

TRAVEL TIME ESTIMATION AND PREDICTION IN
CLOSED TOLL HIGHWAYS

by

MEHMET YILDIRIMOGLU

A Thesis submitted to the
Graduate School – New Brunswick
Rutgers, The State University of New Jersey
in partial fulfillment of the requirements
for the degree of
Master of Science
Graduate Program in Civil and Environmental Engineering
written under the direction of
Dr. Kaan Ozbay
and approved by

New Brunswick, New Jersey

October, 2011

ABSTRACT OF THE THESIS

Travel Time Estimation and Prediction in Closed Toll Highways

by MEHMET YILDIRIMOGLU

Thesis Director:

Dr. Kaan Ozbay

Real-time estimates of traffic conditions are valuable information needed by operators of transportation facilities as well as travelers. This study aims to provide accurate travel time estimates using data collected by the electronic toll collection system instead of sensors and AVI readers specifically deployed for traffic monitoring. This dual use of toll readers for travel time estimation can be an attractive approach since it eliminates additional costs of deploying and maintaining sensors. However, this approach can present an important challenge in terms of accuracy of the estimates because readers are not located on the main roadway, but instead on the ramps, and the demand level associated with particular OD pairs is not always enough to obtain accurate average travel times. Therefore, two estimation methods based on universal kriging and mathematical programming are proposed to estimate single section travel times using vast amount of available data from the electronic toll collection system of NJ Turnpike.

To be valuable, travel time information must be updated continuously in real-time to provide not only estimates of current traffic conditions but also future projections. Time series models are commonly used in transportation area to obtain future traffic states. This thesis compares the prediction performance of a parametric model, ARIMA, a recently developed non-parametric model, SVR, a commonly used non-parametric model, ANN, and tests their performances under both typical and atypical traffic conditions.

ACKNOWLEDGEMENTS

I would like to express my gratitude to my advisor Dr. Kaan Ozbay for his support and guidance over the course of my M.S. study. I would also like to thank my thesis committee members Dr. Hani Nassif and Dr. Husam Najm for being in my thesis committee and their valuable advices. I would like to thank Dr. Bekir Bartin for his help in my study.

I would like to thank my family for their infinite support and care during all stages of my life.; I always felt their endless love.

Special thanks to Eren Erman Ozguven for his guidance and friendship throughout my studies. He has been a good office mate and a good mentor.

I would like to thank my close friends that have been caring and supportive throughout my studies. Many thanks to Ozan Etkin Kara, Mert Kural, Anil Yazici, Sami Demirogluk and Aytug Pala. Special thanks to Cagatay Oz for his moral support and genuine friendship. He has been with me within the last year of my studies.

TABLE OF CONTENTS

ABSTRACT.....	ii
ACKNOWLEDGEMENTS.....	iii
Chapter 1 - Introduction.....	1
1.1 Background	1
1.2 Problem Statement	2
1.3 Thesis Outline	3
Chapter 2 - Literature Review.....	5
2.1 Type and Area of Implementation	5
2.2 Data Resolution and Traffic Parameters	6
2.3 Estimation Methodologies.....	12
Chapter 3 Data Description & Analysis.....	21
3.1 Data Description.....	21
3.2 Data Analysis	24
3.2.1 Bound Analysis of Path Demands and Travel Times	24
3.2.2 Distribution of Link Travel Times	39
Chapter 4 Data Filtering.....	44
4.1 Extreme Outliers	45
4.2 Sets with Enough Data	45
4.3 Sets with Few Observations	47
4.3.1 Higher Than Expected Observations.....	48
4.3.2 Lower Than Expected Observations	48
4.4 Computation of IQR in Sets with Few Observations.....	49
Chapter 5 Travel Time Estimation.....	50
5.1 Universal Kriging.....	54
5.1.1 Methodology	54
5.1.2 Results	63
5.2 Basic Nonlinear Programming (P1)	72
5.2.1 Methodology	72
5.2.2 Results	76

5.3	Extended NLP Algorithm (P2).....	85
5.3.1	Link Assignment	85
5.3.2	Results	87
5.4	Comparison of Algorithms.....	96
5.4.1	Comparison of Kriging and NLP	96
5.4.2	Comparison of Basic and Extended NLP.....	97
Chapter 6	Travel Time Prediction.....	100
6.1	ARIMA.....	100
6.1.1	Model Definition	100
6.1.2	ARIMA Model Fitting	102
6.1.3	Multivariate ARIMA.....	104
6.2	Support Vector Regression.....	106
6.2.1	Model Definition	106
6.2.2	Model Implementation	109
6.3	Artificial Neural Networks.....	109
6.4	Results and Analysis	111
6.4.1	General Performance.....	111
6.4.2	Atypical Traffic Conditions	113
Chapter 7	Conclusion.....	119

LIST OF TABLES

Table 2-1. Summary of the Available Literature	18
Table 3-1. Demand Level for Successive Interchanges.....	25
Table 3-2. Wilcoxon Test Results of Average Travel Times	34
Table 3-3. Wilcoxon Test Results of Upper Bound (95%) Travel Times	34
Table 3-4. Wilcoxon Test Results of Lower Bound (5%) Travel Times.....	35
Table 3-5. Wilcoxon Test Results of Average OD Demands.....	35
Table 3-6. Wilcoxon Test Results of Upper Bound OD Demands.....	36
Table 3-7. Wilcoxon Test Results of Lower Bound OD Demands	36
Table 3-8- Average Travel Times.....	38
Table 3-9- KS Distance.....	40
Table 3-10- Lognormal Distribution Parameters.....	41
Table 5-1- Accuracy of Kriging Algorithm for Different Periods of the Day	70
Table 5-2 - Accuracy of Kriging Algorithm under Congestion.....	70
Table 5-3 - Accuracy of NLP Algorithm for Different Periods of the Day.....	84
Table 5-4 - Accuracy of NLP Algorithm under Congestion.....	84
Table 5-5 - Accuracy of Extended NLP Algorithm for Different Updating Intervals.....	93
Table 5-6 - Accuracy of Extended NLP Algorithm under Congestion for Different Updating Intervals.....	93
Table 5-7 - Comparison of Basic and Extended NLP (15 min).....	98
Table 5-8 - Comparison of Basic and Extended NLP (15 min) under Congestion	98
Table 6-1 - ARIMA Model Orders	103
Table 6-2 - Multivariate ARIMA Model Orders	105

Table 6-3 - Common Kernel Functions	108
Table 6-4 - Forecasting Performance - One-Step Ahead.....	112
Table 6-5 - Forecasting Performance - Two-Step Ahead	112
Table 6-6 - Forecasting Performance - Three-Step Ahead	112
Table 6-7 - Forecasting Performance - One-Step Ahead.....	117
Table 6-8 - Forecasting Performance - Two-Step Ahead	117
Table 6-9 - Forecasting Performance - Three-Step Ahead	118

LIST OF FIGURES

Figure 3-1. New Jersey Turnpike Configuration and Interchanges	21
Figure 3-2. Travel Time and OD Demand Variations within the Day (Monday)	27
Figure 3-3. Average OD Demand Variation for Days of the Week	37
Figure 3-4. Link Travel Time Distribution (11-10)	39
Figure 3-5. Location Parameter	42
Figure 3-6. Scale Parameter	43
Figure 5-1- Travel Time Definitions and Information Delay (Soriguera et al., 2010)	51
Figure 5-2 - Schematic of a typical toll road section	53
Figure 5-3 - Travel Time (sec) Information on Two Dimensional Space	56
Figure 5-4- OLS Estimator	59
Figure 5-5 - Travel Time Data after the Removal of the Trend.....	59
Figure 5-6- Semivariogram.....	61
Figure 5-7 (a)- Graphical Results of the Kriging Algorithm	64
Figure 5-8- Kriging Results for (11,8) Travel Times	69
Figure 5-9 (a) - Graphical Representation of NLP Algorithm.....	78
Figure 5-10- NLP Results for (11,8) Travel Times	83
Figure 5-11- Extended NLP Results for (11,8) Travel Times (15 min)	89
Figure 5-12- Extended NLP Results for (11,8) Travel Times (10 min)	90
Figure 5-13- Extended NLP Results for (11,8) Travel Times (5 min)	91
Figure 5-14 -Extended NLP Results for Different Updating Intervals.....	95
Figure 6-1 - Performance of Congestion Indicator	106
Figure 6-2 - Topological Structure of Neural Network	110

Figure 6-3 - Estimated vs Predicted Values.....	114
---	-----

Chapter 1 - Introduction

1.1 Background

Real-time estimates of traffic conditions and short-term forecasts based on these estimates are valuable information required by transportation agencies and travelers to make better decisions. With the emergence of advanced detection and information dissemination technologies as well as very powerful computational capabilities in the context of intelligent transportation systems, vast amounts of data can now be acquired and processed in real-time.

Although there are tools in use that provide information to traffic control systems as well as traveler information systems, most of them are not designed to give future predictive information. However, the information provided to users should be based on expected traffic conditions in future, rather than current traffic conditions.

An efficient traffic management and information system should be based on providing continuous flow of information about prevailing traffic conditions (flow, speed, density, travel time, demand). To be valuable, every piece of information must be updated continuously in real-time to provide not only estimates of current traffic conditions but also future projections.

1.2 Problem Statement

This study aims to provide accurate travel time estimates using data collected by the electronic toll collection system instead of sensors and AVI readers specifically deployed for traffic monitoring. This dual use of toll readers for travel time estimation can be an attractive approach since it eliminates additional costs of deploying and maintaining sensors. However, this approach can present an important challenge in terms of accuracy of the estimates because readers are not located on the main roadway, but instead on the ramps.

Travel time can be estimated based on two types of speed measurement; spot speed and space mean speed. Spot speed is measured by taking a reference point on the roadway. In practice, it is measured by the use of loop detectors. It is defined as follows:

$$V_t = \frac{1}{m} \sum_{i=1}^m V_i \quad (1.1)$$

where m is the number of vehicles that pass the fixed point.

Space mean speed is measured by taking a roadway segment into account. By tracking individual vehicles on the roadway, average speed can be calculated. Cameras and AVI readers can be employed to obtain the data. Space mean speed is defined as:

$$V_t = (m / \sum_{i=1}^m (\frac{1}{V_i})) \quad (1.2)$$

Direct measurement techniques, such as electronic toll collection system used in this study, provides travel time information once the vehicle reached the point where the readers are located. Therefore, travel time information taken from the system is based on

space mean speed. Hence, especially travel time measurements of long trips are based on the past conditions of the roadway and they are subject to significant information delay.

In a closed toll highway, which is the main focus of this study, it is considerably easy to obtain travel times between all origin-destination pairs. By directly measuring the time taken by the vehicles to travel between certain OD pairs, electronic toll collection system provides necessary information about OD pairs. However, the demand level associated with particular OD pairs is not always enough to obtain accurate average travel times. Especially the demand between consecutive junctions, where the information delay is minimum, can be extremely low, since travelers do not prefer using toll highways for short distance trips.

Therefore, travel time estimation algorithm should be based on a methodology that would address the problems arising from both the configuration of toll collection system and the information delay.

Once accurate travel time estimates are obtained, future traffic states can be predicted using time series models.

1.3 Thesis Outline

The main goal of this thesis is to obtain accurate travel time estimates and to produce short-term traffic forecasts based on these estimates using the data collected by the toll collection system.

Chapter 2 covers the literature review on traffic forecasting, focusing on types of implementations, data resolution and traffic parameters, and time series models encountered in the literature.

Chapter 3 describes the network where developed methods are going to be tested and presents a preliminary data analysis to find out how to approach the problem.

Chapter 4 describes the data filtering algorithm implemented to obtain accurate average itinerary travel times.

Chapter 5 presents two estimation methods based on universal kriging and mathematical programming.

Chapter 6 covers time series models applied to predict future traffic states on the network.

Chapter 7 presents the conclusions and the recommendations of the study along with the scope of research.

Chapter 2 - Literature Review

2.1 Type and Area of Implementation

Type of implementation can be divided into two categories; advanced traffic management systems (ATMS) and advanced traveler information systems (ATIS). Both systems depend on accurate traffic information, however, they differ from each other in several aspects. For real time adaptive traffic control systems, the prediction interval should be significantly decreased. Ledoux (1997), for instance, predicted queue lengths at 1min intervals in a signalized intersection and aimed to integrate it with a real time adaptive urban traffic control system. Cheslow et al. (1992) pointed at the relation of dynamic traffic control to the ability to gather accurate traffic predictions. ATIS would require a larger ITS environment. According to Lieu (2000), such a system must take into account compatibility with other applications, consistency with the actual network, synchronization with data collection methods and computational efficiency.

Most traffic forecasting studies do not clearly indicate what type of system their model would be integrated. As a matter of fact, there is no clear difference between the forecasting models applied by two types of systems. However, ATMS tend to use traffic parameters such as flow, speed and density as control measures, while ATIS tend to provide travel time information, which can be easily comprehended by general public.

Most of traffic forecasting studies are concerned with freeways because there is a greater density of information on freeways and the uninterrupted nature of traffic flows increases the accuracy of the collected data (Billings and Yang, 2006). Some studies that

produce prediction algorithms for freeways are Park and Rilett (1998), Smith and Demetsky (1996) and Van Lint et al. (2003).

In urban networks, due to highly interrupted traffic flow, forecasting tools become more complex. Forecasting applications on urban networks are tended to be integrated with control systems (e.g. signal timing) in addition to traveler information. Some examples of traffic forecasting studies on urban networks are Billings and Yang (2006), Dimitriou et al. (2008), Hamed et al. (1995), Head (1995) and Hong et al. (2011).

2.2 Data Resolution and Traffic Parameters

Data resolution is strongly related to the parameters of time series traffic prediction model. The parameters of the model are defined as follows:

Prediction Horizon: It indicates the time window ahead to which the prediction is referring.

Prediction Step: Time interval upon which the forecasts are updated.

Rolling Horizon: It represents the time window that defines the prediction history. The future time series value is assumed to be affected only by time series values within the rolling horizon.

Rolling Step: Time interval that indicates how the rolling horizon is divided.

Intuitively, the larger the prediction horizon, the larger the model error becomes. The shorter the prediction step, the more difficult the forecasting gets due to high variability in traffic conditions. Vanajakshi and Rilett (2007) concluded that historical

data perform better than time series models for prediction horizons more than 30 minutes, which implies the negative effect of increasing forecasting horizon. Ishak and Al Deek (2002) also concluded that prediction accuracy decreases as the forecasting horizon increases. Dharia and Adeli (2003) investigated the effect of four different forecasting horizons and rolling steps (3,5,10,15 min) and concluded that the smaller the forecasting horizon is (and rolling step at the same time), the smaller the error gets. When it comes to forecasting step, although most of the data collection systems provide high resolution of traffic data (e.g. 30s, 1min), researchers tend to aggregate the data in 5 min intervals or more (Behrisch et al., 2008; Dougherty and Cobbett, 1997; Park et al., 1998).

To conduct a short-term traffic forecasting model, data should be available in such a resolution that would capture the changes in traffic parameters and that would not be subject to strong variations. Highway Capacity Manual (2000) suggests that 15 min interval is the best prediction interval, since traffic parameters show high variations in shorter intervals. Kirby et al. (1997), Miwa et al. (2004), Ulbricht (1994), Van der Voort et al. (1996) and Williams (2001) use 30 min or more as forecasting step based on the argument that wider data aggregation intervals lead to reduced variations in traffic data. Even though it overcomes the fluctuation problem related to the data, these studies may not be able to capture rapid changes in traffic conditions.

Typical trip activities on urban arterials and freeways take no less than 30 min. Therefore, in terms of traveler information systems or extended traffic management systems, there is need for traffic forecasting algorithms that would use a prediction step greater than 5 min and a predictive horizon greater than 30 min. On the other hand, for short-term operational modifications and real-time adaptive traffic control systems (e.g.

signal timing), the prediction horizon can be decreased to 30s or 1 min intervals. For example Davis et al. (1991) and Ledoux (1997) predicted traffic parameters at 1 min intervals to detect congestion and to determine the signal timing respectively. Head (1995) used 5 seconds prediction step and forecasted the traffic flow for multiple steps ahead (30 seconds or 40 seconds) to reschedule the signal timing.

Commonly used parameters in traffic prediction are the three main traffic parameters; flow, speed and density. However, there are other studies that attempt to predict different variables; OD demand (Ashok and Akiva, 2000; Hu and Chen, 2004; Kachroo et al., 1997; Lin and Chang, 2007; Muller et al., 2005; Zhou and Mahmassani, 2007), flow storage rate (difference between inflow and outflow) (Davis et al., 1991), queue length (Ledoux, 1997). Another important prediction parameter is travel time, which will be discussed later in this section.

The studies that focus on the fundamental three traffic parameters do not show a strong agreement on which parameter is more suitable to describe traffic conditions. Lin et al. (2002) used occupancy (as a measure of density) to keep track of traffic conditions. However, for instance, Hong et al. (2011) and Neto et al. (2009) only predicted traffic flow considering the fact that occupancy is subject to strong fluctuations compared with flow. Dougherty and Cobbett (1997) created separate model for each of the three fundamental traffic parameters. While they obtained successful results for flow and occupancy, their forecasts of vehicle speed was much less successful, probably because of the distorting effect of slow moving vehicles.

Some studies deal with the traffic prediction problem forecasting more than one traffic variable at the same time. Mihaylova et al. (2006) employing a stochastic decomposition traffic model, particle filter framework and using only flow observations estimated all the three fundamental characteristics of roadway segments. Innamaa (2000) used both flow and speed measurements for predicting flow. Author concluded that two separate models show a better performance than a single model for speed and flow. Clark (2003) developed a multivariate nonparametric regression model for two of the three traffic state variables and obtained satisfactory results for flow and occupancy. Florio and Mussone (1996) used the idea of flow-speed relationship and predicted three fundamental parameters; however, their model was quite complex due to the incorporation of several variables such as percentage of heavy vehicles, weather conditions, brightness and the presence of VMS.

Besides the traffic parameters described above, travel time is an important traffic parameter, which is defined as the required time to traverse two fixed points along a highway, freeway or urban arterial (Vlahogianni et al., 2003). The concept of travel time, which is easily comprehensible, provides a common layer to the engineers, planners, administrators, politicians and general public. It has the same meaning in all transportation systems, it does not depend on the roadway characteristics unlike the fundamental traffic parameters. Moreover, once it is compared to the free flow travel time, it can be easily taken as a measure of traffic congestion.

According to Travel Time Data Collection Handbook (1998), data can be obtained through loop detectors, test vehicles, license plate matching techniques (automatic vehicle identification, AVI) and ITS probe vehicle techniques. All the

techniques except the one based on loop detectors provide directly measured travel time data (Chen and Chien, 2001; Hunter et al., 2009; Park et al., 1998).

Traffic information from probe vehicles has great potential to improve the accuracy of collected data. With the increasing use of GPS devices and GPS enabled mobile phones, methods dealing with probe data to estimate traffic states become more of an issue. Travel time on urban networks is not a function of flow and speed, but the synthesis of free flow travel time and other factors such as signal timing and conflicts at intersections. Hence, loop detector based travel time estimations do not offer great insight into the problem solution, probe vehicles are widely used to estimate the arterial travel time (Travel Time Data Collection Handbook, 1998; Balke et al., 2005). Another major research direction related to probe vehicles is determining requires sample size of probe vehicles. Chen and Chien (2000) developed a heuristic approach to determine the minimum number of probe vehicles.

Networks are usually equipped with loop detectors that provide information about flow, spot speed and occupancy. So, travel time estimation is based on the spot speed detected by detector infrastructure (Cortes et al., 2001). Double loop detectors provide speed measurement which is necessary to calculate travel time (Dia, 2001); however, in case of single loop detectors, travel time is estimated using flow and occupancy relationship and assumption of mean vehicle length (Dailey, 1997). Coifman (2002) developed a model to measure direct travel time (not based on local velocity measurements) using the data collected by dual loop detectors and correlating vehicle observations at multiple locations, then, Coifman et al. (2007) extended this study for the data collected by single loop detectors. Petty et al. (1998) proposed a method for direct

travel time measurement based on single loop detector data and a stochastic traffic flow model. However, travel time in urban networks is influenced by other factors such as signal timing and confliction at intersections. Therefore, recent research on arterial travel time estimation starts to consider traffic data and signal timings simultaneously. Skabardonis and Geroliminis (2008) and Liu and Ma (2009) developed models based on loop detector data and signal timing information to estimate arterial travel time.

