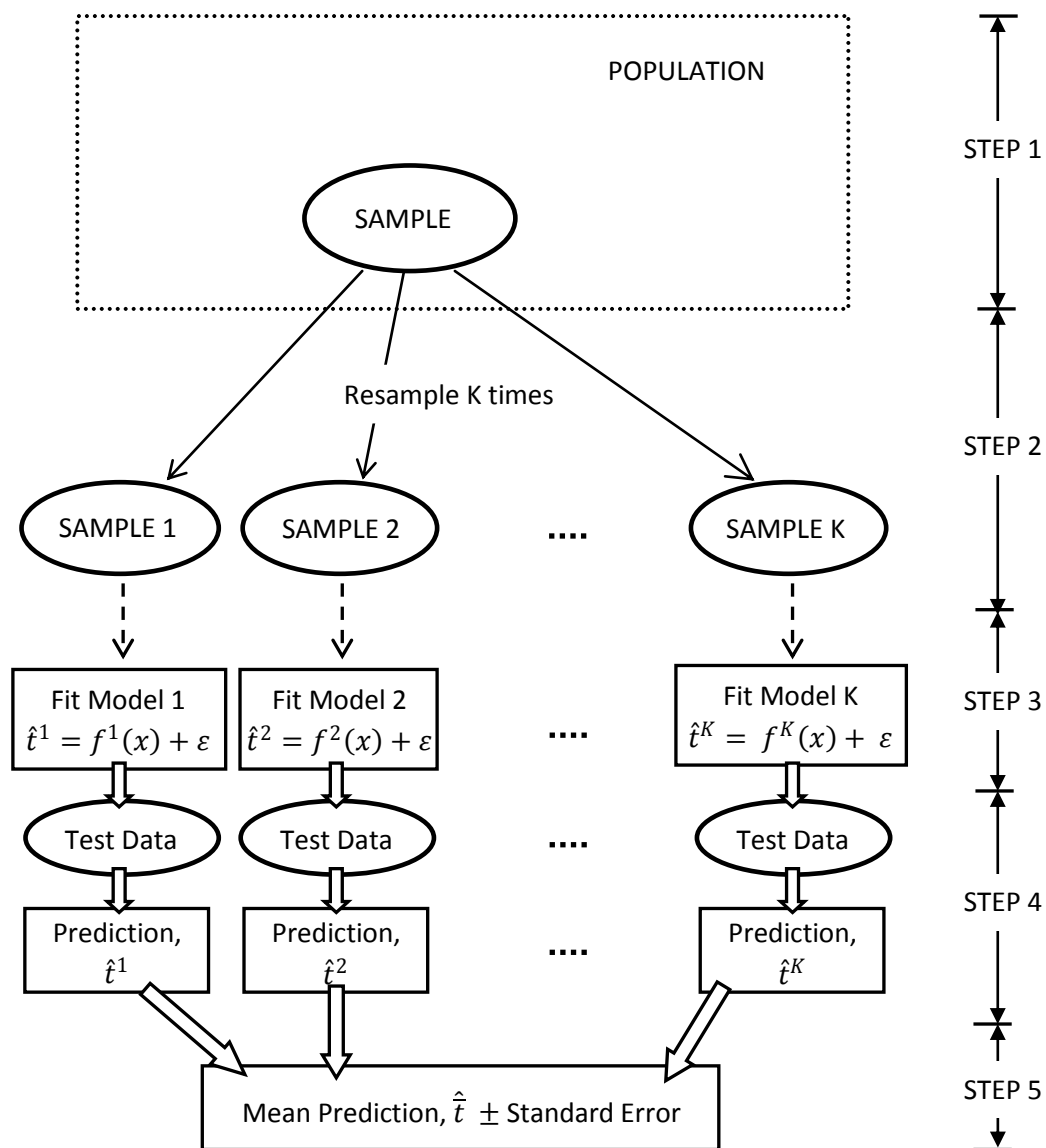
$\sigma_t^2$  = uncertainty.

The two main components that constitute the uncertainty around a forecasted value are: noise inherent in the input data, and uncertainty due to model structure (i.e., uncertainty due to the approximating function being trained on a selected random sample available from the population). Uncertainty related to the input data focuses largely on errors that emanate from failures in traffic monitoring equipment, communication failure between the field and traffic management center, and failure in the traffic management archiving system (Vanajakshi and Rilett 2004; Robinson and Polak 2006). This uncertainty component can be referred to as input data variance and denoted as  $\sigma_e^2$ .

The uncertainty in the model relates to the noise in the parameter, or weight, selection process. For the reason that a model with specified parameter is based on a specific sample, and if the current input is outside of the domain then the prediction would be uncertain. The so-called model uncertainty can be denoted as  $\sigma_m^2$ . The two

sources of uncertainty can be examined separately by constructing intervals around a prediction. Prediction intervals quantify the difference between the observed output (target) and the prediction. Confidence intervals quantify the difference between the prediction and the “true” regression, expressed as  $\sigma_m^2$ . The focus of this dissertation is to construct confidence intervals and therefore provide a range of values that are likely to include the “true value” of the population parameter.

It is generally desirable to keep uncertainties (for example, standard deviations) as low as possible. One method of achieving this would be to take a large enough random sample from the population, although the cost of doing this may be prohibitive (Baltagi 2008). Alternatively, for simple parameters such as the mean, this could be achieved by drawing multiple samples from the same population and calculating the standard error—the standard deviation of the sampling distribution of means (Appiah 2009). In practice, limitations such as time, cost, equipment, and labor constraints make the collection of multiple datasets infeasible. A more practical and commonly used approach is to resample from the initial selected sample and repeat the estimating process a number of times to get a good estimate of the standard error of the predicted values. The standard error is the basis for reliability measures in transportation. This chapter identifies a way of getting an estimate of standard error for highly non-linear models. Three different bootstrap versions are compared when used with neural networks.



**FIGURE 5-2: Schematic of uncertainty estimation process**

### 5.3 GENERAL FRAMEWORK

A conceptualization of the methodology developed in this study for calculating standard errors around forecast travel time values is provided in Figure 5-2. The figure depicts the

sequence of steps taken to calculate predicted travel time values and additionally provide an estimate of standard error (or confidence interval). A detailed description of each step of the process follows.