Attention must be given to the attempts made to forecast travel time using AVI data collected by toll system. Chien and Kuchipudy (2003) used the data collected by road side terminals installed on roadway. The vehicles with electronic toll tags are scanned by road side terminals and entry times are recorded. It can be described as an 'open' toll system where toll plazas are located so that all drivers pay the same average toll fee. As the system identifies the vehicles on the main highway trunk, it is similar to other AVI-based studies encountered in the literature (Dion and Rakha, 2006). However, 'closed' toll systems, where the toll fee is based on the distance travelled along the network and where toll booths are located on the on and off-ramps, are only discussed by Ohba et al. (1999), Faouzi et al. (2009), Faouzi et al. (2010), Soriguera et al. (2007) and Soriguera et al. (2010). Ohba et al. (1999) dealt with a single origin destination pair. Faouzi et al. (2009) developed a data fusion model to combine loop detector and toll data and to improve travel time estimates of a particular OD pair. Faouzi et al. (2010) used the historical average of particular OD travel times to estimate the new ones. Soriguera et al. (2007) developed a simple algorithm to convert OD travel time to single-section travel times and Soriguera et al. (2010) improved the work by incorporating a data filtering algorithm developed by Dion and Rakha (2006) and by extending the simple algorithm.

2.3 Estimation Methodologies

The state-of-art in traffic forecasting (flow, density, speed and travel time) can be divided into two categories; parametric techniques and non-parametric techniques. Among the parametric techniques employed by the studies related to traffic forecasting, the most simple one is the historical average algorithm (Smith and Demetsky, 1997; Faouzi et al., 2010). Williams et al. (1998) and Dion and Rakha (2006) implemented smoothing techniques as a filter that eliminates the high noise in the collected data and to attain better travel time forecasts. Dion and Rakha (2006) employed an exponential smoothing factor as the level of confidence on the travel time estimate, which is determined by the number of observations. Auto-regressive integrated moving average (ARIMA) techniques are also widely used in the traffic forecasting area. Ahmed and Cook (1979) first used the ARIMA technique in traffic forecasting area. They concluded that the ARIMA model outperforms moving average and smoothing models in forecasting traffic flow and occupancy. However, the drawback of ARIMA models is their tendency to focus on the mean values and miss the extremes, which is the main interest of traffic forecasting (Vlahogianni et al., 2003). Davis et al. (1991) compared the performance of ARIMA models to pattern recognition (PR) techniques and concluded that PR outperforms ARIMA.

Examples of ARIMA applications include single ARIMA (Davis et al., 1991; Hamed et al., 1995), adaptive seasonal ARIMA (Shekhar and Williams (2007), a combination of it with Kohonen maps (Van der Voort et al., 1996), multivariate ARIMA (Williams (2001) and the subset ARIMA (Lee and Fambro, 1999) and multivariate spatial temporal auto-regressive (MSTAR) model (Min and Wynter, 2010).

Another common parametric method is the Kalman Filter. It consists of two parts; an estimation equation which is generally called 'state-space' model and a measurement equation which is called 'Kalman Filter'. Its main advantage is the ability to update the variables continuously, incorporation of time series into the model and its multivariate nature. Okutani and Stephanedes (1984) first applied Kalman Filtering technique to predict urban traffic volumes. Wang et al. (2008) and Nanthawichit et al. (2003) used macroscopic traffic flow model equations as the estimation equation of the extended Kalman Filter model, which demonstrates the applicability of the framework to the dynamic system model of freeway traffic. However, simple time series equations can also be incorporated as the estimation equation of Kalman Filter (Dimitriou et al. (2008), Chien and Kuchipudi (2003), Dailey (1997), Kachroo et al., 1997). Stathapoulos and Karlaftis (2003) implemented a multivariate state-space approach to predict urban traffic flow and concluded that it clearly outperformed the simple ARIMA formulation.

Recently, researchers have started to implement non-parametric techniques mainly borrowed from the artificial intelligence area. Non-parametric techniques can be acknowledged as robust and flexible methods that can address nonlinearity and uncertainty issues, compared to parametric techniques described above. Three important non-parametric techniques have been widely used in the area of traffic forecasting; non-parametric regression, neural networks and most recently support vector machines.

Non-parametric regression is based on a predictor which does not have a specific predetermined functional form but is constructed according to the data. As other non-parametric models, non-parametric regression requires large sample size compared to parametric models. The principles of pattern recognition help identify the clusters and

build the predictor. Smith and Demetsky (1996) first implemented nearest neighbor non-parametric regression and concluded that forecasting model produced accurate short-term and long-term traffic flow predictions. Another example of nearest neighbor non-parametric regression models is Rice and Zwet (2004) which concluded that linear regression outperformed nearest neighbor model. Smith and Demetsky (1997) compared the performance of the proposed model to historical average, ARIMA and neural networks and concluded that non-parametric regression outperformed the other models. Smith et al. (2002) developed a non-parametric regression model based on heuristically improved forecast generation methods. The straightforward approach for the forecast generation method is the simple average of the neighbor values that have fallen inside the nonparametric regression neighborhood. Instead of this simple approach, authors develop five calculation methods that are heuristic attempts to improve the performance of the model by taking into account the relative distance of the neighbors to the forecast point. Although it significantly improved the performance of nonparametric regression, ARIMA exhibited better performance than nonparametric regression model. Clark (2003) used a multivariate nonparametric regression to predict two of the three traffic states and achieved satisfactory results.

Neural network is a computational model that is inspired by biological neural networks and is based on pattern recognition techniques (Vlahogianni et al., 2003). Even if the underlying relationship between dependent and independent variables is not clear, the ability of neural networks to address uncertainty and nonlinearity makes them useful for working with databases with large noise. Neural networks have been widely applied in the area of traffic forecasting (Dharia and Adeli, 2003; Dougherty and Cobbett, 1997;

Florio and Mussone, 1996; Huisken and Van Berkum, 2003; Mark et al., 2004; Nikovski et al., 2005). There are various application of neural networks in the traffic forecasting area; multilayer perceptrons (Smith and Demetsky, 1994; Zhang and Rice, 2003; Park and Rilett, 1998), time-delayed recurrent neural networks (Dia, 2001), multi-recurrent neural networks (Ulbricht, 1994), state space neural networks (Van Lint et al., 2002; Van Lint et al., 2003; Van Lint et al., 2005) and neural networks based on optimal weight parameters determined by Kalman Filter (Liu et al., 2006(b); Liu et al., 2006 (c)).

Support vector machines, originally developed to solve pattern recognition problems, with the novelty of Vapnik's ε -insensitive loss function has been applied to solve regression problems (Support Vector Regression, SVR) and has been applied in many forecasting fields, such as financial time series and biology. However, in traffic flow and travel time predictions, SVR has not been widely applied. Ding et al. (2002) in traffic flow prediction and Wu et al. (2004) in travel time prediction are probably the first attempts to implement SVR in traffic field. Vanajakshi and Rilett (2007) applied both SVM and ANN for short-term prediction of travel time and concluded that they produce comparable results. However, their empirical observations indicated that if training data size is small or training data has more variations than testing data SVM becomes a better choice. Lam and Toan (2008) incorporated nearest neighbor method to retrieve patterns closest to the test vector in SVR training and achieved a substantial reduction of training size. The selection of three parameters (σ , ε and C ; kernel function type, insensitive region parameter and penalty parameter, respectively) in SVR model has a significant effect on model performance. Since in traffic applications data are collected in short time intervals and conventional SVR requires complete model training, Su et al. (2007) and

Neto et al. (2009) proposed incremental and online training for SVR to update the prediction function in real-time. Hong et al. (2011) implemented ant colony optimization algorithms (ACO) to determine three model parameters (kernel function type, insensitive region parameter and penalty parameter) in SVR and concluded that the proposed model has a better performance than seasonal ARIMA model.

Another important interest in traffic forecasting is the use of hybrid methods. For example, ATHENA, which is developed by Danech-Pajouh and Aron (1991) implements a clustering method to identify the groups in the data and creates a linear regression model for each group. Van der Voort (1996) combined Kohonen maps with ARIMA and obtained comparable results with ATHENA and a better performance than conventional ARIMA model. There are also some hybrid neural network applications in the field of traffic forecasting. Examples of hybrid neural networks are combined genetic algorithms (GA) and neural networks (Abdulhai et al., 1999; Vlahogianni et al., 2005), combined fuzzy logic and neural networks (Ishak and Alecsandrou, 2003) and bayesian combined neural networks (Zheng et al., 2006). Dimitriou et al. (2008), on the other hand, developed a hybrid, meta-optimized fuzzy-rule based system (FRBS) to predict urban traffic flow and they concluded that it outperforms ARIMA and Kalman Filter.

An important part of the research has concentrated on the comparison of non-parametric techniques with the conventional statistical approaches. Smith and Demetsky (1997) and Clark et al. (1993) compared the performance of neural networks and ARIMA approach and concluded that NN outperforms ARIMA. Kirby et al. (1997) compared ATHENA, ARIMA and neural networks and concluded that ATHENA outperforms both ARIMA and neural networks. Moreover, Smith et al. (2002) and Williams et al. (1998)

reported that seasonal ARIMA models have a comparable performance with non-parametric regression models.

Table 2-1. Summary of the Available Literature

Author	Date	Data	Area		Data Resolution		Traffic Parameters					Parametric			Non-Parametric					
			Freeway	Urban	Step	Horizon	Flow	Occupancy - Density	Speed	OD	Travel Time	ARMA - ARIMA	Kalman Filter	Other	Non-parametric regression	Neural Networks	Support Vector Machine	Other	Hybrid	Simulation - flow theory
Hong et al.	2011	R		✓	60	1	✓					✓					✓			
Min and Wynter	2011	R	✓	✓	5	12	✓		✓			✓								
Faouzi et al.	2010	T	✓		15	1					✓			SA						✓
Ren et al.	2010	R	✓		2	1		✓	✓											
Soriguera et al.	2010	T	✓		15	1					✓			F						
Faouzi et al.	2009	T-R	✓		6	1					✓			F						
Hunter et al.	2009	P		✓	1	1					✓							BN		
Castro-Neto et al.	2009	R	✓		5	1	✓										✓			
Wang et al.	2009	R	✓		1	1	✓		✓				✓							
Behrisch et al.	2008	R	✓	✓	5	6	✓													✓
Dimitriou et al.	2008	R		✓	3	1	✓					✓	✓						✓(b)	
Herrera and Bayen	2008	P-R	✓		1.2s	1	✓				✓		✓	N						
Lam and Toan	2008	R	✓		15	4					✓						✓			
Paterson and Rose	2008	R	✓		1	1					✓									✓
Shekhar and Williams	2008	R	✓		15	1	✓					✓								
Van Lint	2008	R	✓		1	1							✓							
Wang et al.	2008	R	✓		1	1	✓		✓				✓							
Work et al.	2008	P	✓						✓				✓							
Yeon et al.	2008	R	✓		1	1					✓			DTMC						
Lin and Chang	2007	R	✓		2	1				✓			✓							
Mihaylova et al.	2007	R	✓		1	1	✓	✓	✓				✓							✓
Sau et al.	2007	R-T	✓		6	1	✓	✓												
Soriguera et al.	2007	T	✓		15	1					✓			F						
Su et al.	2007		✓				✓										✓			
Vanajakshi and Rilett	2007	R	✓		2	30					✓						✓			
Xie et al.	2007	R	✓		5	1	✓						✓							
Zhou and Mahmassani	2007	R	✓		5	4				✓			✓							
Billings and Yang	2006	P		✓	2.25	1					✓	✓								
Liu et al.	2006	R	✓		5	1					✓									✓
Liu et al. (2)	2006	R		✓	5	1					✓						✓			
Liu et al. (3)	2006	R		✓	10	1					✓						✓			
Sun et al.	2006	R	✓		15	1	✓											BN		
Vlahogianni et al.	2006	R	✓		1.5	1	✓	✓						PR		✓				

Table 2-1. Summary of the Available Literature

			Area		Data Resolution		Traffic Parameters					Parametric			Non-Parametric					
			Freeway	Urban	Step	Horizon	Flow	Occupancy - Density	Speed	OD	Travel Time	ARMA - ARIMA	Kalman Filter	Other	Non-parametric regression	Neural Networks	Support Vector Machine	Other	Hybrid	Simulation - flow theory
Author	Date	Data																		
Wang et al.	2006	R	✓		1	20	✓		✓				✓							
Zheng et al.	2006	R	✓		15	1	✓												✓(b)	
Chu et al.	2005	P-R	✓		30s	1							✓							
Muller et al.	2005	R	✓				✓	✓	✓	✓	✓						✓			✓
Nikovski et al.	2005	R	✓		5	24					✓			LR, TB		✓				
Van Lint et al.	2005	R	✓		1	1					✓					✓				
Vlahogianni et al.	2005	R		✓	3	5					✓								✓(b)	
Wang et al.	2005	R	✓		1	1	✓		✓				✓							
Yang	2005	P		✓	3-5	1					✓		✓							
Hu and Chen	2004	R	✓		5	1				✓										
Mark et al.	2004	P	✓		5	4					✓						✓			
Miwa et al.	2004	P	✓	✓	60	1					✓									
Nakata and Takeuchi	2004	P		✓	15-60	1					✓	✓	✓							
Rice and Van Zwet	2004	R	✓		5	12					✓			LR, PC	✓			NN		
Wu et al.	2004	R	✓		3	1					✓						✓			
Clark	2003	R	✓		10	1	✓	✓	✓						✓					
Dharia and Adeli	2003	P	✓		3-5-10-15	1					✓						✓			
Huisken and Van Berkum	2003	R	✓		6	1					✓						✓			
Ishak and Alecsandrou	2003	R	✓		5	4			✓								✓			
Ishak and Al Deek	2003	R	✓		5	3					✓			NLTS						
Kamarianakis and Prastacos	2003	R	✓		1.5	5	✓	✓				✓								
Nanthawichit et al.	2003	P	✓		3	1			✓		✓		✓							
Stathopoulos and Karlaftis	2003	R		✓	3	1	✓						✓							
Van Lint et al.	2003	R	✓		4	1					✓						✓			
Zhang and Rice	2003	P-R	✓		30s	120					✓			LR						
Chien and Kuchipudi	2002	P-R	✓		5	1					✓		✓							
Ding et al.	2002	R	✓			1	✓													
Ishak and Al Deek	2002	R	✓		5	3					✓			NLTS						
Kwon et al.	2002	P-R	✓		2.5	8					✓			LR-TB						
Lin et al.	2002	R	✓		5	1		✓						HA						
Smith et al.	2002	R	✓		15	1	✓					✓			✓					
Tebaldi et al.	2002	R	✓		1	1	✓							HRM						
Van Lint et al.	2002	R	✓		1	1					✓					✓				

Table 2-1. Summary of the Available Literature

Author	Date	Data	Area		Data Resolution		Traffic Parameters					Parametric			Non-Parametric					
			Freeway	Urban	Step	Horizon	Flow	Occupancy - Density	Speed	OD	Travel Time	ARMA - ARIMA	Kalman Filter	Other	Non-parametric regression	Neural Networks	Support Vector Machine	Other	Hybrid	Simulation - flow theory
Chen and Chien	2001	P-R	✓		5	1					✓		✓							
Dia	2001	R	✓		20s	3			✓		✓					✓				
Williams	2001	R	✓		30	1	✓					✓								
Ashok and Akiva	2000	R	✓		15	3				✓			✓							
Innamaa	2000	R	✓		5	3	✓		✓							✓				
Ohba et al.	2000	T	✓		5	1					✓	✓								
Zhang	2000	R	✓		30s	1	✓									✓				
Abdulhai et al.	1999	R	✓		30s	30	✓	✓											✓(b)	
Lee and Fambro	1999	R	✓		5	1	✓					✓								
Park et al.	1999	R	✓		5	5					✓					✓				
Yasdi	1999	R	✓		5	1	✓									✓				
Park and Rilett	1998	R	✓		5	5					✓					✓				
Williams et al.	1998	R	✓		15	1	✓					✓		S						
Dailey	1997	R	✓		20s	1			✓		✓		✓							
Dougherty and Cobbett	1997	R	✓		5	6	✓	✓	✓							✓				
Kachroo et al.	1997	R-T	✓		15	1				✓			✓							
Kirby et al.	1997	R	✓		30	2	✓					✓				✓				
Ledoux	1997	R		✓	1	1	✓												✓(a)	
Smith and Demetsky	1997	R	✓		15	1	✓					✓		HA	✓	✓				
Van Arem et al.	1997	R	✓		1	1	✓					✓								
Florio and Mussone	1996	R	✓		8.67	1	✓	✓	✓							✓				
Nam and Drew	1996	R	✓		2	1			✓		✓									
Smith and Demetsky	1996	R	✓		15	6	✓								✓					
Van der Voort et al.	1996	R	✓		30	1	✓												✓(a)	
Hamed et al.	1995	R		✓	1	1	✓					✓								
Head	1995	R		✓	5s	1	✓				✓									
Smith and Demetsky	1994	R	✓		15	1	✓									✓				
Ulbricht	1994	R	✓		60	1	✓									✓				
Davis et al.	1991	R	✓		1	1	✓	✓				✓		PR						
Okutani and Stephanedes	1984	R		✓	5	6	✓						✓							
Ahmed and Cook	1979	R	✓		30s	1	✓	✓				✓								

Hybrid models: (a) combination of parametric and non-parametric approaches, (b) combination of fuzzy logic and genetic algorithm with neural networks

PR: Pattern Recognition, F: Fusion, SA: Search Algorithm, N: Nudging, NLTS: Non-linear time series, LR: Linear Regression, TB: Tree-Based methods, HA: Historical Average, PC: Principal Components, HRM: Hierarchical Regression Method, S: Smoothing, DTMC: Discrete Time Markov Chains, BN: Bayesian Networks, NN: Nearest Neighbors

Chapter 3 Data Description & Analysis

3.1 Data Description

New Jersey Turnpike is a toll road in New Jersey and it is among the busiest highways in US. The main line of NJ Turnpike has a length of about 120 miles and connects the municipalities of NJ to New York City. It actually serves one of the most congested areas in US. Roadway configuration and interchanges are shown in **Figure 3-1**.

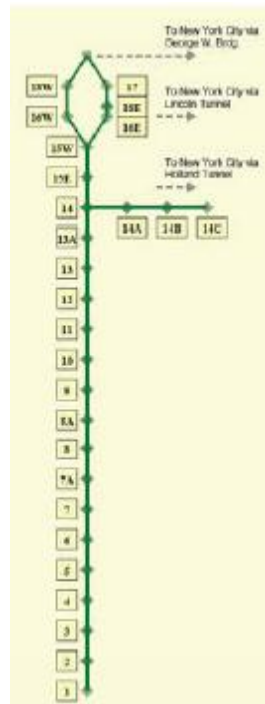


Figure 3-1. New Jersey Turnpike Configuration and Interchanges (Bartin and Ozbay, 2006)

Turnpike has a total of 4 lanes between Exit 1 and Exit 4, 6 lanes between Exit 4 and Exit 8A. Turnpike splits into a dual-dual configuration before Exit 8A (going north), where the outer lanes are open to all vehicles and the inner lanes are limited to cars only. From there to Exit 14, the road ranges from 10 to 14 lanes; starting from south of Exit 8A and until Exit 9, it has a total of 10 lanes (2-3-3-2), 12 lanes (3-3-3-3) between Exit 9 and Exit 11 and 14 lanes (4-3-3-4) between Exit 11 and 14. Between Exit 14 and 18, the Turnpike splits into two spurs; eastern and western. The road also has an extension which contains three exits (Exits 14A, 14B and 14C) and which connects Newark with Lower Manhattan via Holland Tunnel.

The New Jersey Turnpike (NJTPK) is a closed system toll road, using a system of long-distance tickets and the toll fee depends on the distance travelled. Besides the traditional ticket system, E-Z Pass, electronic toll collection system, has been used in NJTPK since 2002. Besides the fact that the system has been an important means to alleviate congestion around toll plazas, it has brought another important benefit to transportation researchers; E-Z Pass provides us complete and accurate traffic information about NJTPK. Each transaction in toll plazas is recorded in the system database with both entry and exit information (time, interchange, type of vehicle, etc.). Data collection system is not available in real-time but, assuming that it will be available soon, we will attempt to forecast traffic patterns along the roadway.