### **5.3.1 Initial Sample Selection: *STEP 1***

In this step, a sample dataset  $x_n = \{(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)\}$  of size  $n$  is selected from the population  $x_N = \{(x_1, y_1), (x_2, y_2), \dots, (x_N, y_N)\}$  of size  $N$ . The population could be a “huge” dataset consisting of 24-hour traffic data for two, three or more years. For a sample dataset, this dissertation uses morning peak hour (7:00 AM to 9:00 AM) traffic data (volume, speed and occupancy) from the period starting April 1, 2007 and ending September 30, 2007. The data were aggregated at 2-minute intervals and therefore  $n = 7930$  records. A simulated dataset that replicates the empirical dataset (in terms of size) is also used. Specific details of both datasets (empirical and simulated) are given in Chapter Three.

### **5.3.2 Resampling: *STEP 2***

Within this step, first, the methodology presented in Chapter Four is applied in order to compute estimated travel times from the volume, speed and occupancy data. Next, a resampling technique is adopted to create “pseudo” samples of the sample travel time dataset—now assumed as the “population”. Three variations of the bootstrap are used in this dissertation for resampling the sample dataset. The bootstrap is a data-driven simulation technique for computing statistical measures of accuracy for statistical estimates. A detailed description of the bootstrap techniques used is given in section 5.4.

### 5.3.3 Fitting Ensemble of Models: *STEP 3*

An ensemble of models is fitted to the estimated mean travel times in each bootstrap dataset. These models could be of a linear or non-linear form and are used to predict future travel time values. For this dissertation, a neural network model will be trained on each dataset. As stated previously, there are a wide range of modeling approaches that can be used for estimating and predicting travel times. However, this approach is generic and could be applicable to all.

For a given bootstrap sample  $\{(x_1^{*b}, y_1^{*b}), (x_2^{*b}, y_2^{*b}), \dots, (x_n^{*b}, y_n^{*b})\}$  a model is fit by:

$$\text{Minimizing } \sum_{i=1}^n [y_i^{*b} - y(x_i^{*b}; w)]^2 \quad (5.2)$$

subject to

$$0 < w \leq 1$$

where:

$w$  = set of model parameters (or weights);

$y(x_i; w)$  = predicted value for input  $x_i$  and model parameter  $w$ ; and

$b$  = bootstrap sample ( $b=1, \dots, B$ ).

#### **5.3.4 Calculate Predicted Values: STEP 4**

The neural network models trained in step three are each used here to make travel time predictions for a given test dataset. Therefore, if  $B$  ensemble models were fitted in step three, then for a given set of values there would be  $B$  number of predictions available (e.g.,  $B$  predictions for a 15-minute ahead time period).

#### **5.3.5 Calculate Mean and Standard Error: STEP 5**

A mean for a given time period, and for all the  $B$  predictions from step four, is computed in this step. Also the standard deviation of the sampling distribution of means (i.e., standard error) is calculated.

### **5.4 BOOTSTRAPPING**

Bootstrapping is a more commonly used technique for computing statistical measures of accuracy for estimates. Bootstrapping is based on the idea that the available dataset is nothing but a particular realization of some unknown probability distribution (Heskes 1997). It works by creating replicates of the original data and then re-estimating the distribution of an estimate or test-statistic on each bootstrap sample.

The characteristics of data, such as periodicity, time-dependence and nonstationarity, have been shown to affect bootstrapping results (Appiah et al. 2008). The “best” type of bootstrap technique to be implemented for a given application is dependent on the structure of the data. The next subsections present detailed descriptions on three bootstrap methods adopted within this dissertation: (i) ordinary bootstrapping,

(ii) block bootstrapping and (iii) gap bootstrapping. The bootstrapping techniques are nonparametric and easily implemented.

### 5.4.1 Ordinary Bootstrapping

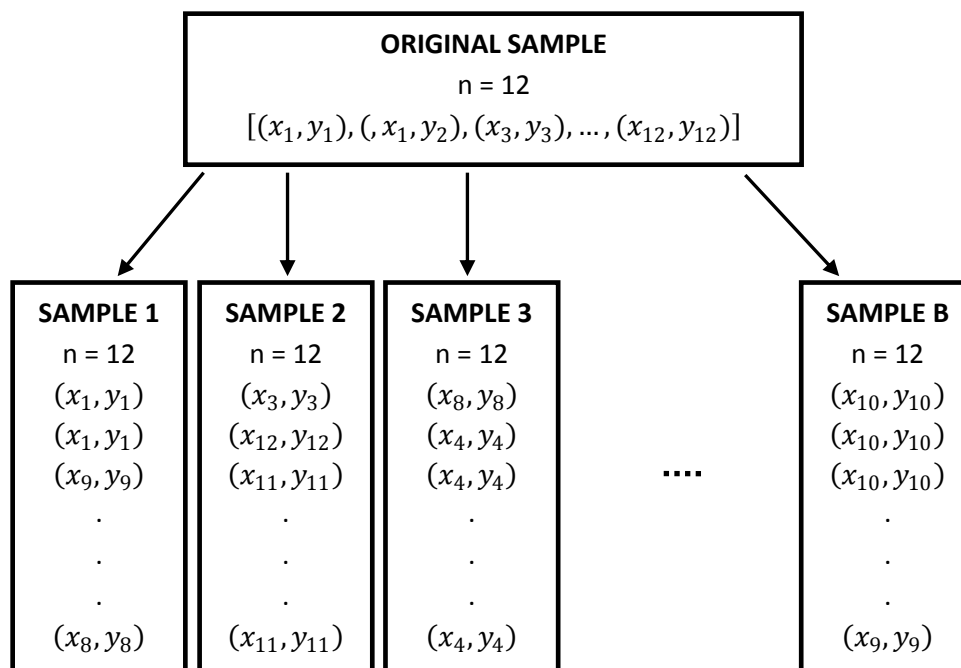
The ordinary bootstrap is the simpler and most widely used version of bootstrapping. It is applied where the data are (or are assumed) independent and identically distributed. Given an original sample  $x_n = \{(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)\}$ , the bootstrap procedure implies that an unknown distribution  $F$  is estimated by constructing an empirical distribution  $\hat{F}_n$  based on the  $n$  original observations. As illustrated in Figure 5-3, the bootstrap samples  $x_n^{*b} = \{(x_1^{*b}, y_1^{*b}), (x_2^{*b}, y_2^{*b}), \dots, (x_n^{*b}, y_n^{*b})\}$  are repeatedly drawn with replacement from the estimated empirical distribution until a total of  $B$  bootstrap samples are obtained (Davison and Hinkley 1997; Chernick 1999). Then, for each bootstrap sample, the bootstrap version  $\hat{\theta}_B^*$  of an estimator  $\hat{\theta}$  is calculated. The ordinary bootstrap uncertainty estimate (standard error) is then obtained as (Tibshirani 1995);