Direct measurement techniques, such as electronic toll collection system used in this study, provides travel time information once the vehicle reached the point where the readers are located or once the vehicle left the roadway. Hence, especially travel time measurements of long trips are based on the past conditions of the roadway. Therefore, a

real time information system must provide travel time estimates that would address information delay problem.

The main research question is: "Based on historical traffic patterns detected by a sensing technology is it possible to predict congestion before it happens?". Most of the previous research on this subject is based on the information obtained through road sensors or transponders. However, travel time estimation based on spot speed may not be accurate, because instantaneous speed averaged for several vehicles cannot account for the difference of the vehicles that travel along the same path at different speeds. On the other hand, AVI data through toll readers at the exit and entrance locations of the road system are much more complete and precise in several aspects such as OD demands and experienced travel times.

To create a dynamic data driven travel time prediction tool, we should first investigate the evolution of traffic patterns in small time intervals. Previous research on the subject show that 15 minutes intervals are small enough to detect traffic patterns and long enough to overcome the variation problem due to low number of probe vehicles. In our case, OD travel times can be calculated as the average travel time of vehicles travelling between that particular OD pair while other vehicles that do not belong to the set of this same OD pair but that cross the corresponding path are not taken into account. Hence, data may be subject to high variations in case of small intervals, because the demand for a particular OD pair can be significantly low compared to the number of vehicles actually crossing the whole or a part of the OD path.

NJTPK has $32 \times 31 = 992$ OD pairs in total, which further complicates our problem. So, the focus of the study is narrowed down to links between Exit 8 and Exit 13A, which contains both the dual and single lane configuration. The real challenge of dynamic travel time prediction is to track traffic parameters under non-recurrent congestion conditions. As a first step, only southbound traffic is considered. This network has $8 \times 7 / 2 = 28$ OD pairs.

3.2 Data Analysis

3.2.1 Bound Analysis of Path Demands and Travel Times

One way to address the information delay problem would be the use of travel time measurements for a single-section (i.e. link between successive interchanges), because they are the shortest sections in the roadway for which information delay could be considered negligible. However, demand level associated with a particular OD pair is not always sufficient to obtain accurate average travel times. Especially the demand between consecutive junctions can be extremely low, since travelers do not prefer using toll highways for short distance trips. The preliminary study on travel time observations showed that simple median of travel time observations results in inaccurate travel time estimates in the case where the demand is less than or equal to 5 travelers. Representative travel time value, defined as the median of observations, is subject to outliers' effect in such low demand cases. Assuming the intervals that have less than or equal to 5 observations (i.e. less than 5 travelers within 15 min period) are insufficient to obtain an accurate average travel time, **Table 3-1** provides the proportion of intervals with insufficient demand for a 1-year period. 3 out of 7 links do not have sufficient demand to

obtain accurate average travel times for more than half of the time. This brings down the number of OD pairs to 21 to investigate the characteristics of the collected data.

Table 3-1. Demand Level for Successive Interchanges

OD	8A-8	9-8A	10-9	11-10	12-11	13-12	13A-13
Insufficient Obs. (%)	99	34	18	75	51	27	7

To start with, one year of toll transaction data (from 10/1/2008 to 9/30/2009) are aggregated for 15 minute intervals, which brings 96 data points (OD demands and average of travel times exerted by the vehicles that reach their destination within the corresponding time period) per day. OD demands and travel times are known to show day-to-day variations. To investigate this phenomenon, dataset is divided into seven; days of the week. For each day and for each period within the day, the average, upper bound (95%) and lower bound (5%) of travel time and OD demand is calculated (**Figure 3-2**).

As seen in **Figure 3-2**, *Monday* mean travel times have almost a constant value throughout the day, which implies free-flowing conditions regardless of the demand on the network. Despite the high volume of traffic on the roadway, travelers experience more or less the same travel time and they drive under free-flowing traffic conditions throughout the day. Besides, trip travel times show large variations during the nighttime. Although OD demand level is extremely low compared to the daytime level, upper bound of travel time values may reach the highest value within the day. Since the effect of a single vehicle spending more time than the usual in the roadway is more in a small set of travelers, we observe unexpectedly high level of variation in travel time values during the nighttime. While the effect of travelers that spend time in service areas or that experience long travel times for another marginal reason is compensated by force of high level of

OD demands during the daytime, this cannot be accomplished in the nighttime due to low level of OD demands. Moreover, travelers are more likely to have a break and to spend more time in the roadway during nighttime, because they are probably not in a rush to catch up on work.

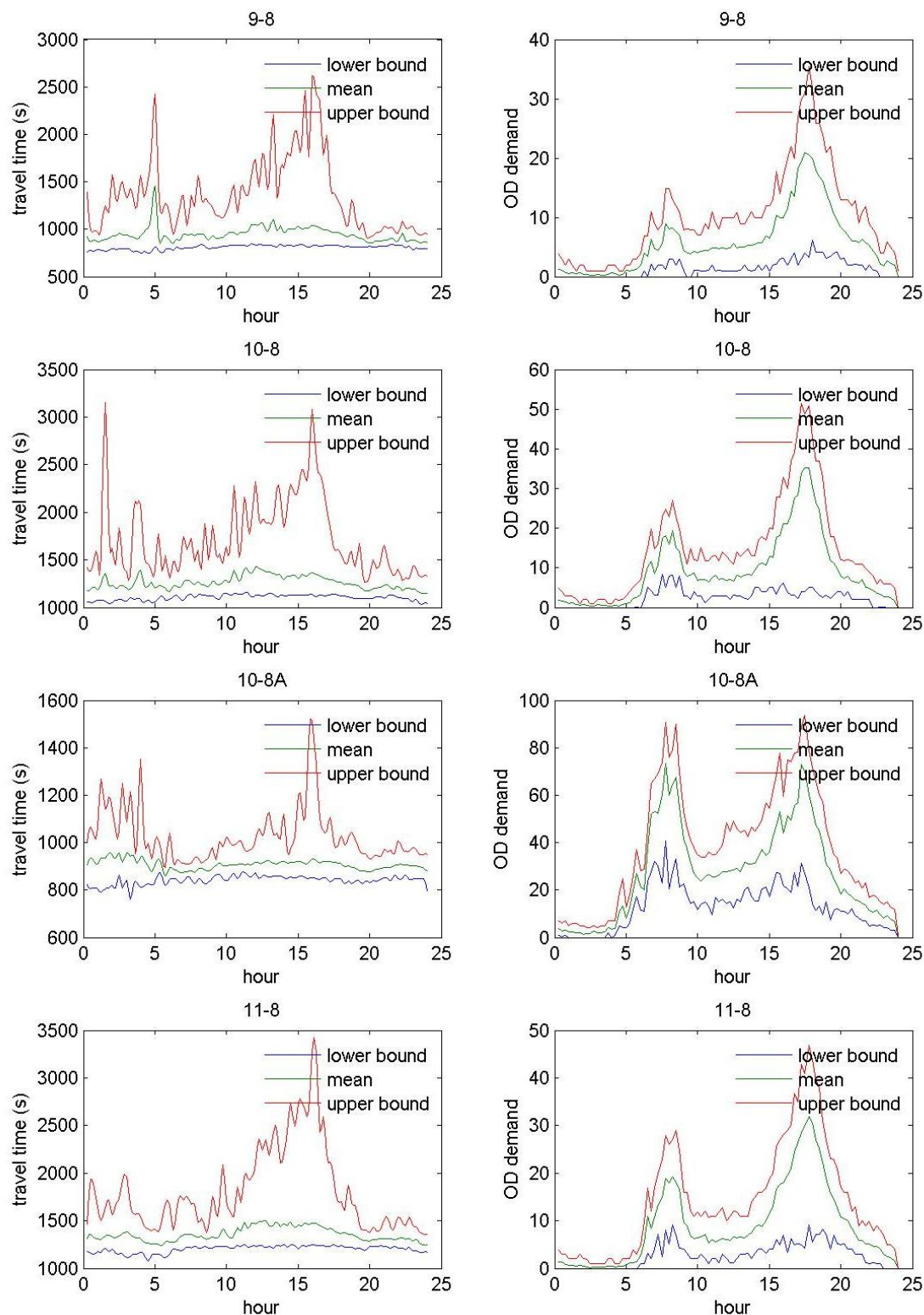


Figure 3-2. Travel Time and OD Demand Variations within the Day (Monday)

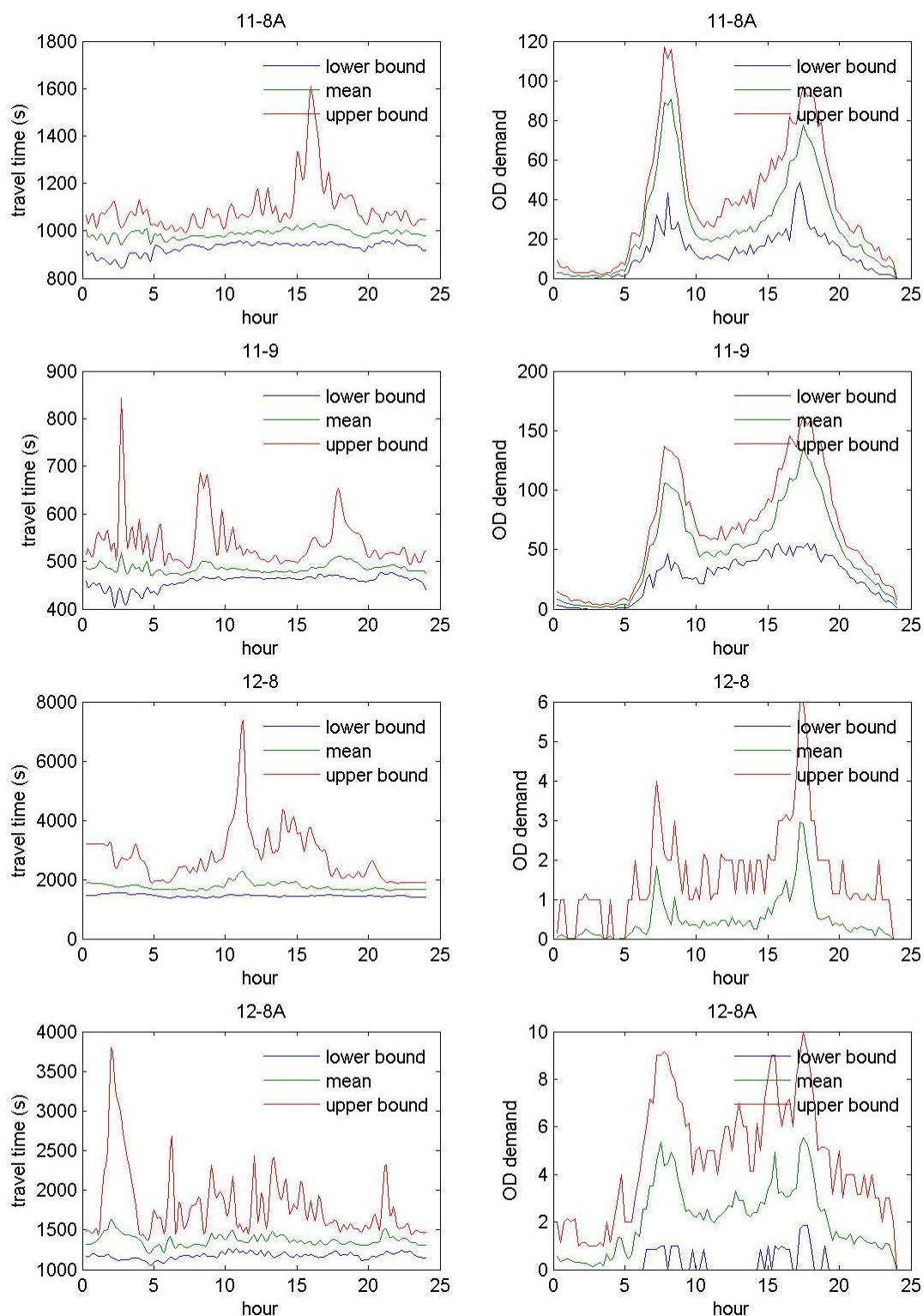


Figure 3-2. Travel Time and OD Demand Variations within the Day (Monday)
(continued)

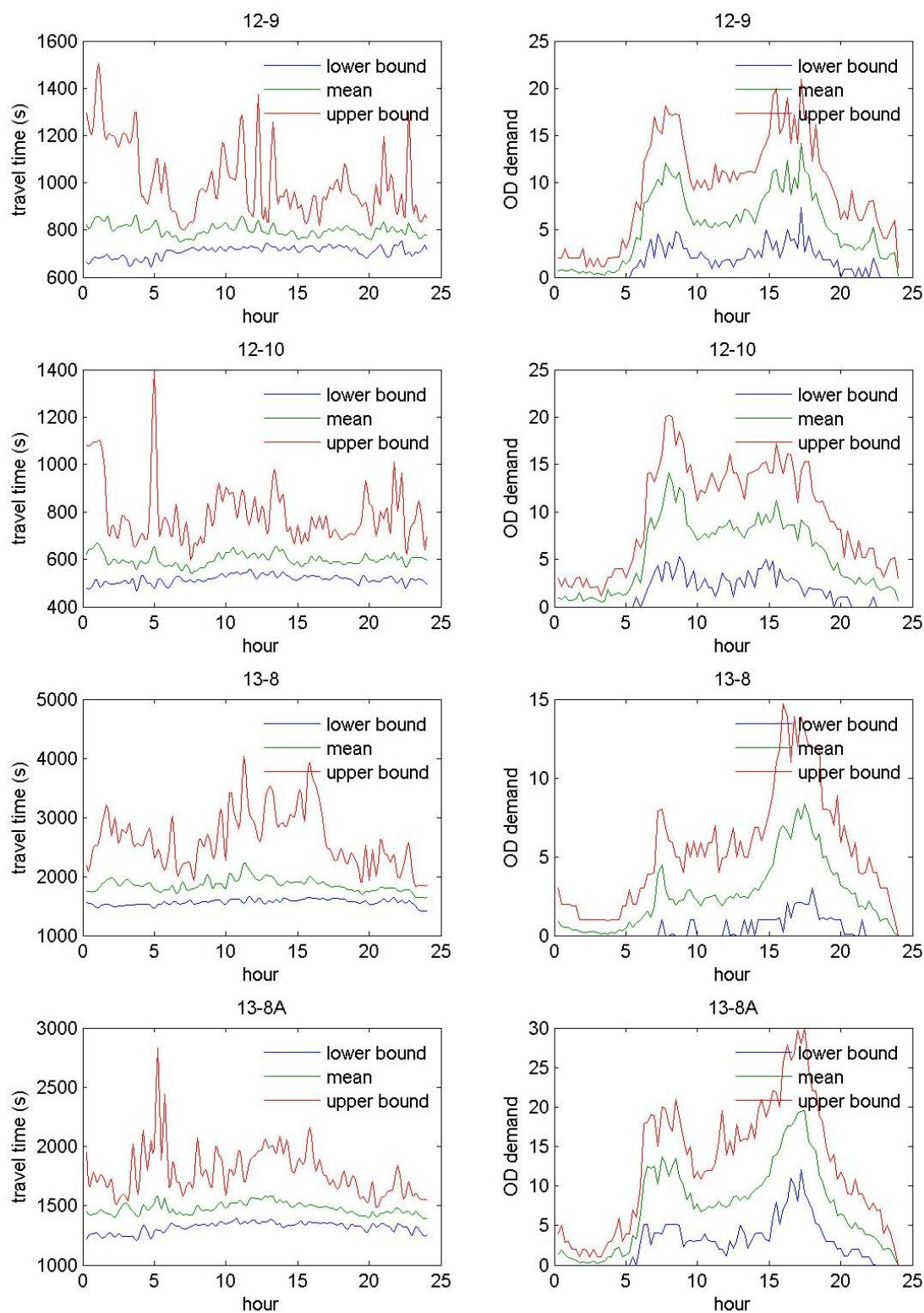


**Figure 3-2. Travel Time and OD Demand Variations within the Day (Monday)
(continued)**

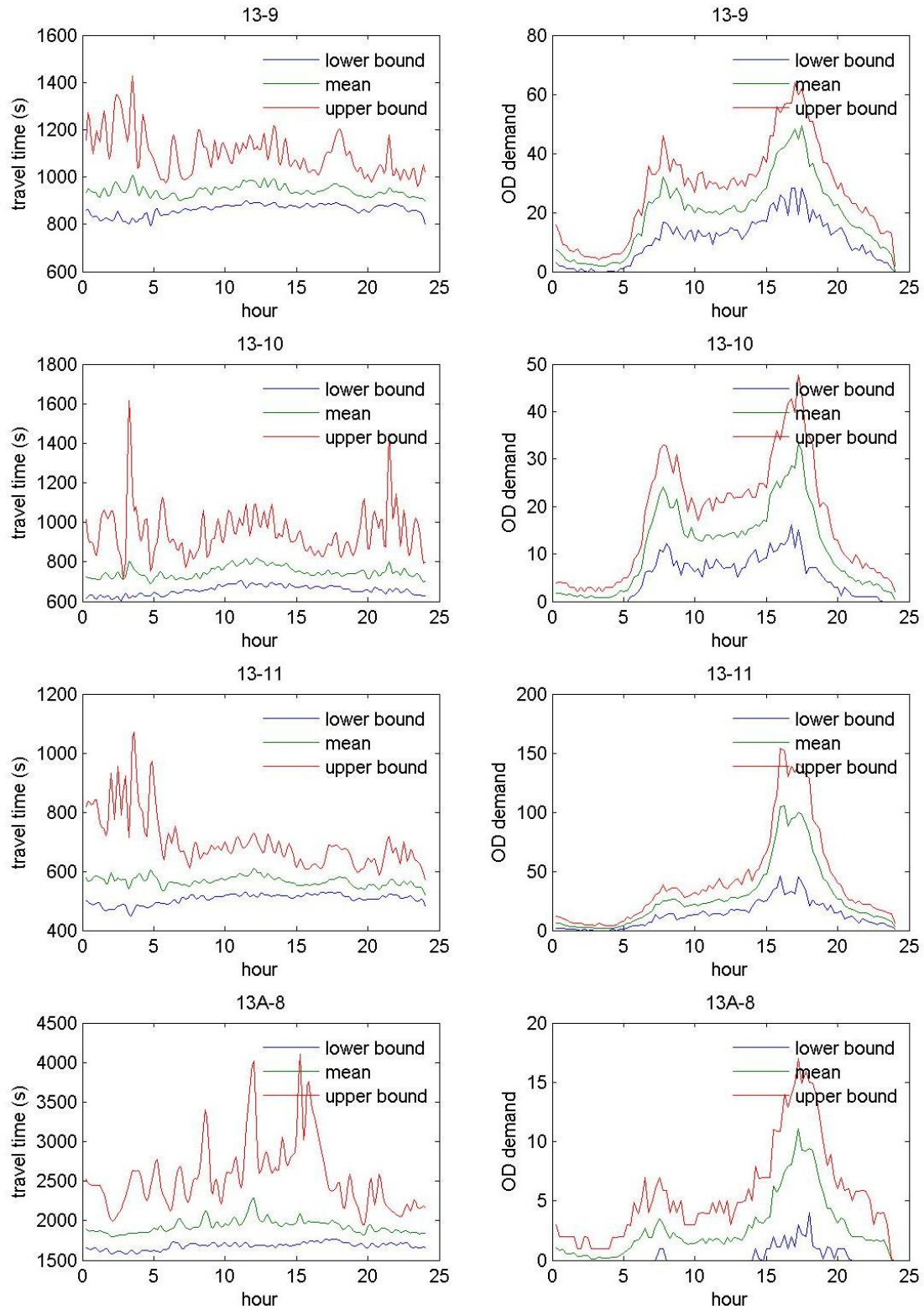


Figure 3-2. Travel Time and OD Demand Variations within the Day (Monday)
(continued)

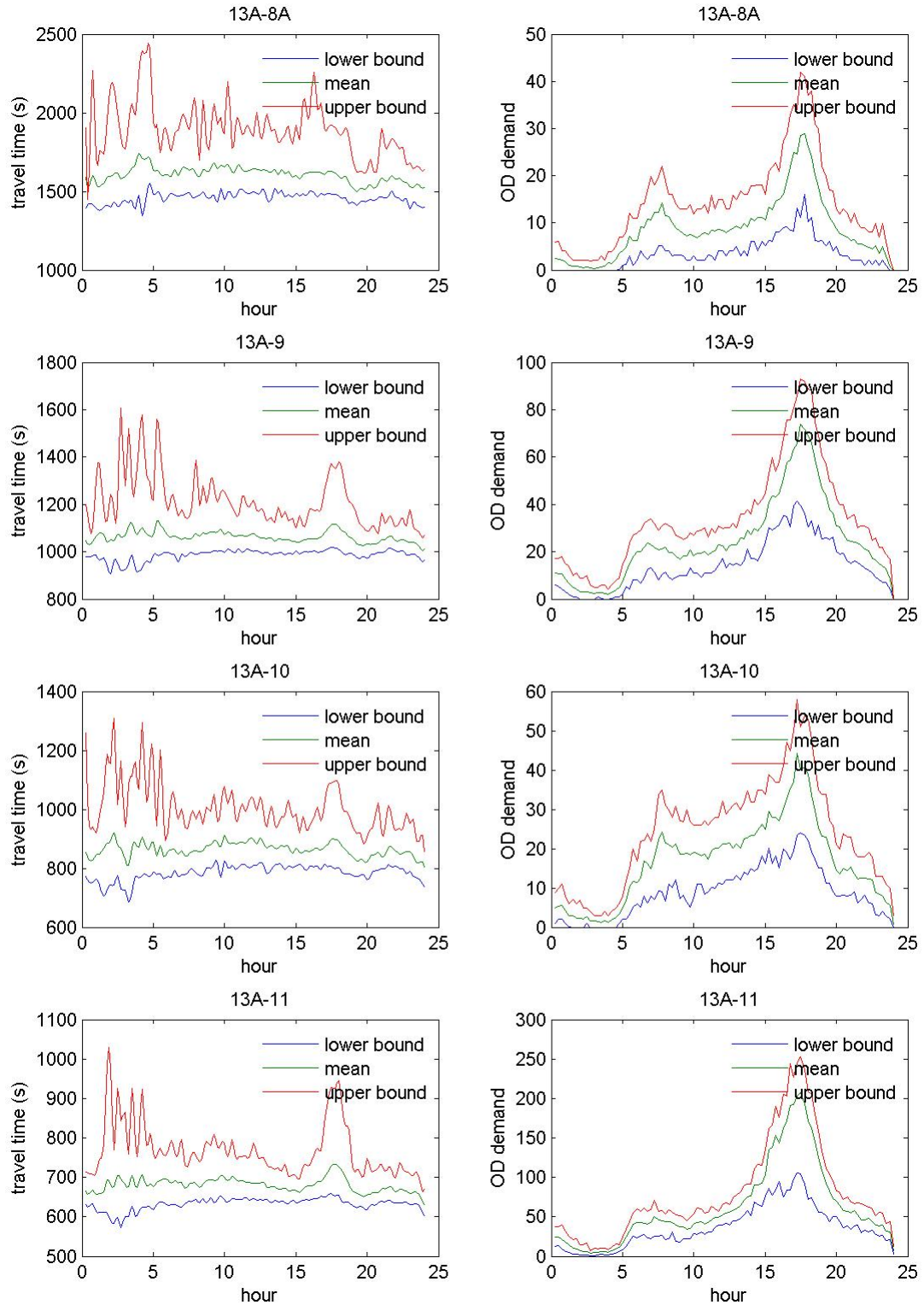


Figure 3-2. Travel Time and OD Demand Variations within the Day (Monday)
(continued)

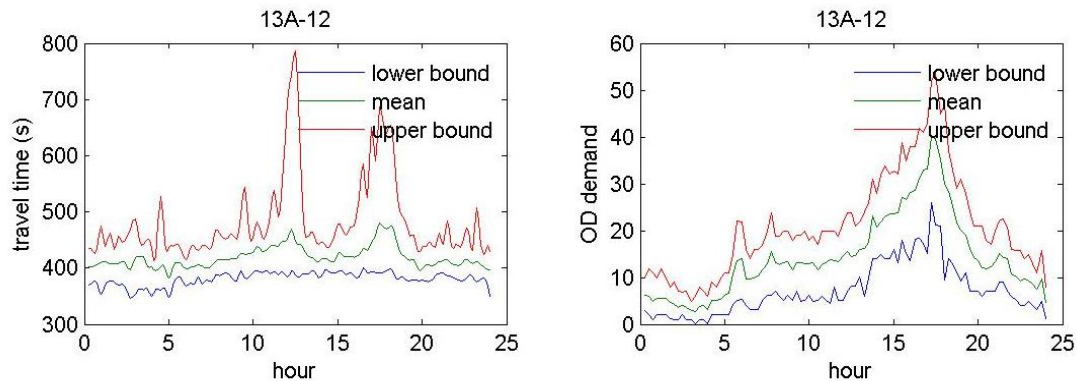


**Figure 3-2. Travel Time and OD Demand Variations within the Day (Monday)
(continued)**

A dynamic travel time prediction algorithm would require, as input, time-dependent OD matrix or time-dependent travel time information. The best way to obtain best estimates of these variables is to use historical data. However, we should first investigate the differences within the historical dataset to determine the best historical estimates for the corresponding day. A robust statistical test should be applied to compare the daily travel time and OD demand distributions. Wilcoxon rank sum test (Wilcoxon, 1945) is a non-parametric test for detecting whether two independent samples of observations follow an identical distribution or not. It is one of the best known non-parametric tests. To determine the significant differences of OD demand or travel time distribution throughout the day, Wilcoxon test is applied and the results are given in **Table 3-2** to **Table 3-7**. Within these results, the most informative is the one that belongs to average distribution, because, lower and upper bounds are highly affected by the existence of outliers. However, at this step, we only attempt to identify best historical estimate for the corresponding time period.

Wilcoxon test goes over 21 OD demand and travel time distribution throughout the day and tests the validity of the null hypothesis that two independent samples of observations follow the same identical distribution. The first value given in **Table 3-2** to **Table 3-7** indicates the number of OD pairs that do not conform to null hypothesis and the second indicates the percentage of them in 21 OD pairs. The test on the average travel times (**Table 3-2**) shows that, except 'Wednesday' and 'Thursday' whose 90% of OD pairs follow an identical travel time distribution, there is no pair of days that are significantly similar regarding the travel time distribution. On the other hand, **Table 3-5** and **Table 3-6** show that four days of the week have similar OD distributions regarding the average and upper bound values. Overall, Wilcoxon test results indicate that travel time values do not follow an identical distribution for weekdays (or weekend) and it is not possible to treat weekdays (or weekend) within the same group. Although 4 out of 5 weekdays have an identical distribution regarding OD demand and they can be treated within the same group in terms of demand level, same conclusion cannot be drawn for travel time observations.

Figure 3-3 shows average OD demand variations for some of the pairs. The trend observed in the graphs depicts the findings of Wilcoxon test; average OD demand distribution throughout the days 'Thursday', 'Wednesday', 'Thursday' and 'Friday' have an identical distribution.

Table 3-2. Wilcoxon Test Results of Average Travel Times

	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
MON	rejected (%)	15 71	20 95	17 81	21 100	18 86	18 86
TUE	15 71	rejected (%)	15 71	11 52	19 90	17 81	15 71
WED	20 95	15 71	rejected (%)	2 10	10 48	13 62	13 62
THU	17 81	11 52	2 10	rejected (%)	14 67	14 67	12 57
FRI	21 100	19 90	10 48	14 67	rejected (%)	8 38	14 67
SAT	18 86	17 81	13 62	14 67	8 38	rejected (%)	5 24
SUN	18 86	15 71	13 62	12 57	14 67	5 24	rejected (%)

Table 3-3. Wilcoxon Test Results of Upper Bound (95%) Travel Times

	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
MON	rejected (%)	11 52	13 62	9 43	17 81	20 95	20 95
TUE	11 52	rejected (%)	12 57	7 33	17 81	16 76	16 76
WED	13 62	12 57	rejected (%)	6 29	7 33	13 62	16 76
THU	9 43	7 33	6 29	rejected (%)	12 57	15 71	16 76
FRI	17 81	17 81	7 33	12 57	rejected (%)	6 29	7 33
SAT	20 95	16 76	13 62	15 71	6 29	rejected (%)	5 24
SUN	20 95	16 76	16 76	16 76	7 33	5 24	rejected (%)

Table 3-4. Wilcoxon Test Results of Lower Bound (5%) Travel Times

	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
MON	rejected (%)	21 100	21 100	21 100	21 100	16 76	14 67
TUE	21 100	rejected (%)	1 5	3 14	13 62	15 71	16 76
WED	21 100	1 5	rejected (%)	1 5	7 33	16 76	16 76
THU	21 100	3 14	1 5	rejected (%)	8 38	16 76	16 76
FRI	21 100	13 62	7 33	8 38	rejected (%)	17 81	20 95
SAT	16 76	15 71	16 76	16 76	17 81	rejected (%)	11 52
SUN	14 67	16 76	16 76	16 76	20 95	11 52	rejected (%)

Table 3-5. Wilcoxon Test Results of Average OD Demands

	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
MON	rejected (%)	20 95	20 95	19 90	20 95	6 29	8 38
TUE	20 95	rejected (%)	0 0	0 0	0 0	16 76	7 33
WED	20 95	0 0	rejected (%)	0 0	0 0	15 71	18 86
THU	19 90	0 0	0 0	rejected (%)	0 0	14 67	18 86
FRI	20 95	0 0	0 0	0 0	rejected (%)	17 81	19 90
SAT	6 29	16 76	15 71	14 67	17 81	rejected (%)	19 90
SUN	8 38	7 33	18 86	18 86	19 90	11 52	rejected (%)

Table 3-6. Wilcoxon Test Results of Upper Bound OD Demands

	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
MON	rejected (%)	17 81	20 95	19 90	20 95	9 43	9 43
TUE	17 81	rejected (%)	0 0	0 0	0 0	13 62	15 71
WED	20 95	0 0	rejected (%)	0 0	0 0	13 62	16 76
THU	19 90	0 0	0 0	rejected (%)	0 0	14 67	18 86
FRI	20 95	0 0	0 0	0 0	rejected (%)	13 62	18 86
SAT	9 43	13 62	13 62	14 67	13 62	rejected (%)	18 86
SUN	9 43	15 71	16 76	18 86	18 86	13 62	rejected (%)

Table 3-7. Wilcoxon Test Results of Lower Bound OD Demands

	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
MON	rejected (%)	17 81	17 81	16 76	17 81	9 43	9 43
TUE	17 81	rejected (%)	0 0	9 43	4 19	17 81	17 81
WED	17 81	0 0	rejected (%)	10 48	4 19	17 81	17 81
THU	16 76	9 43	10 48	rejected (%)	6 29	8 38	15 71
FRI	17 81	4 19	4 19	6 29	rejected (%)	16 76	17 81
SAT	9 43	17 81	17 81	8 38	16 76	rejected (%)	17 81
SUN	9 43	17 81	17 81	15 71	17 81	9 43	rejected (%)

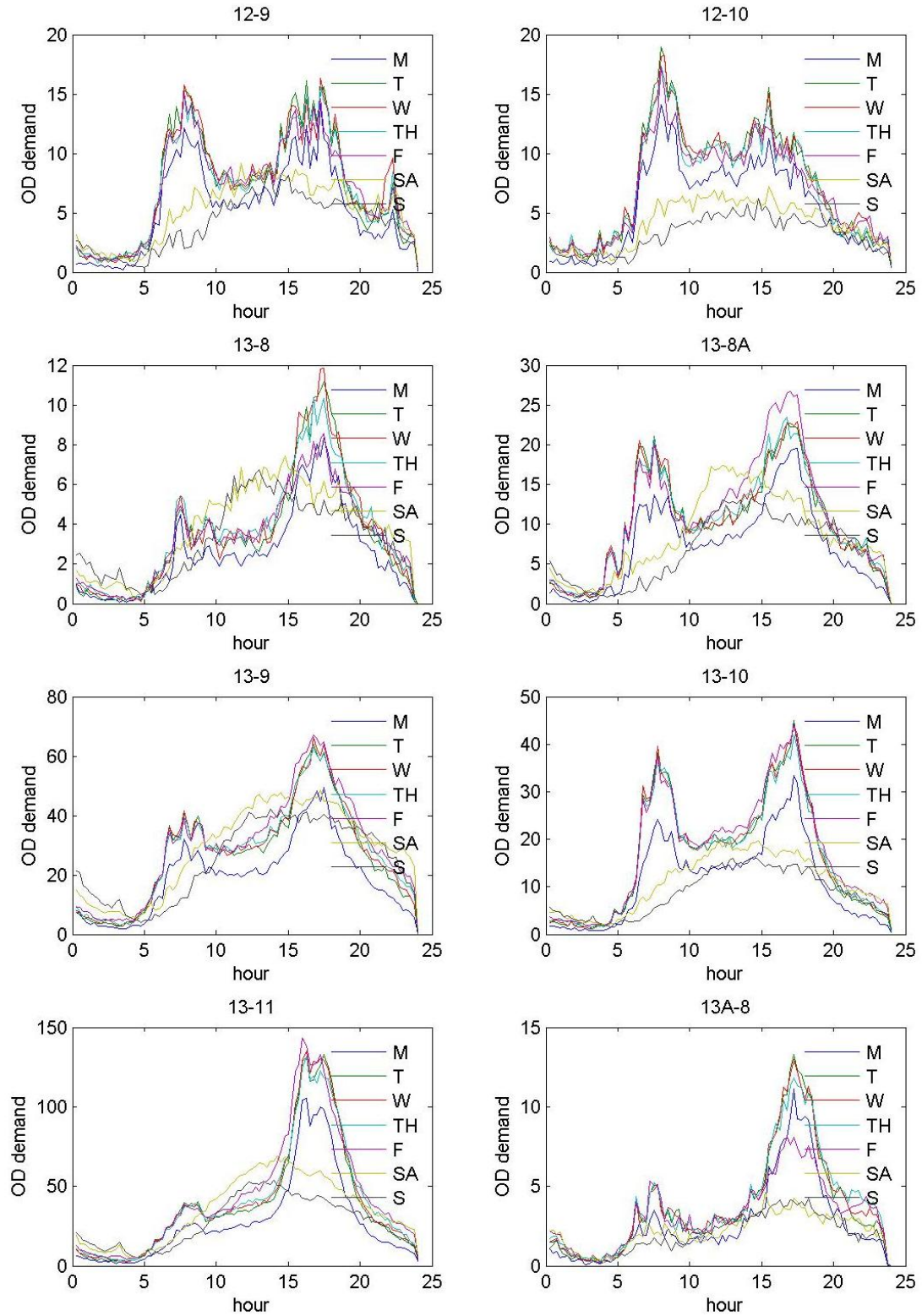


Figure 3-3. Average OD Demand Variation for Days of the Week

Table 3-8 shows the mean travel times for all itinerary travel times observed throughout one year.

Table 3-8- Average Travel Times

OD	8A-8	9-8	9-8A	10-8	10-8A	10-9	11-8
Avg. TT (s)	328	837.2	509.2	1099.8	771.8	262.6	1255.9
OD	11-8A	11-9	11-10	12-8	12-8A	12-9	12-10
Avg. TT (s)	928	418.8	156.1	1563.4	1235.4	726.2	463.6
OD	12-11	13-8	13-8A	13-9	13-10	13-11	13-12
Avg. TT (s)	307.5	1747.1	1419.1	909.9	647.2	491.1	183.6
OD	13A-8	13A-8A	13A-9	13A-10	13A-11	13A-12	13A-13
Avg. TT (s)	1791.8	1543.8	1034.6	771.9	615.8	308.3	124.7

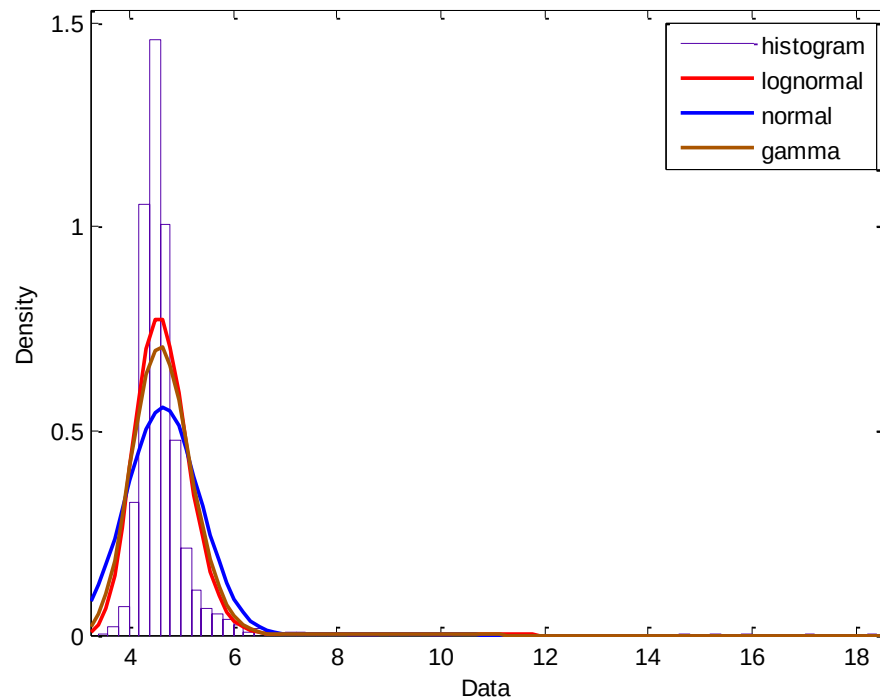
Data analysis shows that it is not possible to categorize travel times with regards to days of the week or time of the day. Mean travel times follow almost a constant value throughout the day regardless of peak hours, which indicates free-flowing conditions for most of the time. Since such periodic changes are not observed in the measured travel times, a robust approach must be brought to deal with the problem. Even if there were such periodic changes, this would not be the best way to deal with the problem, because travelers experience high delays in case of incident related congestion, which cannot be modeled with seasonal procedures (daily or weekly travel time patterns). Besides, long itinerary travel times cannot be used to inform drivers because of the information delay problem. In addition to that, number of OD pairs grows exponentially with increasing number of links. Beyond some point, it would be computationally expensive to deal with every itinerary separately. So, there is a clear need for the reduction in the dimensions to estimate travel times and the goal in the estimation process will be to reduce the dimensions without reducing the size of available data.

3.2.2 Distribution of Link Travel Times

To compare traffic conditions on the network for different days of the week, link travel times are modeled with three common distributions namely, normal, gamma and poisson distributions. Parameters of the models are estimated using maximum-likelihood technique. Kolmogorov-Smirnov distance is calculated to compare the performance of the models.

Figure 3-4 shows the performance of the models for one year (10/1/2008 - 9/30/2009) of historical travel time observations for the link between Exits 11 and 10.

Figure 3-4. Link Travel Time Distribution (11-10)



To compare travel time distributions for different days of the week, separate models are constructed. Lognormal distribution has a better fit than the others with respect to KS distance (smaller KS distance indicates a better performance).