$$\text{standard error (se)} = \left\{ \frac{1}{B-1} \sum_{b=1}^B [\hat{\theta}^{*b} - \bar{\theta}^*] \right\}^{1/2} \quad (5.3)$$

where:

$$\text{bootstrap mean } \bar{\theta}^* = \frac{1}{B} \sum_{b=1}^B \hat{\theta}^{*b} \quad (5.4)$$

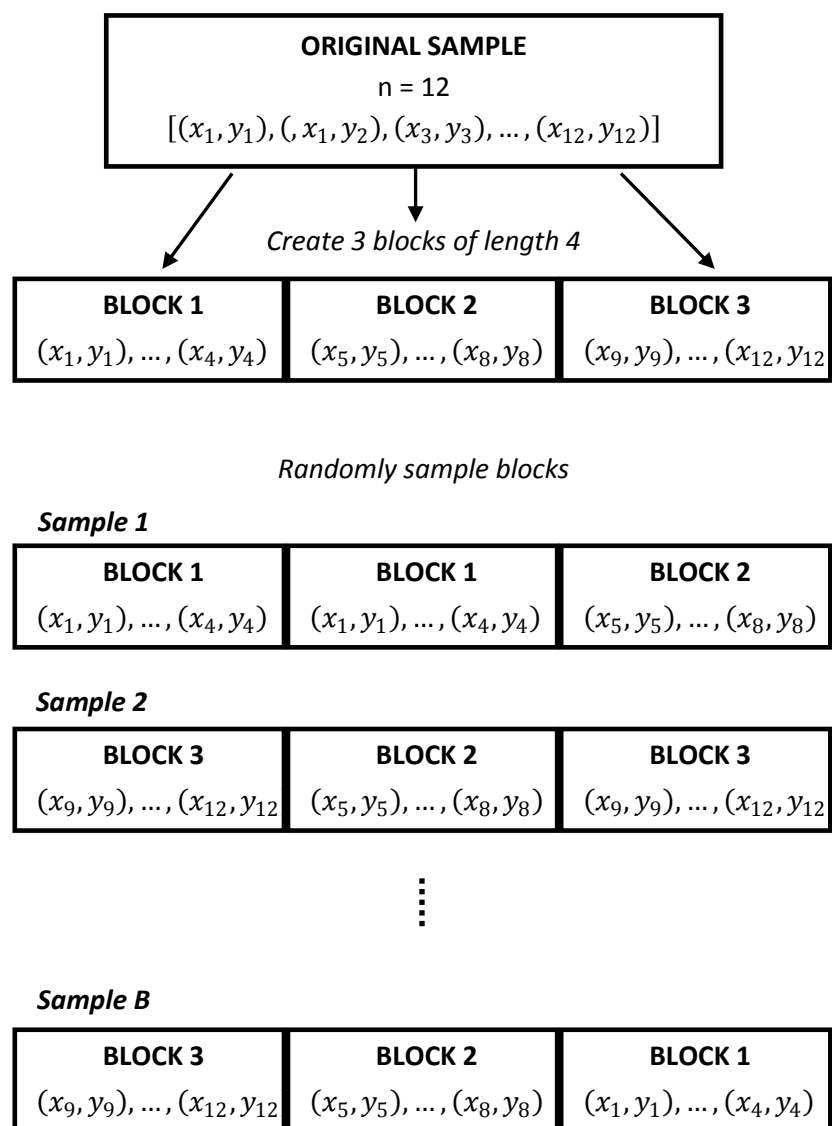




**FIGURE 5-3: Illustration of the ordinary bootstrap method**

#### 5.4.2 Block Bootstrapping

The widespread deployment of Intelligent Transportation Systems has enabled traffic data such as volume, speed and occupancy to be readily available. In Chapter Three, an exploratory analysis into the characteristics of these traffic data revealed that, for a time series of either link volumes, speeds, occupancy rates or travel times, the data have a weak dependence (Monday at 8:00 AM is similar to Monday at 8:02 AM but does not say anything about next Monday at 8:02 AM). This type of data presents challenges for estimated model uncertainty evaluation.



**FIGURE 5-4: Illustration of the block bootstrap method**

Implementing the ordinary bootstrapping method results in the data being “scrambled” in such a way that aspects of any dependence structure in the original dataset are lost. The ordinary bootstrap is therefore not appropriate for dealing with dependent data because the resampling does not capture the dependence structure. Over the years, a

number of nonparametric procedures that implement bootstrapping on dependent data have been proposed. These include the block, sieve, local, wild, and Markov bootstrap and sub-sampling (Kunsch 1989; Shi 1991; Mammen and Nandi 2004). At present, “the best known method for implementing bootstrapping with dependent data” is the block bootstrapping method (Hardle et al. 2003). This method is illustrated in Figure 5-4. The basic concepts of block bootstrapping are similar to those of ordinary bootstrapping discussed in subsection 5.4.1.

With the block bootstrap, a bootstrap sample is created by dividing the data into contiguous blocks that are randomly sampled. This can be contrasted to sampling individual observations in the ordinary bootstrap method. These blocks are subsequently placed end-to-end in the order sampled. The blocks could be created as non-overlapping or overlapping with fixed or varying lengths. Four of the most common block bootstrapping methods are the moving block bootstrap (Kunsch 1989), the non-overlapping block bootstrap (Carlstein 1986), the circular block bootstrap (Politis and Romano 1992) and the stationary block bootstrap (Politis and Romano 1994). A synopsis of these methods, as presented by Lahiri (1999), is given below.