Table 3-9- KS Distance

Link	<i>Monday</i>			<i>Tuesday</i>		
	Normal	Gamma	Lognormal	Normal	Gamma	Lognormal
8A-8	0.28	0.27	0.26	0.30	0.27	0.26
9-8A	0.29	0.26	0.24	0.26	0.22	0.20
10-9	0.20	0.18	0.17	0.22	0.20	0.18
11-10	0.22	0.18	0.16	0.20	0.17	0.15
12-11	0.22	0.19	0.18	0.19	0.17	0.16
13-12	0.28	0.23	0.20	0.15	0.12	0.11
13A-13	0.24	0.20	0.18	0.28	0.23	0.21

Link	<i>Wednesday</i>			<i>Thursday</i>		
	Normal	Gamma	Lognormal	Normal	Gamma	Lognormal
8A-8	0.30	0.28	0.26	0.28	0.26	0.25
9-8A	0.28	0.24	0.22	0.24	0.21	0.19
10-9	0.21	0.19	0.18	0.28	0.24	0.22
11-10	0.20	0.17	0.15	0.23	0.18	0.17
12-11	0.22	0.19	0.17	0.21	0.19	0.17
13-12	0.24	0.20	0.19	0.14	0.12	0.11
13A-13	0.29	0.25	0.23	0.27	0.22	0.19

Link	<i>Friday</i>			<i>Saturday</i>		
	Normal	Gamma	Lognormal	Normal	Gamma	Lognormal
8A-8	0.22	0.21	0.20	0.25	0.26	0.24
9-8A	0.36	0.33	0.31	0.36	0.33	0.30
10-9	0.20	0.18	0.17	0.16	0.14	0.13
11-10	0.23	0.19	0.17	0.18	0.16	0.14
12-11	0.22	0.19	0.17	0.23	0.21	0.20
13-12	0.16	0.14	0.13	0.16	0.13	0.12
13A-13	0.29	0.25	0.23	0.19	0.15	0.13

Link	<i>Sunday</i>		
	Normal	Gamma	Lognormal
8A-8	0.27	0.26	0.24
9-8A	0.33	0.28	0.26
10-9	0.24	0.19	0.16
11-10	0.19	0.16	0.14
12-11	0.24	0.21	0.20
13-12	0.17	0.14	0.12
13A-13	0.20	0.17	0.15

Since lognormal distribution exhibits the best performance, lognormal model parameters are used to interpret the differences between days of the week. In a lognormal distribution, μ and σ are called location and scale parameters, respectively. The scale parameter determines the tail structure of the lognormal distribution. A larger scale parameter indicates a larger density at the tail. In other words, it represents the likelihood of high travel time observations (i.e. unexpected traffic conditions) in the roadway on that specific day.

The most significant difference in model parameters is observed for the link between Exits 9 and 8A. While the scale parameter of the first four weekdays is within a range of 0.09 to 0.12, it is 0.22, 0.21 and 0.16 for Friday, Saturday and Sunday respectively.

Table 3-10- Lognormal Distribution Parameters

Link	<i>Monday</i>		<i>Tuesday</i>		<i>Wednesday</i>		<i>Thursday</i>	
	mu	sigma	mu	sigma	mu	sigma	mu	sigma
8A-8	2.14	0.39	2.09	0.35	2.09	0.33	2.13	0.37
9-8A	2.26	0.12	2.26	0.10	2.27	0.12	2.26	0.09
10-9	1.83	0.08	1.84	0.09	1.84	0.08	1.85	0.11
11-10	1.53	0.11	1.53	0.11	1.53	0.11	1.53	0.11
12-11	1.92	0.14	1.92	0.13	1.94	0.15	1.93	0.14
13-12	1.55	0.11	1.55	0.07	1.56	0.11	1.55	0.07
13A-13	1.22	0.11	1.23	0.14	1.23	0.15	1.22	0.12

Link	<i>Friday</i>		<i>Saturday</i>		<i>Sunday</i>	
	mu	sigma	mu	sigma	mu	sigma
8A-8	2.19	0.38	2.15	0.40	2.14	0.40
9-8A	2.31	0.22	2.29	0.21	2.26	0.16
10-9	1.84	0.08	1.80	0.06	1.80	0.09
11-10	1.54	0.12	1.51	0.10	1.51	0.11
12-11	1.94	0.15	1.91	0.14	1.91	0.16
13-12	1.55	0.08	1.51	0.08	1.50	0.08
13A-13	1.26	0.18	1.16	0.09	1.15	0.10

Lognormal model parameters can be also used to determine the effect of number of observations on the representative average travel time (i.e. the median value of travel time observations). A separate lognormal model is fitted for representative average travel times that result from 1 to 20 vehicles. That is, the first model is constructed using travel time observations that result from one single vehicle; the second is constructed using the observations that result from both one and two vehicles; and so on. **Figure 3-5** and **Figure 3-6** show the change in location and scale parameters with increasing number of observations. Note that the last model uses all the observations, although it is represented as 20 in the graphs.

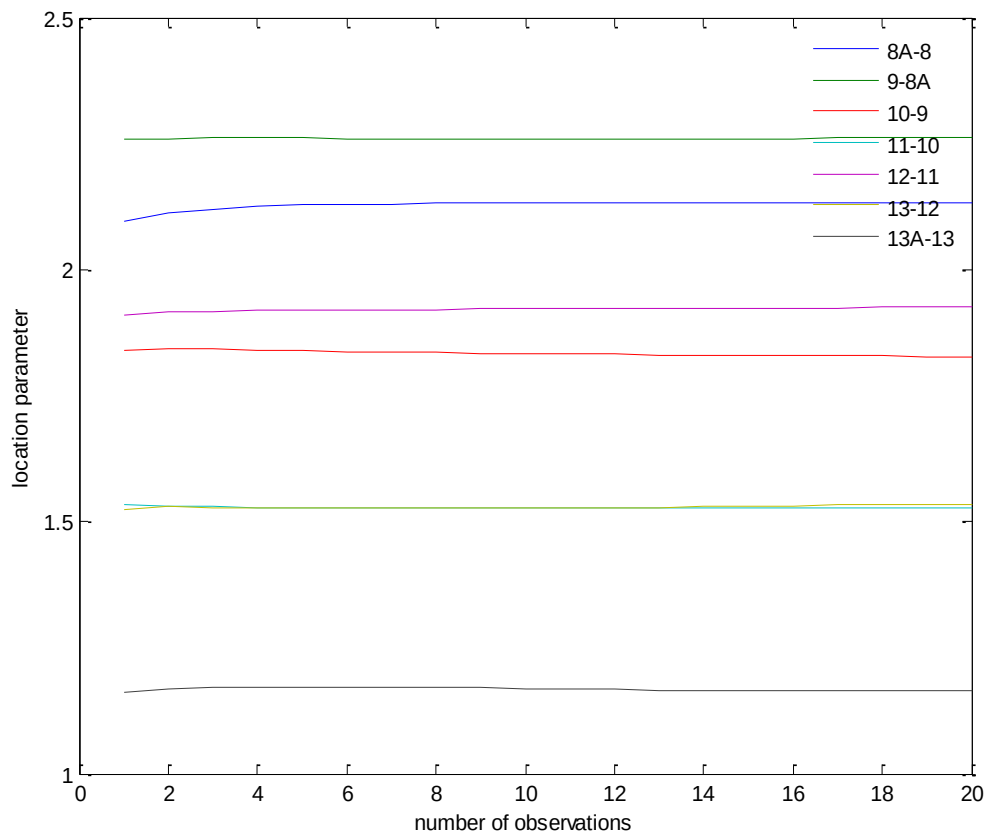


Figure 3-5. Location Parameter

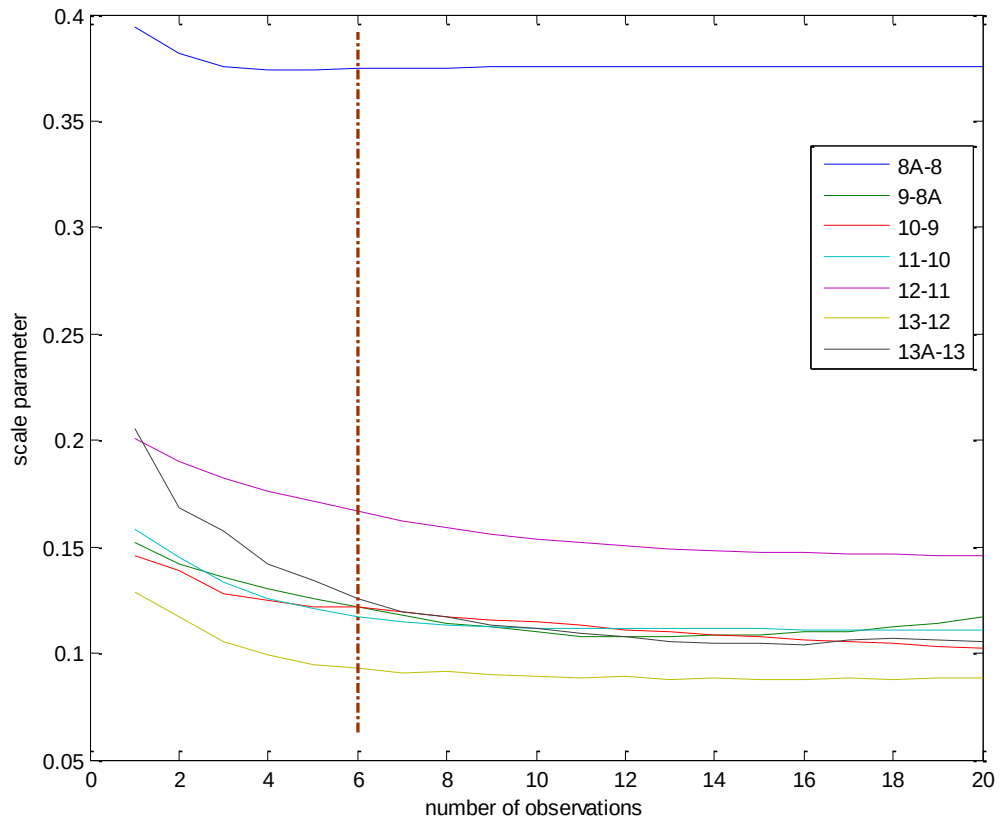


Figure 3-6. Scale Parameter

Location parameter, which represents the expected travel time, does not change significantly with increasing number of observations. However, scale parameter has relatively high values for the number of observations less than 6. In the case of sufficient number of observations, the median value provides a good representative average. However, in the case of low number of observations, median value can be affected by outlier observations, as seen in **Figure 3-6**. This phenomenon depicts the importance of the sufficient number of observation assumption defined in **Table 3-1**.

Chapter 4 Data Filtering

Automatic vehicle identification (AVI) systems record the exact times at which vehicles cross the detector location. However, the data collected by AVI systems require a filtering process to remove the outliers. High variability in travel time observations within the time interval and between consecutive time intervals are the main problems to address in the filtering process. Atypical travel time measurements may arise due to the following reasons:

- High travel time observations due to vehicles making stops during their trips
- Low travel time observations due to travelers dodging traffic jam (i.e. emergency vehicles)
- Few observations for certain itineraries

Although the definition of outliers is as simple as above, it is not obvious how to decide whether a measurement is an outlier or not. In the case of high number of observations, the median value is a good representative average and there is no need to determine outlier observations. However, in the case of low number of observations, outlier measurements should be removed to eliminate their effects on the average travel time.

Data filtering method applied in this study follows the conventions of Dion and Rakha (2006) and Soriguera et al. (2010). In case there are enough observations, the median value is used and only an exponential smoothing process is applied to eliminate

the high variability between consecutive time intervals. However, sets with few observations requires a more detailed filtering process.

4.1 Extreme Outliers

Travel time observation at time interval p , between origin i and destination j is considered as an extreme outlier if:

$$\left\{ \begin{array}{l} t_{i,j}^p < 0 \\ i = j \\ \frac{l_{i,j}}{t_{i,j}^p} > 100mph \end{array} \right. \quad (4.1)$$

where $l_{i,j}$ is the total length of the itinerary, including on and off ramps.

4.2 Sets with Enough Data

The number of observations at time interval p , between origin i and destination j $N_{i,j}^p$ is considered to be sufficiently large if it is greater than a threshold value $N_{i,j}^{*p}$, which equals 6 observations in this study. As mentioned above, with enough observations, there is no need to eliminate the outliers. Instead, the problem is solved by the use of median value ($\hat{t}_{i,j}^p$), which is insensitive to the outliers in the dataset. 75%, 25% percentiles ($\hat{q}_{3(i,j)}^p, \hat{q}_{1(i,j)}^p$ respectively) are identified and the interquartile range (IQR) is computed using the following equation:

$$IQR_{i,j}^p = \hat{q}_{3(i,j)}^p - \hat{q}_{1(i,j)}^p \quad (4.2)$$

To address the variability of travel times in the consecutive time intervals, $\hat{t}_{i,j}^p$ and percentile values should be exponentially smoothed. Assuming the lognormal distribution of travel times, exponential smoothing is done in a logarithmic scale.

$$t_{i,j}^p = \exp (\alpha_{i,j}^p * \ln(\hat{t}_{i,j}^p) + (1 - \alpha_{i,j}^p) * \ln(t_{i,j}^{p-1})) \quad (4.3)$$

$$q_{3(i,j)}^p = \exp (\alpha_{i,j}^p * \ln(\hat{q}_{3(i,j)}^p) + (1 - \alpha_{i,j}^p) * \ln(q_{3(i,j)}^{p-1})) \quad (4.4)$$

$$q_{1(i,j)}^p = \exp (\alpha_{i,j}^p * \ln(\hat{q}_{1(i,j)}^p) + (1 - \alpha_{i,j}^p) * \ln(q_{1(i,j)}^{p-1})) \quad (4.5)$$

$$IQR_{i,j}^p = q_{3(i,j)}^p - q_{1(i,j)}^p \quad (4.6)$$

The exponential smoothing factor α used in the above equations is a low-pass filter that leads to better travel time estimates. Particularly if the time intervals are very short, significant fluctuations can be observed in travel times. However, they do not necessarily represent actual traffic conditions in the highway; thus, such a filter is needed. Smoothing factor α is an adaptive factor that depends on the number of observations in the set and it can be seen as a reliability index. As there are few observations, the representative average travel time will be less reliable and it will be smoothed towards the past travel time value. Representative average travel time becomes almost a perfect observation, as the number of observations goes up. Exponential smoothing factor α is calculated using Eq. (4.7).

$$\alpha_{i,j}^p = 1 - (1 - \beta)^{N_{i,j}^p} \quad (4.7)$$

β is the user defined sensitivity parameter which is set to a value of 0.2 after a trial and error process.

4.3 Sets with Few Observations

If the set does not have enough observations ($0 < N_{i,j}^p < N_{i,j}^{*p}$), the median of the set cannot be used to represent the average travel time. The data filtering process should be implemented to determine the outliers and to remove them. The median of the remaining observations can then be used in Equations (4.3) to (4.6) for exponential smoothing process.

To identify whether an observation is an outlier or not, certain boundaries must be defined:

$$t_{max}^{i,j(p)} = \exp(\ln(q_{3i,j}^{p-1}) + 0.5 * \ln(IQR_{i,j}^{p-1})) \quad (4.8)$$

$$t_{MAX}^{i,j(p)} = \exp(\ln(q_{3i,j}^{p-1}) + 2 * \ln(IQR_{i,j}^{p-1})) \quad (4.9)$$

$$t_{MIN}^{i,j(p)} = \exp(\ln(t_{i,j,0}) - 0.5 * \ln(IQR_{i,j,0})) \quad (4.10)$$

$$t_{min}^{i,j(p)} = \max\{\exp(\ln(q_{1i,j}^{p-1}) - 0.5 * \ln(IQR_{i,j}^{p-1})), t_{MIN}^{i,j(p)}\} \quad (4.11)$$

where $t_{i,j,0}$ is the free-flow travel time and $IQR_{i,j,0}$ is the variation interval of 15 mph around free-flow speed of 65 mph (e.g. difference between travel times achieved at 50 mph and 80 mph average speed).

These boundaries are used to create two confidence intervals namely

$(t_{min}^{i,j(p)}, t_{max}^{i,j(p)})$ and a broader one $(t_{MIN}^{i,j(p)}, t_{MAX}^{i,j(p)})$. Outliers can then be identified using these two intervals for the following situations;

- $t_{i,j,k}^{(p)} \in [t_{min}^{i,j(p)}, t_{max}^{i,j(p)}]$; $t_{i,j,k}^{(p)}$ is considered valid

- $t_{i,j,k}^{(p)} \notin [t_{MIN}^{i,j(p)}, t_{MAX}^{i,j(p)}]$; $t_{i,j,k}^{(p)}$ is considered an outlier and removed from the set.
- $t_{i,j,k}^{(p)} \in [t_{max}^{i,j(p)}, t_{MAX}^{i,j(p)}]$; $t_{i,j,k}^{(p)}$ is considered doubtful
- $t_{i,j,k}^{(p)} \in [t_{MIN}^{i,j(p)}, t_{min}^{i,j(p)}]$; $t_{i,j,k}^{(p)}$ is considered doubtful

where k is the vehicle number in the set.

4.3.1 Higher Than Expected Observations

The vehicle might have stopped for a short time or might have traveled considerably slower than the other cars. Then, these observations should be considered an outlier. However, a rapid change in traffic conditions might also lead to the same phenomenon; then the observations should be considered valid. Other detector data may be needed to determine such rapid changes in traffic conditions. Since such data are not available in this study, if the number of originally valid observations is greater than or equal to the half of the total number of observations ($N_{i,j}^p/2$) and if;

$$t_{i,j,k}^{(p)} \geq t_{i,j,l}^{(p)} + 0.5 * IQR_{i,j}^{p-1} \quad (4.12)$$

where $t_{i,j,l}^{(p)}$ is the maximum of originally valid observations, then $t_{i,j,k}^{(p)}$ is considered outlier and removed.

4.3.2 Lower Than Expected Observations

A traveler dodging the traffic jam can cause such a doubtful observation, which should be considered as an outlier. Besides, sudden travel time decrease as a result of congestion dissipation can also cause this problem, in which case the observation should be considered as valid. However, this type of outlier is not as problematic as the previous

one, because there are few outliers of this nature and in congestion dissipation, traffic flows at capacity and it is difficult to find sets with few data (Soriguera et al., 2010).

If the number of originally valid observations is greater than or equal to the half of the total number of observations ($N_{i,j}^p/2$) and if:

$$t_{i,j,k}^{(p)} \leq t_{i,j,l}^{(p)} - 0.5 * IQR_{i,j}^{p-1} \quad (4.13)$$

where $t_{i,j,l}^{(p)}$ is the minimum of originally valid observations, then $t_{i,j,k}^{(p)}$ is considered outlier and removed.

4.4 Computation of IQR in Sets with Few Observations

In case of sets with few observations, it may not be meaningful to compute $\hat{q}_{3(i,j)}^p$ and $\hat{q}_{1(i,j)}^p$ directly; therefore, following equations are used to determine percentile values:

$$\hat{q}_{1(i,j)}^p = \hat{t}_{i,j}^p - (t_{i,j}^{p-1} - q_{1(i,j)}^{p-1}) \quad (4.14)$$

$$\hat{q}_{3(i,j)}^p = \hat{t}_{i,j}^p + (q_{3(i,j)}^{p-1} - t_{i,j}^{p-1}) \quad (4.15)$$

Chapter 5 Travel Time Estimation

In a closed toll highway, it is considerably easy to obtain travel times between all origin-destination pairs along the roadway. Toll collection system provides necessary information about OD pairs on the network by directly recording the time taken by the vehicles to travel between certain OD points. However, OD paths are composed of single-section (link) roadway portions and most of the time, the addition of measured single-section travel times does not necessarily provide an accurate OD travel time estimation. Inconsistency between the measured OD travel times, which arises from the differences among experienced travel times, creates the need to determine travel times for shortest itineraries possible (single section between consecutive junctions in a closed toll highway).

Direct travel time measurement techniques provide the data once the vehicle left the roadway network. Hence, this type of travel time measurement will be based on the past situations on the roadway. In case of long and congested OD paths this can be the source of a considerable delay in acquiring path travel time data.

Soriguera et al. (2010) compares the effects of different types of travel time measurement in case of rapid changes in traffic conditions (i.e. incident). Travel time information collected from the system is named as measured travel time (MTT). MTT is estimated using section travel times and used to form OD travel times defined as instantaneous travel time (ITT). The expected travel time for a driver entering the roadway at the present instant is called predicted travel time (PTT). **Figure 5-1** illustrates an example of the implications of different types of travel time estimation approaches.

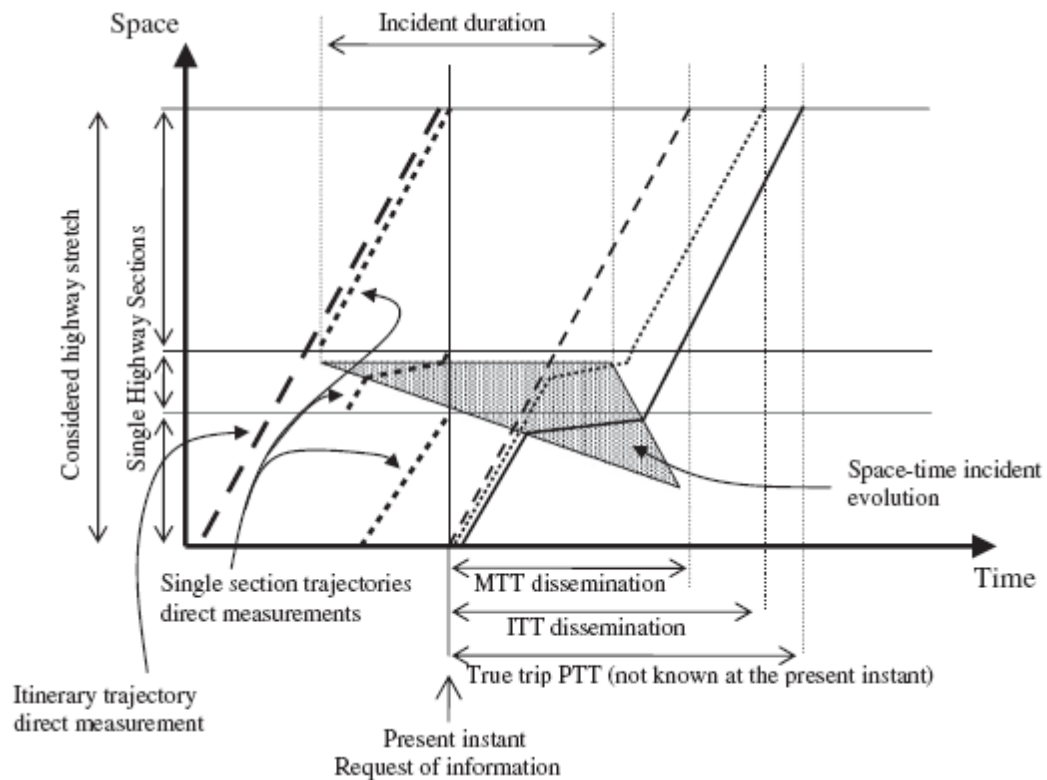


Figure 5-1- Travel Time Definitions and Information Delay (Soriguera et al., 2010)

The information delay in case of MTT and long OD routes (with more than one single section) brings negative effects under rapidly changing traffic conditions. On the other hand, the estimation of single-section travel times reduces the prediction error for the next period. However, it should be noted that single-section travel times can be reconstructed by the use of other OD travel time measurements. A naive method to consider only the measurements of the vehicles that travel between consecutive junctions would not work in the case of closed toll highways because of the limited number of observations. The volume of traffic between consecutive junctions in a closed highway system is quite low compared to through traffic. Furthermore, an estimation based on

single section measurement only, would be biased by the experience of those vehicles; however, travel time estimation should be in accordance with through traffic as well.

Another point that must be taken into account is the entrance/exit times of the vehicles. As toll detectors are located at the end of on/off ramps and the distance between the detectors and the main highway section can be between hundreds of yards to a couple of miles, every junction should be investigated separately. The exit time includes both the time needed to travel along the off-ramp and the time required to pay the fee. In case of vehicles equipped with electronic toll tag readers, the time required to pay fee can be assumed as negligible. Since the proposed methodology utilizes only ETC data, a constant entry/exit time can be identified for each junction. Considering a constant acceleration/deceleration and the distance of the ramp from the main trunk (where the vehicle is assumed to travel at 65 mph) to the toll booth (where the vehicle is assumed to travel at 5 mph), constant entry/exit times can be identified for each junction. In order to take into account the length of the inner junction which is located between the beginning of the off-ramp and the end of the on-ramp (**Figure 5-2**), a constant speed of 65 mph is assumed and half of the junction travel time is subtracted from both entrance and exit times. This modification has little effect in practice, since the inner junction lengths are quite short compared to section lengths. Entrance/exit times are then subtracted from the associated raw data before conducting further analysis. The assumption of free access to the mainline and to the toll booth holds in NJ Turnpike. However, an alternative approach must be brought in case of ramp metering schemes or highly congested ramps where queues are commonly observed. Some type of additional surveillance equipment can be incorporated at the very end of the ramps and entrance/exit times can be directly

measured if ramp travel times are considered to be critical. Service times are more or less constant for the vehicles equipped with toll tag readers, while the travelers that receive a traditional ticket which is collected at the exit toll booth, are subject to wait times on the queue.

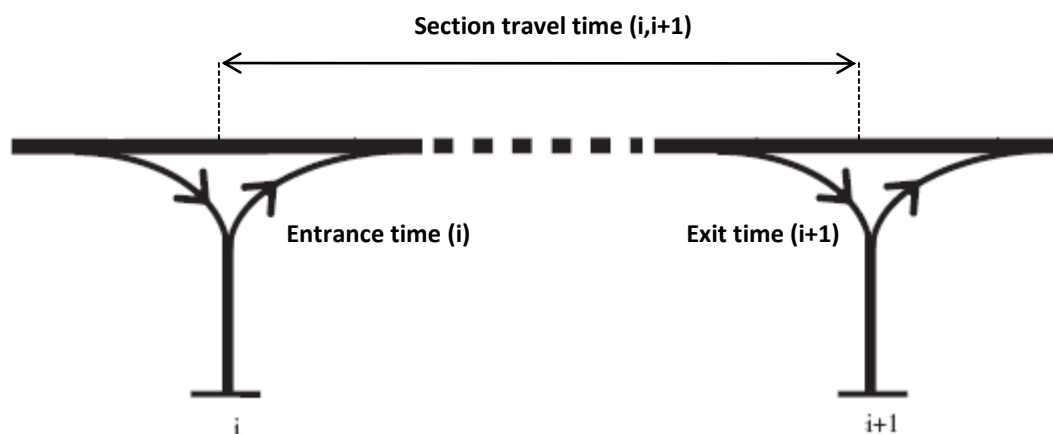


Figure 5-2 - Schematic of a typical toll road section

Assumption of constant entrance/exit times would also work in the case of congestion along the main line. In highway configurations, the congestion along the mainline would block the access to the off-ramp; however, once the vehicles reach the beginning of the off-ramp, they will experience the same constant exit time. By intuition, it is known that the demand for exiting the highway does not exceed the capacity of the off-ramp, although high number of vehicles that want to get rid of the congestion in the mainline may lead to long queues at the toll booth. Note that toll plaza configurations of the NJ Turnpike have some lanes dedicated to the EZ-Pass users. Therefore, they almost never suffer from the queues at the toll booth. The assumption of constant 65 mph speed at the inner junction may not work in the case of congestion along the mainline.

However, as already mentioned, these lengths are quite short compared to section lengths and do not have great effects on travel time estimation.

In a real time application, to determine single section travel times, it is needed to select OD pairs that cross the particular single section at the corresponding time interval. Since the toll collection system provides travel time data once the vehicle left the roadway, it is required to determine the sections that the vehicle crossed during the same time interval. However, considering the average travel time between the endmost points of the network, which is less than 30 minutes (**Table 3-8**), and the time interval selected as 15 minutes, instantaneous travel time assumption can be seen sufficient to deal with travel time estimation problem. This issue will be further discussed in the next sections.

Two methods are developed to estimate the single section travel times without considerably reducing the amount of available data namely kriging and nonlinear optimization.

5.1 Universal Kriging

5.1.1 Methodology

Kriging is a geostatistics technique that is used to interpolate the value of a random field at an unobserved location from the observations at nearby locations. Based on the stochastic properties of the random variable or random field, different types of kriging can be applied;

- *Simple Kriging* assumes a constant and known mean throughout the study area.
- *Ordinary Kriging* assumes the mean is constant but unknown.

- *Universal Kriging* (Kriging with a Trend) assumes mean is neither known nor constant, but varies smoothly throughout the study area.

Universal kriging can be applied to estimate single section travel times in an imaginary two dimensional space (origin and destination) with the distance between them as the drift function. Miura (2010) implemented universal kriging to estimate travel times in London using a large dataset that contains 1000 trips. In this study, the capability of kriging algorithm for small scale real-time applications is investigated. Note that each link travel time (OD pairs with successive interchanges) will be represented by a unique point in the imaginary 2D space and its value will be calculated by the interpolation of other points in the space. However, kriging returns the exact same value for input points while interpolating them for unobserved locations. Therefore, even though they are actually measured, single section travel time values (link travel times) cannot be input in the kriging algorithm.

Since universal kriging is a special interpolation technique to deal with trended datasets, the first step is to detect the existence of a trend and remove it from the data. Note that trend is described as a functional variation of the values in the study area and it is needed to be removed to conduct kriging analysis. Travel time values exhibit a strong linear trend with increasing distance between origin and destination points. However, it is difficult to identify a single trend direction in the imaginary two dimensional space. It is possible to represent travel time as a function of origin and destination points. However, the absence of a trend-free direction in the imaginary two dimensional space brings the necessity of another method to identify the trend. **Figure 5-3** which shows travel time data for trips in NJTPK, clearly indicates that there is a significant trend in both vertical

and horizontal directions.

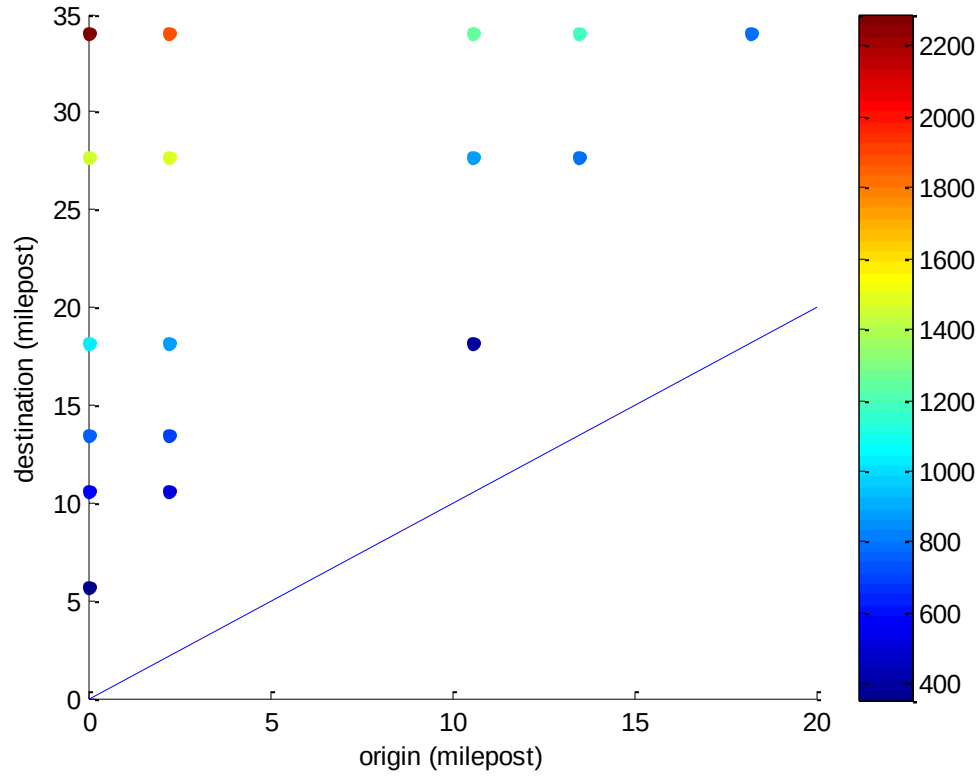


Figure 5-3 - Travel Time (sec) Information on Two Dimensional Space

The estimation of travel time by universal kriging is described here following the notation used by Cressie (1993) and Miura (2010). Let D be a fixed subset of two dimensional space where each point represents a single journey. An arbitrary point in the space $\mathbf{s} \in D$ that consists of a pair of origin and destination has the following travel time model:

$$z(\mathbf{s}) = \beta f(\mathbf{s}) + \delta(\mathbf{s}) \quad (5.1)$$

where $f(\mathbf{s})$ is the drift function, distance between origin and destination, β is the generalized least squares (GLS) coefficient and $\delta(\mathbf{s})$ is a zero-mean function of residual time and it has the following properties:

$$E(\delta(\mathbf{s})) = 0 \quad (5.2)$$

$$Cov(\delta(\mathbf{s}), \delta(\mathbf{s} + \mathbf{h})) = C(\mathbf{h}) \quad (5.3)$$

where $\mathbf{h}$ is an arbitrary two dimensional vector and $C(\mathbf{h})$ is the covariogram function. A random variable satisfying (2) and (3) is called second-order stationary. This implies that $\delta(\mathbf{s})$ has a constant mean for all $\mathbf{s} \in D$ and its covariance function is independent of the vector $\mathbf{s}$.

The covariogram model which is based on semivariogram values plays a crucial role on the interpolation of unobserved locations. Therefore, attention must be paid to the semivariogram model. If there was no trend in one of the directions (although it is never the case for travel time applications), the variogram model could be the representation of the spatial dependence in that trend-free direction, and then the problem could be resolved by assuming isotropy and by applying one-dimensional variogram in any direction in the space. It is unfortunate in this case that there is no such a trend-free direction. When there is not, the usual estimators of semivariogram model show a confounding of mean effects.

A number of authors have proposed solutions to the variogram estimation in case of trend existence; residuals can be used to estimate the variogram. However, generalized least squares (GLS) estimator cannot be known before constructing the semivariogram

model. This brings the discussion right back to where it started. Neuman and Jacobson proposed an iterative approach: start with an ordinary least squares (OLS) estimator, construct the variogram model, determine GLS estimator based on the variogram model and so forth. This iterative approach stops when GLS and OLS estimators look almost the same. On the other hand, Cressie (1993) showed that the bias due to the use of OLS estimators in the calculation of residuals is not important when there is adequate number of observations.

Define the OLS residuals:

$$\mathbf{R} = \mathbf{Z} - \mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{Z} \quad (5.4)$$

where $\mathbf{X}$ is $n \times p$ matrix whose (i,j) th element is $f_{i,j}(\mathbf{s}_i)$ and $\mathbf{Z}$ is $n \times 1$ vector whose (i) th element is $z(\mathbf{s}_i)$. In this study, $f_{i,1}(\mathbf{s}_i)=1$ and $f_{i,2}(\mathbf{s}_i)$ is the distance between origin and destination, which compose the elements of the linear regression equation with an intercept, as seen in Equation (5.1).

Figure 5-4 presents the OLS estimator and the data points with the associated OD names. The residuals are defined as the variation of data points from the linear line.

Figure 5-5 shows the residuals of travel time data, which clearly indicates the removal of the trend. The residuals of travel time values are going to be used for the determination of the semivariogram and covariogram, in other words to construct the correlation structure of the data.

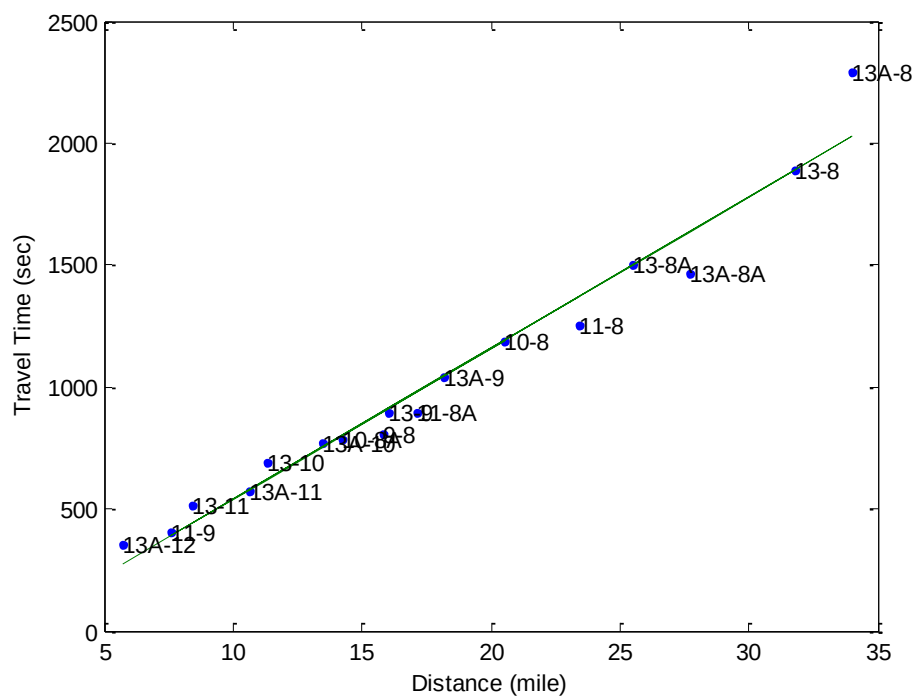


Figure 5-4- OLS Estimator

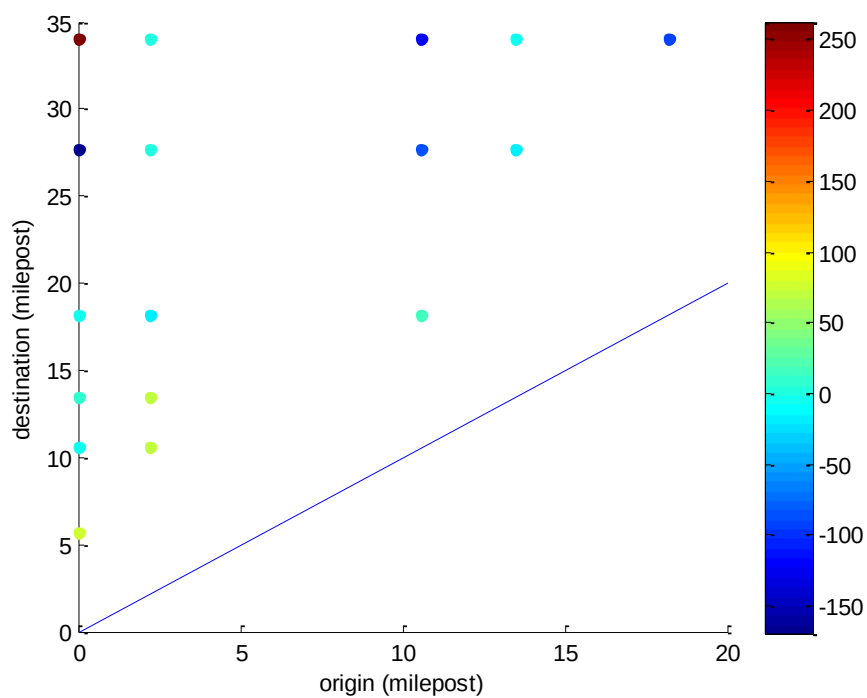


Figure 5-5 - Travel Time Data after the Removal of the Trend

The variogram estimator is:

$$2\hat{\gamma}(h) = \sum_{i=1}^{n-h} (R(i+h) - R(i))^2 / (n-h) \quad (5.5)$$

The covariogram estimator is then:

$$C(\mathbf{h}) = C(\mathbf{0}) - \hat{\gamma}(\mathbf{h}) \quad (5.6)$$

where $C(\mathbf{0})$ is equal to the sill value of the semivariogram, $\hat{\gamma}(\cdot)$.

Since the spatial structure of travel time data is now independent of direction and the covariogram satisfies Equations (5.2) and (5.3), an isotropic semivariogram model which is only a function of $\|h\|$ can be constructed. This study adopts a combination of nugget and gaussian models to build the semivariogram model.

- Nugget Effect Model:
$$n(h) = \begin{cases} 0 & \text{if } \|h\| = 0 \\ 1 & \text{otherwise} \end{cases}$$
- Gaussian Model:
$$g(h, a) = 1 - \exp\left(\frac{-3\|h\|^2}{a^2}\right)$$

The semivariogram model is then;

$$\gamma(h) = \alpha_1 * n(h) + \alpha_2 * g(h, \alpha_{13}) \quad (5.7)$$

where α_1 , α_2 and α_3 are the parameters that will be determined using the least squares method and minimizing the error between theoretical and empirical semivariogram curves.

Figure 5-6 shows the empirical semivariogram curve and the best-fitting semivariogram model obtained by least squares method. Fitted theoretical semivariogram values are used in the further steps of the kriging modeling.