Given the set of observations  $x_n = \{(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)\}$ , let  $l = (1 < l < n)$  denote the expected block length. Next, form the time series  $\{X_{0i}\}_{i \geq 1}$  where  $X_{0i} = X_j$  for some integers  $i = mn + j, 1 \leq j \leq n$ , and  $m \geq 0$ . As well, blocks of length  $k$  are defined based on the series  $x_{01}, x_{02}, x_{03}, \dots$  by  $B(i, k) = (x_{0i}, \dots, x_{0,i+k-1}), i \geq 1, k \geq 1$ . Different versions of the block bootstrapping method are obtained by

resampling from suitable collections of all  $b = n/l$  feasible blocks  $\{B(i, k) = i \geq 1, k \geq 1\}$ .

The moving block bootstrapping method resamples blocks randomly with replacement from the sub-collection  $\{B(i, k): i = 1, \dots, n - l + 1, k = l\}$ , whereas in the non-overlapping block bootstrapping, resampling is conducted from the collection of disjoint blocks  $\{B((i - 1)l + 1, l): 1 \leq i \leq b\}$ . The circular block bootstrapping method resamples from the collection  $\{B(i, l): 1 \leq i \leq n\}$ . Thus, in contrast to the non-overlapping and moving block bootstraps, the circular method uses elements from the periodically extended time series  $\{X_{0i}\}_{i \geq 1}$  beyond  $X_{0n}$ . Unlike the prior methods, in stationary block bootstrapping a random block length  $l$  that is generated from a geometric distribution is used. The bootstrap sample in this resampling scheme is therefore stationary.

By using blocks, some of the dependence structure in the data is maintained and the resulting estimates from block bootstrapping tend to be less biased than those from ordinary bootstrapping. However, “even for estimators as simple as the sample mean, a bias correction which is often laborious is still needed for block bootstrapping to yield accurate estimates of model uncertainties” (Lahiri 1999).

### 5.4.3 Gapped Bootstrapping

Spiegelman and Lahiri proposed a gapped bootstrapping procedure that is appropriate for data that can be partitioned into approximately exchangeable subsets (personal communication, November 2007). Whereas the distribution of the entire data is

not exchangeable or stationary, it is entirely reasonable that many multivariate subsets will be exchangeable. If the estimation method that is being used is efficient, then gapped bootstrapping gives an asymptotically unbiased estimate of standard errors. When the exchangeability of partitions is only approximate, then gapped bootstrapping produces conservative estimates of standard error that on average are overestimates of the true standard error asymptotically (Spiegelman, personal communication, 2007). The gapped bootstrapping methodology as presented by Spiegelman and Lahiri is discussed in detail below.

Let a multivariate time series of observations be denoted by the  $p \times q$  matrix  $X$  (i.e.,  $p$  observations of  $q$  variables). Let the  $i$ th row of the data matrix be denoted by  $X_{(i)}$ . The rows of  $X$  are then partitioned into  $m$  groups  $X_i, i = 1, 2, 3, \dots, m$  such that there are  $k = T/m$  observations in each column of the partition matrices. It is assumed that the random matrices  $X_1, X_2, X_3, \dots, X_m$  have an exchangeable distribution. That is, for any permutations of the integers  $1, 2, 3, \dots, m$ , say,  $j_1, j_2, j_3, \dots, j_m$ , the random matrices  $X_{j_1}, X_{j_2}, X_{j_3}, \dots, X_{j_m}$  have the same joint distribution as the random matrices  $X_1, X_2, X_3, \dots, X_m$ . As well, it is assumed that for any random matrix  $X_i$  the rows are independent random vectors.

Denote  $\hat{\theta}$  as the estimate of the unknown population parameter  $\theta$  based on the entire data and let  $\hat{\theta}_1, \hat{\theta}_2, \hat{\theta}_3, \dots, \hat{\theta}_m$  be estimates based on the submatrices  $X_1, X_2, X_3, \dots, X_m$ , respectively. That is,  $\hat{\theta}$  is the solution to the equation  $\sum_{i=1}^n \Psi(X_{(i)}, \theta) = \Psi(X, \theta) = 0$  and  $\hat{\theta}_i$  are solutions to the equations  $\Psi(X, \theta) = 0, i = 1, 2, 3, \dots, m$ . Note that because the subsample estimators are based on independent random data, ordinary bootstrapping

may be used within each partition matrix to obtain an estimator of the standard error,  $\hat{\sigma}(\hat{\theta}_i)$  of each  $\hat{\theta}_i$ ,  $i = 1, 2, 3, \dots, m$ . The main result of the method is that the usual covariance matrix estimator obtained from  $\hat{\theta}_1, \hat{\theta}_2, \hat{\theta}_3 \dots, \hat{\theta}_m$  provides a consistent estimate of the covariance matrix of  $\hat{\theta}$  and the rate of convergence is  $\sqrt{n}$ . Further, the estimator

$$\text{bootstrap mean } \bar{\theta} = \sum_{i=1}^m \hat{\theta}_i / m \quad (5.5)$$

is an asymptotically efficient estimator of  $\theta$ . If the distribution of  $X_1, X_2, X_3, \dots, X_m$  is not exchangeable, that is estimates  $\hat{\theta}_1, \hat{\theta}_2, \hat{\theta}_3 \dots, \hat{\theta}_m$  are heteroskedastic, then  $\bar{\theta}$  is not an efficient estimator of  $\theta$ . Further, in the case of heteroskedasticity, the resulting estimate of uncertainty will be too large. For large  $n$ , it can be shown that  $\hat{\theta} \approx \bar{\theta}$  (C. H. Spiegelman, personal communication, November 2007). Because the two estimators are asymptotically equivalent, the variance of  $\hat{\theta}$  may be approximated with the estimator for the variance of  $\bar{\theta}$  given by:

$$\text{Var}(\bar{\theta}) = \left( \sum_{i=1}^m \text{Var}(\hat{\theta}_i) + \sum_{i \neq j} \text{Cov}(\hat{\theta}_i, \hat{\theta}_j) \right) / m^2 \quad (5.6)$$

where:

$\text{Var}(\hat{\theta}_i)$  = the ordinary bootstrap estimator for the variance of  $\hat{\theta}_i$

$\text{Cov}(\hat{\theta}_i, \hat{\theta}_j)$  = the variance estimate of  $(\hat{\theta}_i - \hat{\theta}_j)$  given by

$$\sum_{i \neq j} (\hat{\theta}_i - \bar{\theta})(\hat{\theta}_j - \bar{\theta})^t / m(m-1) \quad (5.7)$$

The gapped bootstrapping method has previously been applied to the evaluation of uncertainties in the estimation of origin-destination matrices (Appiah et al. 2008; Appiah 2009). Traffic volume data from ITS sources were used to estimate split proportions using bootstrapping. The research identified that the gapped bootstrap uncertainty estimates are, on average, larger than those of the ordinary and block bootstrap.

#### **5.4 IMPLEMENTATION**

Mean travel times were forecast for 15 two-minute time periods (30-minutes ahead) using the methodology outlined in section 5.3. An overall mean travel time (at each two minute interval) as well as its corresponding bootstrap estimate of uncertainty (standard error) was then computed. The overall means and standard error values were computed for three separate days.

The ordinary bootstrap estimates were computed using 250 realizations of the original travel time data that were randomly sampled. The block bootstrap estimates were calculated by dividing the original data into 25 blocks each consisting 305 rows (i.e., travel time values for five days). Each bootstrap sample was then formed by randomly drawing the blocks with replacement and laying them end-to-end. The overall mean and standard error of predicted travel times (block bootstrap estimates) were computed as calculated from 250 such samples.

The gapped bootstrap estimates were obtained by breaking the original data into 42 subsets of independent data, where the elements of the  $i^{\text{th}}$  subset are the  $i^{\text{th}}$  two minute

travel times for each of the 125 days in the training dataset. That is, the 1<sup>st</sup> subset consists of 7:00 AM travel times, the 2<sup>nd</sup> subset consists of 7:02 AM travel times, the 3<sup>rd</sup> subset consists of 7:04 AM travel times and so on. The predicted overall mean travel times for each two minute period were obtained by averaging the two minute predictions from the 42 independent subsets. Component-wise variance estimators of the 42 subsets were calculated by performing ordinary bootstrapping within each subset. These were calculated using 250 realizations of each subset by resampling across the rows of the subsets. Assuming a constant covariance among the subsets, the final gapped bootstrap uncertainty estimates were computed by combining the component-wise variance estimates with the usual covariance matrix estimator obtained from the subsets.

## **5.5 RESULTS**

### **Empirical Data from the San Antonio Test Bed**

The predicted overall mean travel times and their corresponding estimates of standard error, computed using the three bootstrapping methods, are presented in Table 5.1. It can be observed that the mean travel time values computed using the three techniques are identical. However, the estimated standard errors are clearly different. A general observation indicates that the uncertainty estimates are lower for the ordinary bootstrap than those of the block and gapped bootstrap. As well, the gapped bootstrap estimates are the largest. The gapped bootstrap method seems able to capture the dependence structure in the dataset more than the ordinary and block bootstrap methods.



**TABLE 5.1 Predicted Means and Standard Errors for Empirical Data**

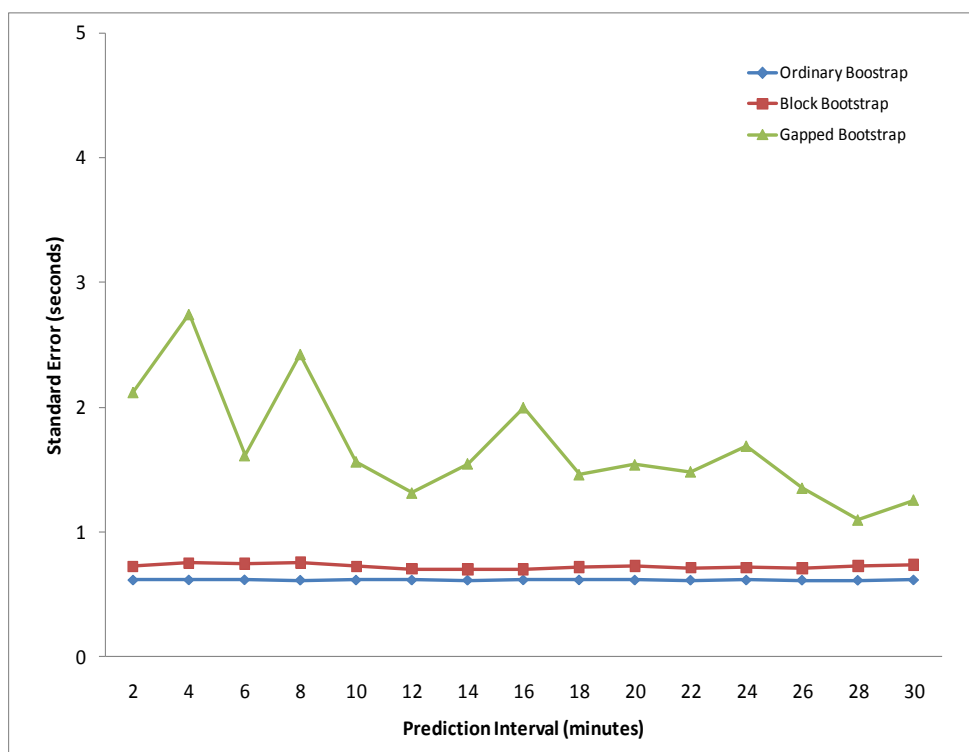
Prediction Interval in minutes															
	2	4	6	8	10	12	14	16	18	20	22	24	26	28	30
<b>DAY 1</b>															
Ord	26 (0.616)	26 (0.617)	26 (0.618)	26 (0.615)	26 (0.616)	26 (0.616)	26 (0.615)	26 (0.617)	26 (0.617)	26 (0.616)	26 (0.615)	26 (0.616)	26 (0.615)	26 (0.614)	26 (0.617)
Blk	26 (0.725)	26 (0.754)	26 (0.748)	26 (0.756)	26 (0.727)	26 (0.706)	26 (0.702)	26 (0.701)	26 (0.721)	26 (0.730)	26 (0.714)	26 (0.716)	26 (0.710)	26 (0.728)	26 (0.738)
Gap	28 (2.120)	28 (2.745)	28 (1.614)	27 (2.425)	28 (1.564)	28 (1.314)	28 (1.548)	26 (1.998)	27 (1.461)	27 (1.540)	28 (1.484)	28 (1.690)	27 (1.353)	28 (1.098)	27 (1.258)
<b>DAY 2</b>															
Ord	27 (0.823)	27 (0.824)	27 (0.819)	27 (0.824)	27 (0.824)	27 (0.821)	27 (0.824)	27 (0.823)	27 (0.822)	27 (0.823)	27 (0.822)	27 (0.824)	27 (0.824)	27 (0.825)	27 (0.824)
Blk	27 (0.850)	27 (0.891)	27 (0.870)	27 (0.879)	27 (0.858)	27 (0.846)	27 (0.843)	27 (0.843)	27 (0.848)	27 (0.846)	27 (0.831)	27 (0.833)	27 (0.834)	27 (0.838)	27 (0.843)
Gap	29 (1.753)	28 (1.852)	28 (2.304)	27 (2.245)	27 (1.547)	28 (1.882)	27 (1.783)	26 (1.298)	27 (1.161)	27 (1.704)	27 (1.911)	27 (1.427)	27 (1.489)	27 (1.817)	27 (1.491)
<b>DAY 3</b>															
Ord	25 (1.586)	25 (1.590)	25 (1.590)	25 (1.587)	25 (1.584)	25 (1.590)	25 (1.585)	25 (1.587)	25 (1.584)	25 (1.586)	25 (1.585)	25 (1.588)	25 (1.587)	25 (1.591)	25 (1.587)
Blk	25 (1.550)	25 (1.366)	25 (1.335)	25 (1.338)	25 (1.332)	25 (1.310)	25 (1.305)	25 (1.287)	25 (1.310)	25 (1.307)	25 (1.281)	25 (1.275)	25 (1.264)	25 (1.275)	25 (1.255)
Gap	27 (3.232)	26 (4.723)	28 (4.217)	27 (2.409)	27 (2.726)	26 (2.850)	27 (2.566)	27 (2.829)	27 (2.201)	26 (2.860)	27 (2.720)	27 (3.065)	27 (3.649)	27 (2.812)	27 (4.375)