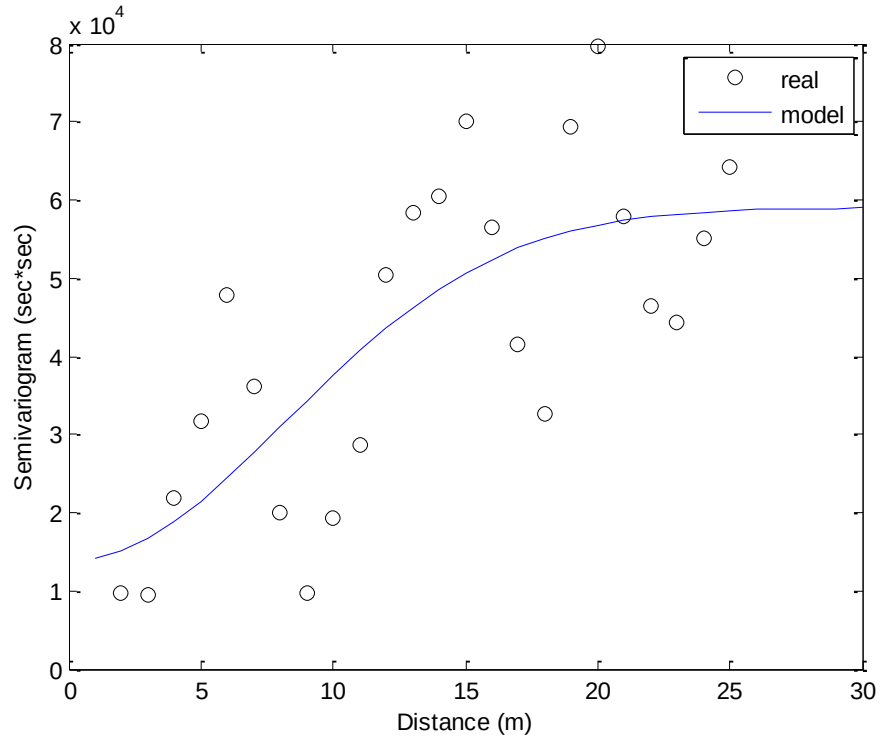


Figure 5-6- Semivariogram

Let $\mathbf{s}_i$ be the two dimensional origin-destination vector of i th trip and $z(\mathbf{s}_i)$ be the associated travel time. The estimated travel time at arbitrary $\mathbf{s}$, unobserved origin-destination pair, $\hat{Z}(\mathbf{s})$ is the weighted mean of $z(\mathbf{s}_i)$.

$$\hat{Z}(\mathbf{s}) = \sum_{i=1}^n \lambda_i z(\mathbf{s}_i) \quad (5.8)$$

where λ_i is the weight parameter associated with i th trip and arbitrary $\mathbf{s}$. The coefficient vector $\boldsymbol{\lambda} = \{\lambda_1, \lambda_2, \dots, \lambda_n\}$ that minimizes the mean squared prediction error is given by:

$$\boldsymbol{\lambda} = \{\mathbf{c} + \mathbf{X}(\mathbf{X}'\boldsymbol{\Sigma}^{-1}\mathbf{X})^{-1}(\mathbf{x} - \mathbf{X}'\boldsymbol{\Sigma}^{-1}\mathbf{c})\}'\boldsymbol{\Sigma}^{-1} \quad (5.9)$$

where $\mathbf{c}=(C(\mathbf{s}-\mathbf{s}_1),\dots,C(\mathbf{s}-\mathbf{s}_n))'$, Σ is $n \times n$ matrix whose (i,j) th element is $C(\mathbf{s}_i-\mathbf{s}_j)$ and $\mathbf{x}$ is the travel time associated with arbitrary $\mathbf{s}$ vector calculated by generalized least square estimator. Estimated travel time value of $\hat{Z}(\mathbf{s})$ can be also written as the following:

$$\begin{aligned}\hat{Z}(\mathbf{s}) &= \lambda \mathbf{z} \\ &= \hat{\beta}_{gls} f(\mathbf{s}) + \mathbf{c}' \Sigma^{-1} (\mathbf{z} - \hat{\beta}_{gls} \mathbf{X})\end{aligned}\quad (5.10)$$

where $\mathbf{z}=\{z(\mathbf{s}_1),\dots,z(\mathbf{s}_n)\}$ and GLS estimator $\hat{\beta}_{gls}$ is:

$$\hat{\beta}_{gls} = (\mathbf{X}' \Sigma^{-1} \mathbf{X})^{-1} \mathbf{X}' \Sigma^{-1} \mathbf{z} \quad (5.11)$$

Since travel time data are collected every 15 minutes, the explained methodology should be repeated at the end of each period as follows

1. start with an OLS estimator,
2. calculate the residuals,
3. construct the semivariogram,
4. fit a theoretical semivariogram curve,
5. calculate the weight parameters based on kriging equations and return the single-section travel times.

The goal of this study is to determine single-section travel times without considerably reducing the amount of collected data. However, kriging equations return the exact same value for observed locations and generate interpolated values for unobserved locations. Hence, even if there is a non-zero demand between consecutive junctions of the roadway, they cannot be incorporated into the kriging equations. 7 out of 28 OD pairs in the study area cannot be used in the kriging method because of this

reason, which leads to the loss of 25% of available data. Since the demand between consecutive junctions is not commonly observable, this can be seen as a disadvantage of kriging approach. Another disadvantage of the kriging algorithm is that it is impossible to address the information delay in the collected data. Single-section travel times are identified using the assumption of instantaneous travel times.

5.1.2 Results

Figure 5-7 provides the graphical representation of the proposed algorithm for one week (07/24/2009-07/30/2009) and 28 OD pairs. Note that the first day of the week is Friday. The graphical representations show that the proposed methodology complies with every itinerary travel time information and it is able to detect the location of congestion. For example, in the first two days, there is a clear delay for OD pairs whose destinations are either junction 8 or 8A. Note that the link between 8 and 8A is the last section of the interested network and single sections are not incorporated in the kriging equation. Results show that the algorithm provides accurate results for other OD pairs, as well, which are not affected by the congestion on the links of (8A-8) and (9-8A) This proves the ability of the methodology to identify the congestion location.

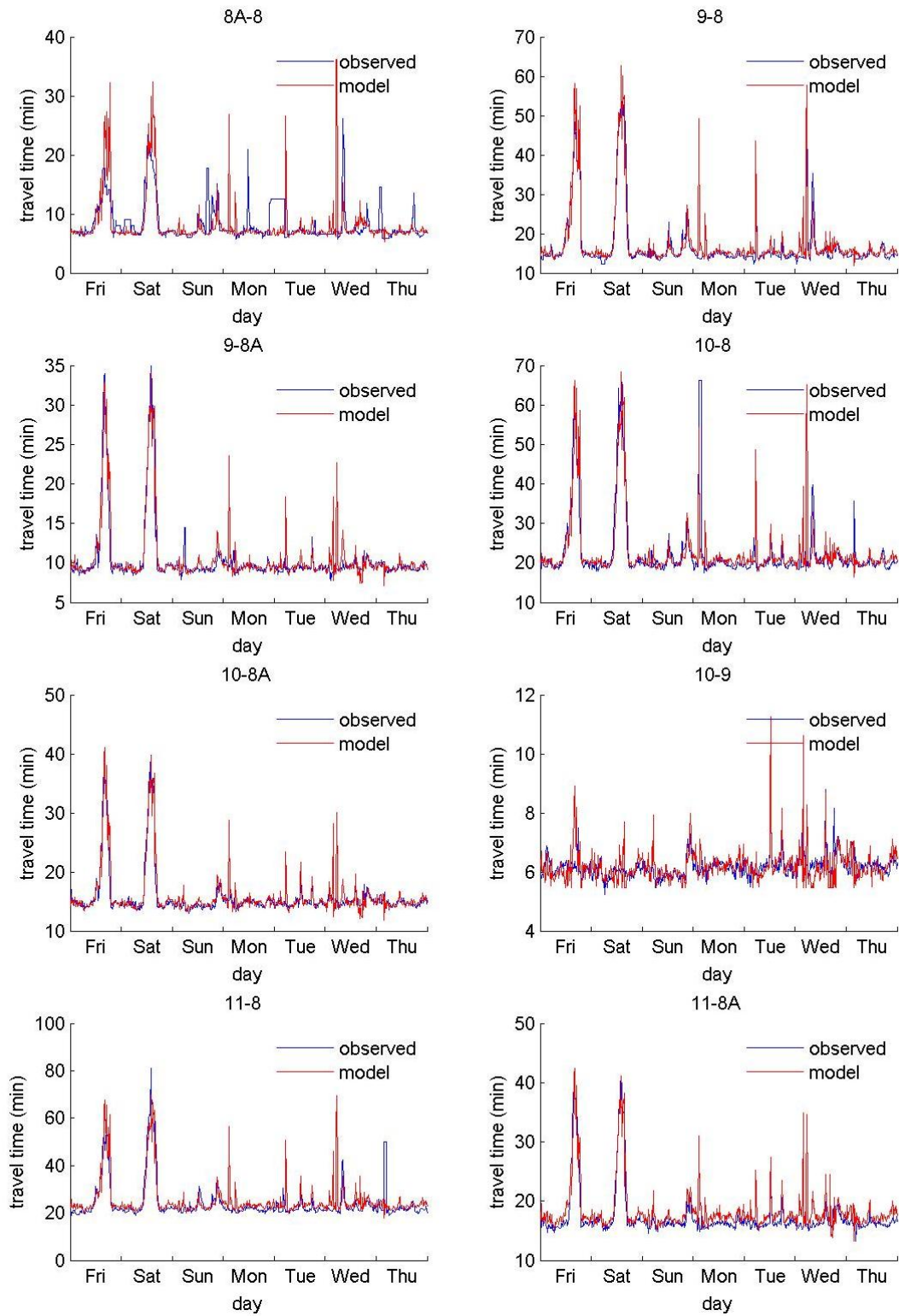


Figure 5-7 (a)- Graphical Results of the Kriging Algorithm

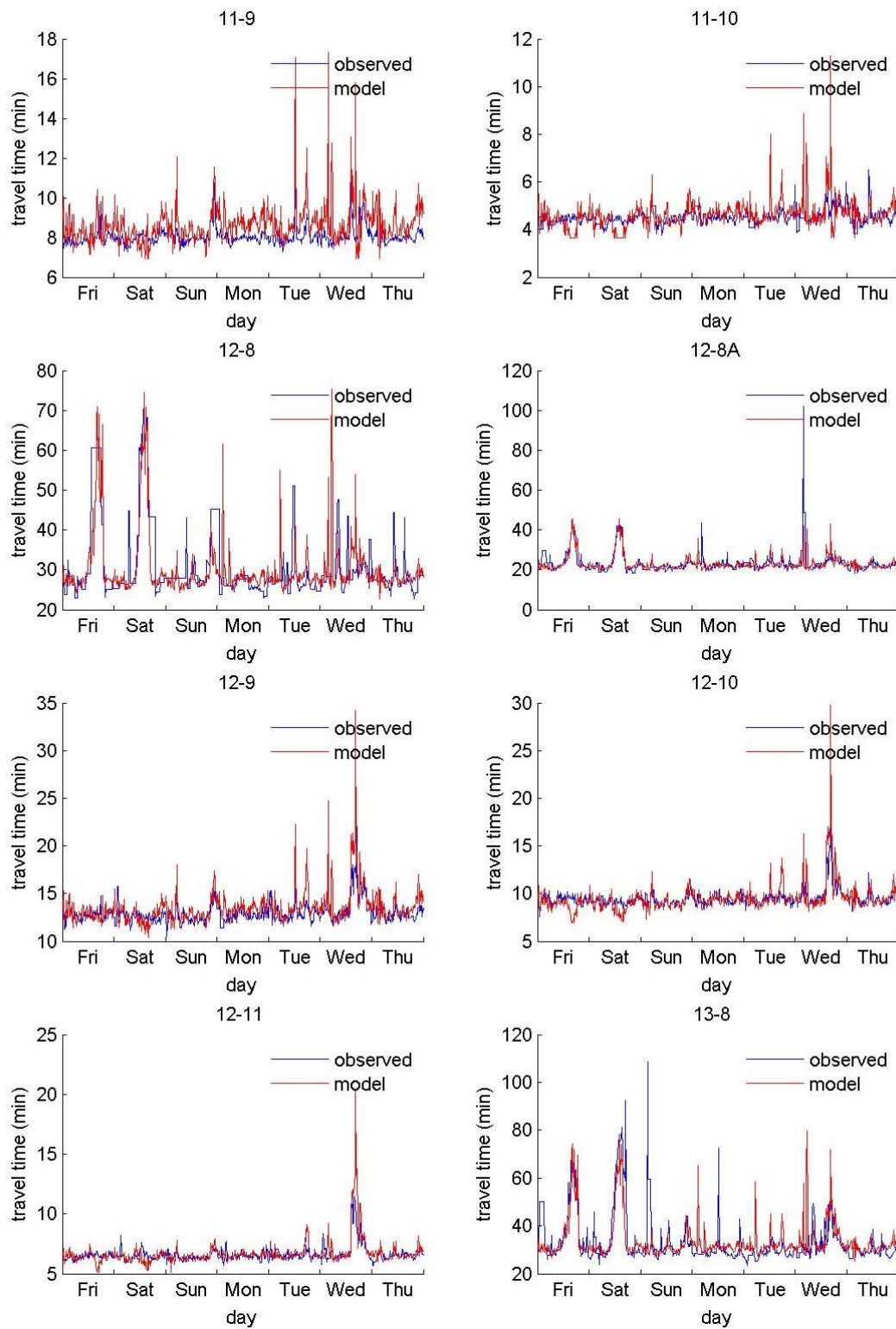


Figure 5-7 (b) - Graphical Results of the Kriging Algorithm

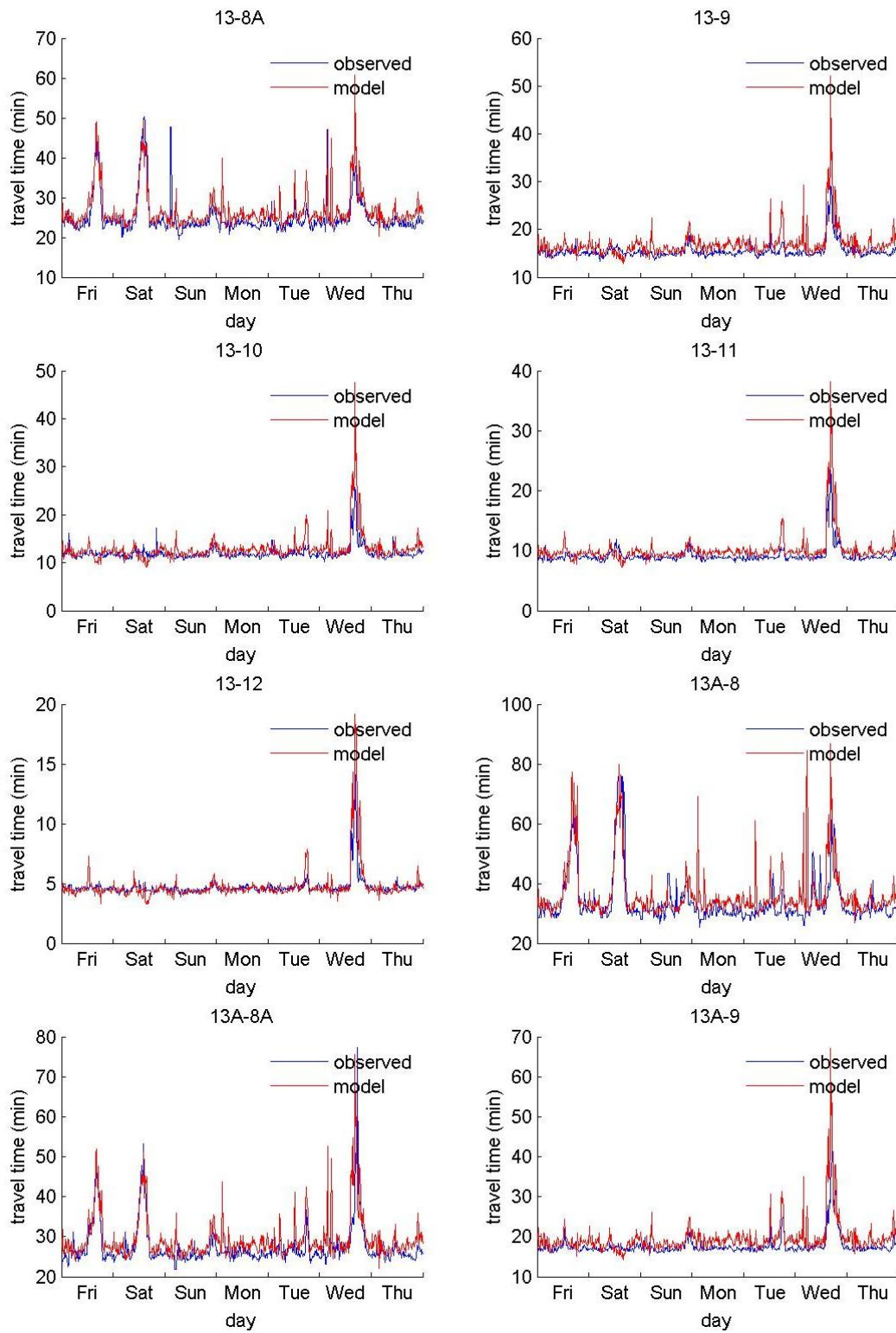


Figure 5-7 (c) - Graphical Results of the Kriging Algorithm

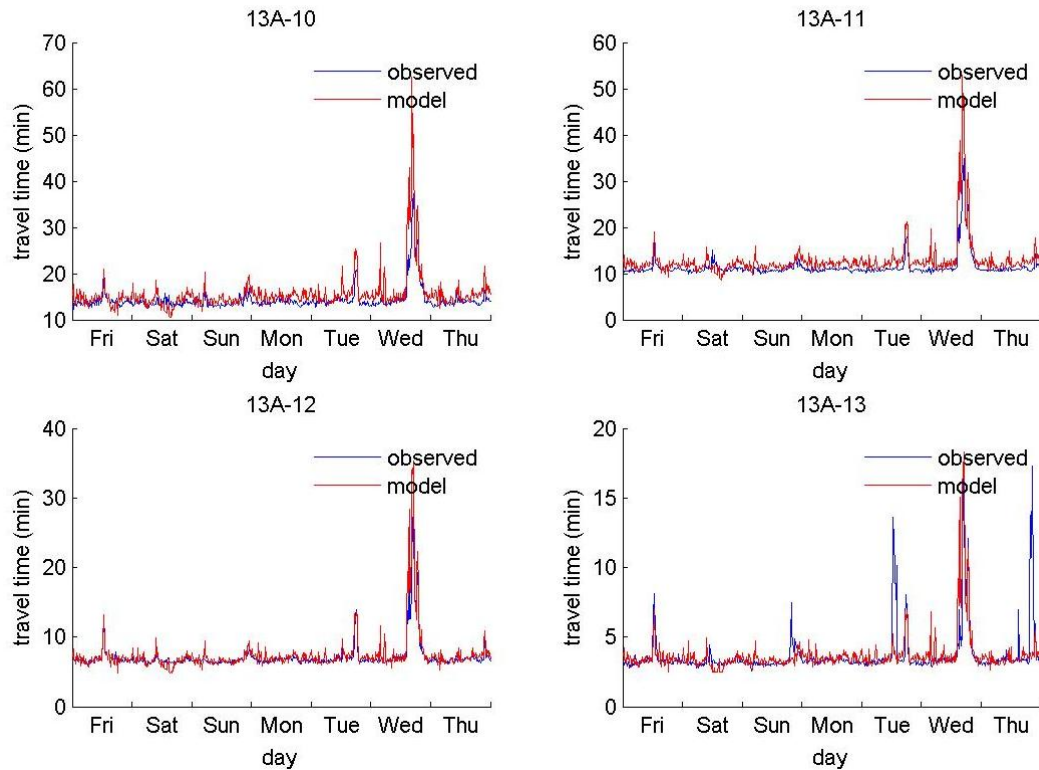


Figure 5-7 (d) - Graphical Results of the Kriging Algorithm

Although single section measurements are not included in the analysis, the proposed algorithm provides accurate results for them as well. The first section in the network is used only by the travelers whose origin is the first junction and travel time estimation of the first link is based on their experiences, as the closest points in the imaginary two dimensional space are those OD pairs. However, the increase in (13A-13) travel time values on the fifth and seventh day are not captured by the algorithm, since the delay is not observed for other travelers that originated from the same junction. This fact also implies that these measurements are outliers, which is a common phenomenon for successive OD pairs with low demand levels.