\*Bootstrap Method: Ord = Ordinary; Blk = Block and Gap = Gapped

\*Predicted travel times are in seconds

\*Value in parenthesis is the estimated uncertainty (Standard Error)

To illustrate the approach, the standard error values computed for day 1 of the test dataset are shown in Figure 5-5. The block bootstrap uncertainty estimates were on average only 1.2 times larger than the ordinary bootstrap estimates suggesting that the block bootstrap does not adequately address the dependence structure in the dataset which was identified in Chapter Four. As expected, the gapped bootstrap provided substantially larger estimates of standard errors for the predicted travel times than the ordinary bootstrap (on average 2.7 times) and the block bootstrap (on average 2.3 times).



**FIGURE 5-5: Estimated standard errors for empirical data– Day 1**

### 5.5.2 Simulated Data from the Nebraska I-80 Test Bed

The results for analyses on the simulated dataset are presented in Table 5.2. It can be observed that the predicted mean travel times computed using the three bootstrap methods are identical. On average, the computed estimates of standard error are marginally different (1.2 – 1.4 times between each method). This is in contrast to results from the empirical dataset where the gapped bootstrap uncertainty estimates were approximately two times larger than those of the other bootstrap methods. The estimates of standard error that were computed on test day 1 are presented in Figure 5-6. It can be observed that there are marginal differences in the estimated uncertainties between the three bootstrap methods. The block bootstrap estimates are marginally larger than the gapped bootstrap (1.4 times) and the ordinary bootstrap (1.3 times).

The results from the simulated data prompted an exploratory analysis into the characteristics of the dataset. Specifically, to see if any dependent structure is evident in the dataset. The results indicated that the data were periodic and nonstationary but no time dependence was evident (refer to Chapter Three). Therefore, in the absence of a time dependent structure in the dataset, the three bootstrapping methods provided identical estimates of uncertainty.

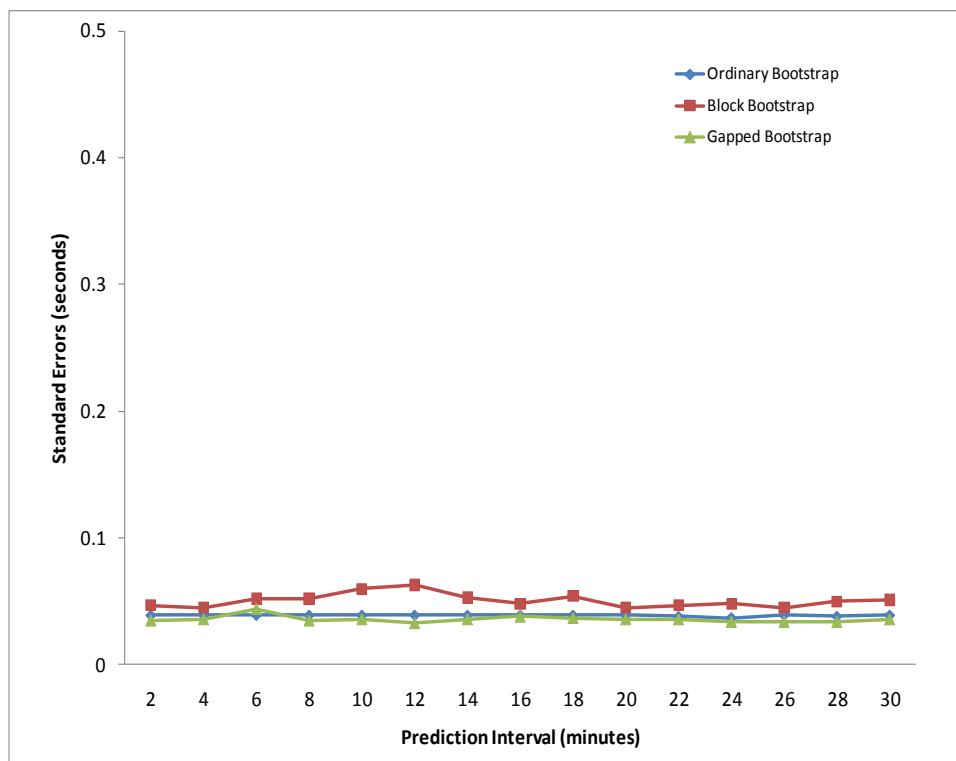
**TABLE 5.2 Predicted Means and Standard Errors for Simulated Data**

Prediction Interval in minutes															
	2	4	6	8	10	12	14	16	18	20	22	24	26	28	30
<b>DAY 1</b>															
Ord	34 (0.039)	34 (0.039)	34 (0.039)	34 (0.039)	34 (0.039)	34 (0.039)	34 (0.039)	34 (0.039)	34 (0.039)	34 (0.039)	34 (0.038)	34 (0.037)	34 (0.039)	34 (0.038)	34 (0.039)
Blk	34 (0.047)	34 (0.045)	34 (0.052)	34 (0.052)	34 (0.060)	34 (0.063)	34 (0.053)	34 (0.048)	34 (0.054)	34 (0.045)	34 (0.047)	34 (0.048)	34 (0.045)	34 (0.050)	34 (0.051)
Gap	34 (0.035)	34 (0.036)	34 (0.044)	34 (0.035)	34 (0.036)	34 (0.033)	34 (0.036)	34 (0.038)	34 (0.037)	34 (0.036)	34 (0.036)	34 (0.034)	34 (0.034)	34 (0.034)	34 (0.036)
<b>DAY 2</b>															
Ord	34 (0.039)	34 (0.039)	34 (0.039)	34 (0.039)	34 (0.039)	34 (0.039)	34 (0.040)	34 (0.040)	34 (0.039)	34 (0.039)	34 (0.039)	34 (0.039)	34 (0.039)	34 (0.039)	34 (0.039)
Blk	34 (0.043)	34 (0.039)	34 (0.048)	34 (0.051)	34 (0.065)	34 (0.061)	34 (0.047)	34 (0.047)	34 (0.049)	34 (0.041)	34 (0.045)	34 (0.047)	34 (0.045)	34 (0.054)	34 (0.051)
Gap	34 (0.027)	34 (0.027)	34 (0.027)	34 (0.028)	34 (0.027)	34 (0.028)	34 (0.028)	34 (0.027)	34 (0.029)	34 (0.027)	34 (0.028)	34 (0.028)	34 (0.026)	34 (0.028)	34 (0.028)
<b>DAY 3</b>															
Ord	34 (0.045)	34 (0.045)	34 (0.045)	34 (0.045)	34 (0.045)	34 (0.046)	34 (0.045)	34 (0.045)	34 (0.045)	34 (0.046)	34 (0.046)	34 (0.045)	34 (0.046)	34 (0.046)	34 (0.045)
Blk	34 (0.052)	34 (0.046)	34 (0.054)	34 (0.052)	34 (0.057)	34 (0.061)	34 (0.054)	34 (0.054)	34 (0.066)	34 (0.058)	34 (0.054)	34 (0.051)	34 (0.045)	34 (0.046)	34 (0.049)
Gap	34 (0.041)	34 (0.111)	34 (0.100)	34 (0.060)	34 (0.052)	34 (0.045)	34 (0.084)	34 (0.040)	34 (0.060)	34 (0.050)	34 (0.185)	34 (0.160)	34 (0.149)	34 (0.040)	34 (0.062)

\*Bootstrap Method: Ord = Ordinary; Blk = Block and Gap = Gapped

\*Predicted travel times are in seconds

\*Value in parenthesis is the estimated uncertainty (Standard Error)



**FIGURE 5-6: Estimated standard errors for simulated data– Day 1**

## 5.6 CONCLUDING REMARKS

The last decade has seen the transportation engineering field benefit extensively through research aimed at developing innovative travel time forecasting models. The motivation for many of these researchers was to accurately predict a point estimate of the mean travel time in comparison to the observed value. However, any information on the quality (distributional properties) of the forecast is unavailable. This means no measure of the consistency or reliability of the forecast is available. This measure of the reliability is known to influence drivers' decision making and, in the case of the engineer, provides a means of assessing different models for implementation. Statistically, this would mean quantifying the uncertainty associated with a given prediction.

This chapter presented a methodology that not only provides an accurate prediction of travel time but also provides a measure of the uncertainty surrounding the particular prediction. More importantly, the methodology is a generic approach to estimate uncertainties that is not a function of the travel time estimation or prediction model. A statistical non-parametric approach known as bootstrapping is adopted for assessing uncertainties in the travel time prediction environment. Because ITS data is known to be periodic, non-stationary and dependent—and since the choice of the bootstrap technique to be adopted is dependent on the structure of the dataset—three methods were compared. These bootstrap methods are the ordinary bootstrap, the block bootstrap and a recently proposed gapped bootstrap method.

The results indicate that while the ordinary bootstrap is not suitable for dependent data, the block bootstrap does not seem to provide any advantage when applied to the datasets used in this study. As expected, the gapped bootstrap technique appears to adequately address the uncertainty in both dependent and independent data when compared to the ordinary and block bootstrap methods.

## CHAPTER 6

### CONCLUSIONS AND FUTURE RESEARCH

#### 6.1 CONCLUSIONS

Because of the importance of pre-trip travel time information to travelers, many existing studies have focused primarily on developing models that possess a good predictive ability. That means, providing a predicted point estimate of mean travel time that is closely related to the observed value (Mazloumi et al. 2010). However, to influence driver responses, the predicted travel time must be consistent; drivers must be able to both trust and rely on the travel time estimate (Van Berkum and Van Mede 1993; Mahmassani and Liu 1999). There has been limited research on any insight into the reliability or uncertainty margin that exists around the predicted point estimate. Some of the notable research that make provision for modeling uncertainty in predicted values of travel time are those presented by Eisele (2001), Van Lint (2004) and Mazloumi et al (2010). A limitation to these researches is that the methodologies suggested are applicable to data that are assumed to be independent and identically distributed. However, this is generally not the case for the readily and widely available intelligent transportation systems' data.

This dissertation explored approximately six months of traffic data available from intelligent transportation systems sources through the TransGuide project in San Antonio, Texas. Specifically, inductive loop detector data consisting of volume, speed and occupancy rate from a section of Interstate 35 were analyzed. The data were “cleaned”

and screened for quality control before being analyzed for its characteristics. As expected the data were found to exhibit a periodic and non-stationary behavior. Additionally, the data were seen as having a time dependent structure. Given that the traffic data exhibits periodicity, non-stationarity and time dependence, there was a need to consider these characteristics when quantifying uncertainty within the travel time prediction process.

This dissertation presents a methodology that predicts the mean travel time and also provides a measure of the uncertainty surrounding the predicted estimate. The methodology is applied in this work to a neural network prediction model. Still, the methodology is generic and could be applicable to other estimation and prediction models such as Kalman filtering and Support Vector Regression. As well, the method could be used for other traffic variables such as flow and speed. This dissertation adopted a statistical non-parametric bootstrapping technique for modeling the uncertainties.

Whereas the ordinary bootstrap has been used previously for uncertainty modeling within the travel time prediction environment, it is ideal for dealing with data that are independent and identically distributed. This dissertation demonstrates the application of two other bootstrapping methods—the block bootstrap and the gapped bootstrap. The block bootstrap is currently the best known method for implementing the bootstrap with dependent data (Hardle et al. 2003). The gapped bootstrap is a recently developed technique that is uniquely suited for handling uncertainties in dependent data.

The main conclusions from the work in this dissertation are as follows.



- Archived traffic volume, speed, and occupancy data from an Intelligent Transportation Systems (ITS) source were found to exhibit periodic, non-stationary and time dependent characteristics.
- Predicted values of mean travel time computed using three bootstrap methods are identical. This suggests that the choice of the resampling technique will not affect the predicted point estimate.
- The uncertainty estimates from the ordinary and block bootstrap methods are not different. In comparison to the ordinary bootstrap, the block bootstrap does not adequately capture the dependence structure in a dataset. Therefore, while the ordinary bootstrap is not suitable for dependent data, the block bootstrap does not seem to provide any advantage when applied to the datasets used in this study.
- The estimates from the gapped bootstrap are larger (at least for the empirical dataset) than the ordinary and block bootstrap estimates. For the simulated dataset, which does not have a time dependent structure, the estimates of uncertainty from the three methods were marginally different. This suggests that the gapped bootstrap method adequately captures the dependent structure evident in a dataset when compared to the ordinary and block bootstrap methods. As well, unlike the ordinary bootstrap which is suitable only for data that are independent, it appears the gapped bootstrap can adequately address uncertainties for both independent and dependent structured datasets.

## 6.2 FUTURE RESEARCH

Though this research provided contributions to the existing transportation literature in the area of quantifying uncertainties in travel time prediction modeling, there are a number of topics that must be addressed as part of future research.

- In the absence of directly measured travel times (e.g., AVI data), this dissertation was restricted primarily to work related to mean travel times. However, if the travel times are skewed, the mean becomes influenced and may not describe the data correctly. In that case, the median becomes a more robust measure in that it is not heavily influenced by outliers and skewed data. Future work aimed at developing a model to predict the median travel time and quantifying model uncertainty is recommended.
- In this dissertation, the simulated dataset revealed no dependent structure and therefore a confirmation of the results from analyses on the empirical dataset was not possible. That is, the gapped bootstrap method adequately addresses uncertainty in dependent data when compared to the ordinary and block bootstrap methods. Future research that would confirm the results with other data is recommended.
- This dissertation made a strong case for the gapped bootstrap uncertainty estimator given that the existing methods, including the ordinary and block bootstrap, might not be appropriate. However, a “standard” to which a comparison of the various estimates can be drawn is not available. A study where such a “standard” can be established is recommended.

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**APPENDIX A**

**GLOSSARY OF FREQUENTLY USED TERMS**

**Accuracy**

The difference between a value (such as travel time) measured in the field and a computed (in terms of estimation or prediction) value should be as small as possible. In this sense, accuracy is closely related to validity.

**Advanced Traveler Information Systems (ATIS)**

The use of intelligent transportation systems technologies and communication methods for providing information to motorists.

**Artificial Neural Network (ANN)**

An information-processing structure whose design is motivated by the design and functioning of the human brain and the components thereof.

**Bootstrapping**

A resampling technique that can produce probability based inferences about a population related parameter, based on a sample estimate.

**Confidence Interval**

Is a range of values that encompass the population parameter of interest, such as the population mean, with a degree of certainty that is specified up front. In most cases, the degree of certainty expected from a confidence interval is  $1-\alpha$ , where  $\alpha$  is taken as five percent.

**Detectors**

A system for indicating the presence or passage of vehicles.

**Estimation**

A calculation of traffic state variables, for the most recent, or current, period for which measurements are available.

**Inductance Loop Detectors (ILD)**

A traffic monitoring technique, where in-wire loops buried below the road surface detect vehicles as they cross the loop, due to a change in inductance.

**Intelligent Transportation Systems (ITS)**

The application of computers, advanced technologies and communication methods to the transport sector to improve the efficiency or safety of a surface transport system.

**Link Travel Time**

The time taken to traverse a route between any two successive points of interest (or detectors).

**Mean Absolute Percentage Error (MAPE)**

A statistical measure used to determine the error in a set of data in comparison with the current set of data.

**Occupancy**

The proportion of time period that a detector is occupied by vehicles (vehicles are above the detectors).



**Prediction/Forecasting**

A calculation of future traffic state variables.

**Prediction Interval**

A range that encompasses unknown future values with a prescribed probability.

**Reliability**

The consistency with which a neural network, or other model, will provide an accurate estimate or prediction of travel time.

**Spot Speed**

The speed obtained from a detector at a single location along a link.

**Uncertainty**

The quantification of how far an estimated statistic is from the “true value” of the population parameter. Generally, uncertainty is presented in the form of confidence intervals or standard errors.

**Validation**

The process to determine whether a model provides an accurate representation of the real-world system being studied. It involves comparing the model output to generated analytical solutions or collected field data.