Another intriguing point about the results is the unnecessary jumps in the estimated travel time values, which are not accompanied by observed values. In case of missing measurements, observed travel time information is represented by the last observed travel time value. Besides that, these jumps are mostly observed during night hours, where the demand level is quite low compared to daytime hours.

To compute the error in travel time estimation, OD pair between exits 11 and 8 is selected and a detailed graphical representation of results is given in **Figure 5-8**. The error is calculated for different periods of the day and considering various demand levels. **Table 5-1** shows the estimation error generated by the algorithm. Note that peak hours are considered to be between 6am-9am and 4pm-7pm, night hours to be between 11pm-6am, and off-peak hours to be the rest. The algorithm provides accurate travel time information, with a mean absolute error less than 16% for all the hours except nighttime. Note that trip travel times are incorporated in the application, if there is demand associated with that particular OD pair; any sort of travel time assumption is not used for the periods without demands. When the covariogram model is not well constructed due to low number of OD pairs with enough observations, which is likely to happen during nighttime, kriging algorithm is not able to produce accurate results. However, considering the value of travel time information, one should focus on the periods of the day where traffic demand is high and traveler information system is really needed.

Obtained error values in **Table 5-1** are calculated for several demand patterns associated with this OD pair. However, the particular travel time along the OD path is actually affected by the traffic conditions and demand on the mainline.

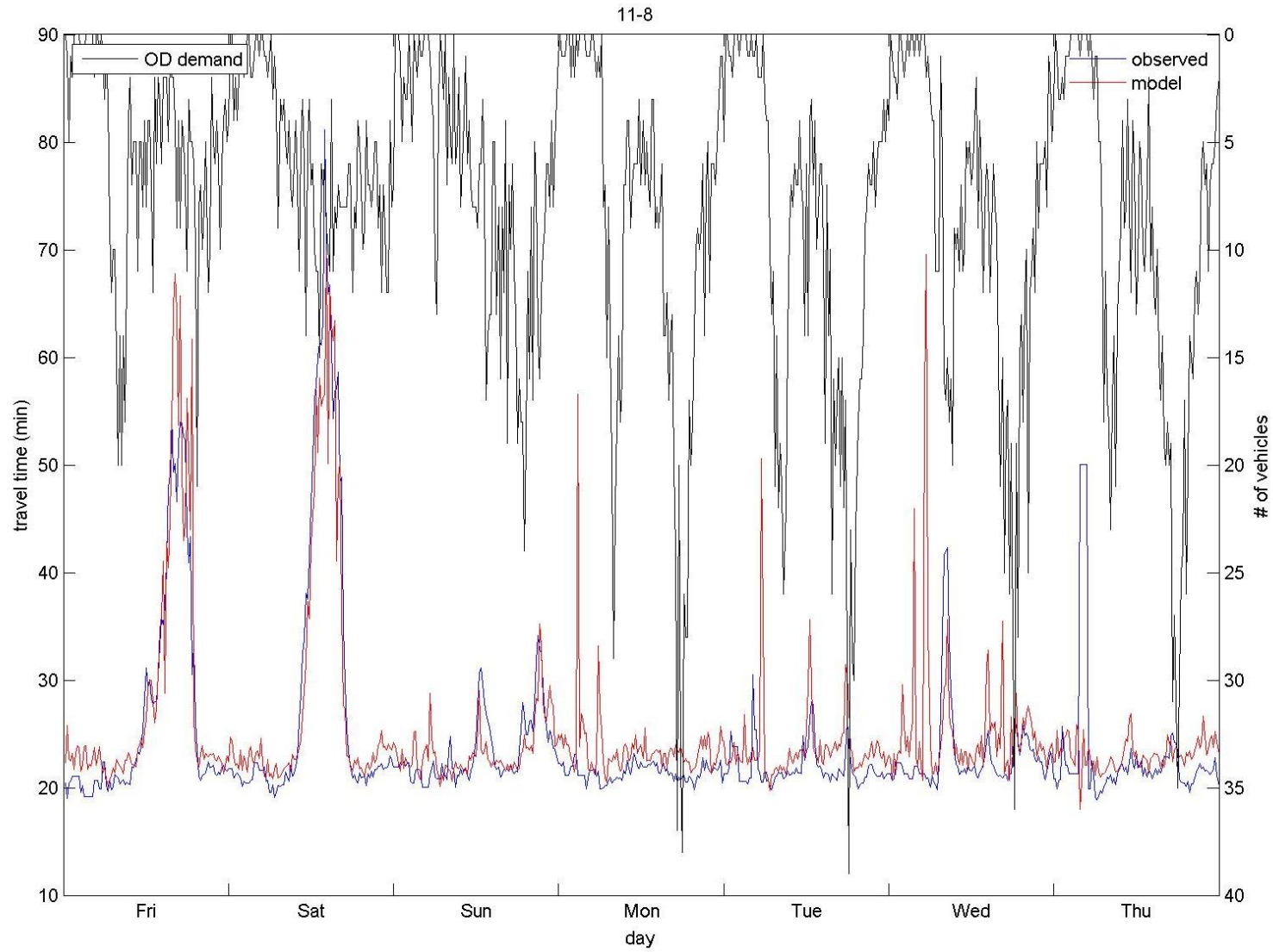


Figure 5-8- Kriging Results for (11,8) Travel Times

Table 5-1- Accuracy of Kriging Algorithm for Different Periods of the Day

Test Day	Period of the Day	Travel Time Absolute Error	
		Mean (min)	Relative
weekdays	Peak Hours	3.03	0.11
	Off-Peak Hours	1.89	0.08
	Night Hours	4.51	0.20
weekend	6am-12pm	1.44	0.06
	0am-6am	2.87	0.14
7/24/2009 <i>Friday</i>	Peak Hours	6.03	0.16
	Off-Peak Hours	2.12	0.07
	Night Hours	2.21	0.11
7/27/2009 <i>Monday</i>	Peak Hours	1.93	0.09
	Off-Peak Hours	1.45	0.07
	Night Hours	4.97	0.24
7/28/2009 <i>Tuesday</i>	Peak Hours	1.88	0.09
	Off-Peak Hours	2.03	0.09
	Night Hours	3.76	0.17
7/29/2009 <i>Wednesday</i>	Peak Hours	3.79	0.13
	Off-Peak Hours	1.94	0.09
	Night Hours	6.96	0.33
7/30/2009 <i>Thursday</i>	Peak Hours	1.51	0.07
	Off-Peak Hours	1.84	0.09
	Night Hours	4.34	0.15

Table 5-2 - Accuracy of Kriging Algorithm under Congestion

Test Day	Period of the Day	Traffic Condition	Travel Time Absolute Error	
			Mean	Relative
7/24/2009	11.00-20.00	Non-recurrent	6.59	0.14
7/25/2009	09.30-20.00	Non-recurrent	5.99	0.11
7/26/2009	11.00-16.00	Recurrent	2.18	0.08
7/26/2009	18.00-23.00	Recurrent	2.22	0.08
7/29/2009	06.30-09.00	Recurrent	5.74	0.16

As the travel time indicates the congestion level on the roadway, it is possible to detect non-recurrent or recurrent congested periods and to measure the performance of the algorithm under such conditions. **Table 5-2** provides the error caused by the algorithm under recurrent and non-recurrent congestion.

Travel time information is most valuable when the traffic conditions deviate from expected ones(i.e. incident) and accurate estimations are mostly needed during these periods. From the results shown in **Table 5-2**, it can be concluded that under congested conditions the kriging algorithm produces fairly accurate results and it is capable of capturing the effect of rapidly changing traffic conditions (non-recurrent congestion), which is probably due to an incident. The mean absolute error of travel time estimations under recurrent and non-recurrent traffic conditions ranges from 0.08 to 0.16.

The results of the kriging application have proved the ability to estimate single-section travel times under free-flowing conditions as well recurrent or non-recurrent congestion. However, as already mentioned, the delay in travel time information (especially for long itineraries) makes it difficult to apply the proposed algorithm for larger networks. Since the median travel time for the longest itinerary is less than 30 minutes (2 time intervals), the assumption of instantaneous travel time does not cause a significant problem in this case. However, there is a clear need for an algorithm that would address the time delay in the obtained travel time information and that would improve the estimation performance.

5.2 Basic Nonlinear Programming (P1)

5.2.1 Methodology

Travel time between entrance i and exit j can be represented by the following equation:

$$t_{i,j} = t_{ent(i)} + t_{i,i+1} + t_{i+1,i+2} + \dots + t_{j-1,j} + t_{ext(j)} \quad (5.12)$$

where $t_{ent(i)}$ is the entrance time at the junction i , and $t_{ext(j)}$ is the exit time at the junction j .

As already discussed, entrance and exit times for vehicles equipped with electronic tag readers can be assumed constant. So, Equation (5.12) should be rewritten as:

$$t_{i,j} - t_{ent(i)} - t_{ext(j)} = t_{i,i+1} + t_{i+1,i+2} + \dots + t_{j-1,j} \quad (5.13)$$

However, the above equation does not take the information delay into account. In a real time application, it is needed to determine the time period in which the vehicle traversed a particular section. If this information was available, Equation (5.13) could be rewritten as:

$$t_{s(i,j)}^{(p)} = t_{i,j}^{(p)} - t_{ent(i)} - t_{ext(j)} = t_{i,i+1}^{(p-\Delta t_{i+1,j})} + t_{i+1,i+2}^{(p-\Delta t_{i+2,j})} + \dots + t_{j-1,j}^{(p)} \quad (5.14)$$

where p is the current time interval and $\Delta t_{i+1,j}$ is the time lag between interchanges $i+1$ and j . However, in a closed toll system, readers are not located on the mainline and it is not possible to acquire such data. One way of solving this problem could be the use of average link travel times estimated from one year of historical data. According to average

travel times, links that can be reached in one time-step can be identified and incorporated into the equation. However, it should be noticed that itinerary travel times are obtained by the average of all the vehicles that reached their destination at time interval "p" and the exact exit times of vehicles are not used in this study.

Since the average travel time for the longest route is less than 30 minutes, two intervals are going to be enough for the determination of link travel times. If the end of the considered link is more than 15 minutes away from the destination point of the path, the link travel time associated with the previous time interval is used to construct Equation (5.14). In some cases, the beginning of a link can be traversed in the previous time interval, while the end of the link is traversed during the current interval. Then, the interval is identified based on the times spent in different intervals while traversing the link and the link travel time is associated with the time interval in which the majority of the time is spent and the corresponding time interval is associated with the link in the mathematical model.

Considering path travel times, different estimations of single-section travel times can be obtained. So, the question is how to fuse different single-section travel times coming from different path travel times. The objective of the fusion is to identify single section travel times that are compatible with all the measured path travel times. Such a problem can be modeled as a nonlinear programming problem NLP1;

$$\min \sum_{i=1}^{n-1} \sum_{j=i+1}^n (t_{s(i,j)}^{(p)} - \hat{t}_{i,i+1}^{(p-\Delta t_{i+1,j})} - \hat{t}_{i+1,i+2}^{(p-\Delta t_{i+2,j})} - \dots - \hat{t}_{j-1,j}^{(p)})^2 * x_{i,j} \quad (5.15)$$

$$s. t. \quad \hat{t}_{i,i+1}^{(p)} \geq \frac{l_{i,i+1}}{v_{\max(i,i+1)}} \quad i = 1, 2, \dots, n-1 \quad (5.16)$$

$$0.8 \leq \frac{\hat{t}_{i,i+1}^{(p-1)}}{\hat{t}_{i,i+1}^{*(p-1)}} \leq 1.2 \quad i = 1, 2, \dots, n-1 \quad (5.17)$$

$$x_{i,j} = \begin{cases} 0 & d_{i,j} = 0 \\ 1 & d_{i,j} > 0 \end{cases} \quad \begin{matrix} i = 1, 2, \dots, n-1 \\ j = 2, 3, \dots, n \end{matrix} \quad (5.18)$$

where

n is the number of interchanges in the roadway,

$\hat{t}_{i,i+1}^{(p)}$ is the travel time estimation for the link between interchanges i and

$i+1$, $l_{i,i+1}$ is the length of the link,

$V_{\max(i,i+1)}$ is the maximum speed assumed on the link,

$\hat{t}_{i,i+1}^{*(p-1)}$ is the link travel time estimated at the end of previous time interval,

$d_{i,j}$ is the demand between interchanges i and j , and $x_{i,j}$ is a dummy variable that determines whether there is a valid measurement or not.

Equation (5.15) is the objective function that attempts to minimize the difference between the measured travel times and the ones that are constructed by the addition of estimated link travel times. Equation (5.16) is the constraint on the estimated travel link travel times and does not allow them to be smaller than the minimum link travel time calculated by the length of the section and the maximum speed assumed on that section. Considering measured travel times, maximum speed is assumed to be 80 mph, although the maximum posted speed limit is 65 mph. Equation (5.17) compares the link travel times of the previous time interval that are calculated at the end of the current time interval “i” and of

the previous interval “i-1”. It basically attempts to create travel time estimates that are consistent with the ones calculated at the previous time interval. One may think that past travel times do not have great importance in the sense that they cannot be used to inform drivers about future conditions; however, any time series application that could be used to predict traffic conditions in future needs a rolling horizon. Rolling horizon represents the time window that defines the prediction history. Hence, updating past travel time values within a certain range would help us to produce better travel time predictions in the future. Equation (5.18) is a dummy variable that basically decides on the inclusion of a variable into the objective function.

Equation (5.15) can be better represented by the use of link – OD matrices. For two time intervals that are going to be considered in this application, two matrices that describe the relationship between OD pairs and the link are created. For example, $S_{n_l * n_{OD}}^p$ contains 1 when the link can be traversed in the same interval by the corresponding OD traveler.

$$S_{n_l * n_{OD}}^p = \begin{matrix} & \begin{matrix} 8A-8 & 9-8A & 10-9 & 11-10 & 12-11 & 13-12 & 13A-13 \end{matrix} \\ \begin{matrix} 8A-8 \\ 9-8 \\ 9-8A \\ 10-8 \\ 10-8A \\ \dots \\ \dots \\ 13A-12 \\ 13A-13 \end{matrix} & \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 1 & 0 & 0 & 0 & 0 \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ 0 & 0 & 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \end{matrix}$$

$$S'^{p-1}_{n_l * n_{OD}} = \begin{matrix} & \begin{matrix} 8A-8 & 9-8A & 10-9 & 11-10 & 12-11 & 13-12 & 13A-13 \end{matrix} \\ \begin{matrix} 8A-8 \\ 9-8 \\ 9-8A \\ 10-8 \\ 10-8A \\ \dots \\ \dots \\ 13A-12 \\ 13A-13 \end{matrix} & \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 1 & 0 & 0 & 0 & 0 \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \end{matrix}$$

So, Equation (5.15) can be rewritten as;

$$\min ||\mathbf{t}_s^{(p)} - \hat{\mathbf{t}}^{(p)} * S^p - \hat{\mathbf{t}}^{(p-1)} * S^{p-1}|| \quad (5.19)$$

where $\mathbf{t}_s^{(p)}$ is the vector of all itinerary travel time at the time interval p, $\hat{\mathbf{t}}^{(p)}$ is the vector of link travel time estimates for time interval p. Eq. (5.19) is equivalent to Eq. (5.15), but it is represented as an euclidean norm function (i.e. $||\mathbf{x}|| = \sqrt{x_1^2 + x_2^2 + \dots + x_n^2}$).

5.2.2 Results

Figure 5-9 provides the graphical representation of the proposed algorithm for one week (07/24/2009-07/30/2009) and 28 OD pairs.

NLP algorithm produces link travel time estimates compatible with the path travel times, as seen in **Figure 5-9**. Like the kriging application, NLP algorithm is able to detect the location of congestion. For example, in the first two days, there is a clear delay for OD pairs whose destinations are either junction 8 or 8A. However, the algorithm is still able to capture free-flowing conditions for other OD pairs. The jumps generated by the kriging algorithm especially for night hours are significantly reduced by NLP algorithm, which demonstrates the robustness of the algorithm even in low demand cases. Note that

single-section travel time measurements are included in NLP equations and the algorithm uses these additional data whenever available.

For example, the increase in (13A-13) travel time values on *Tuesday* and at the end of *Thursday* are captured by the algorithm; but, the estimated travel time does not fully represent the delay observed. Since the same delay is not observed for other travelers that originated from the same junction, NLP algorithm does not allow the link travel time estimate to go up. This type of outlier measurement, which is a common phenomenon in direct measurement techniques, is somehow balanced by the fusion analogy brought by NLP algorithm.

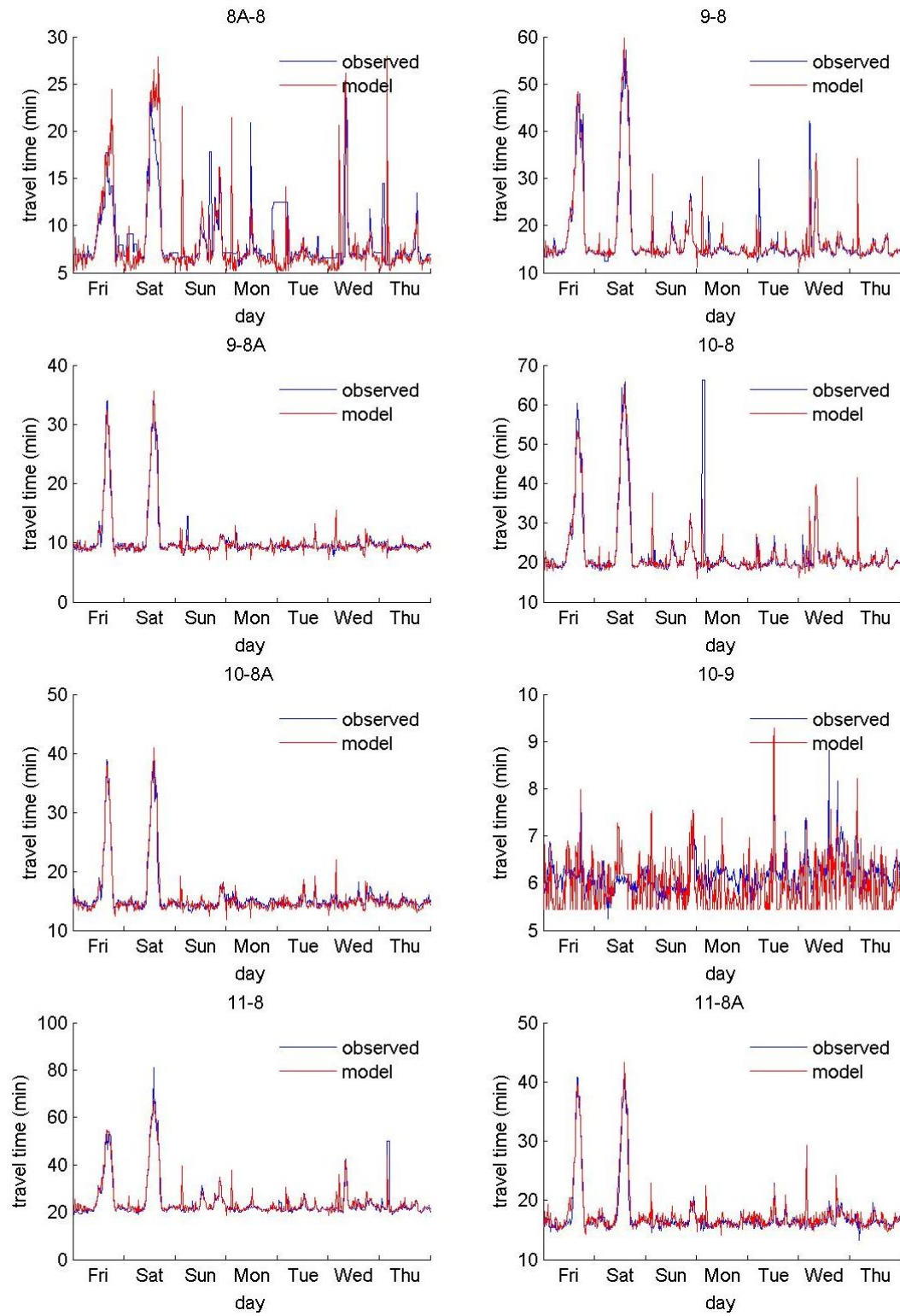


Figure 5-9 (a) - Graphical Representation of NLP Algorithm

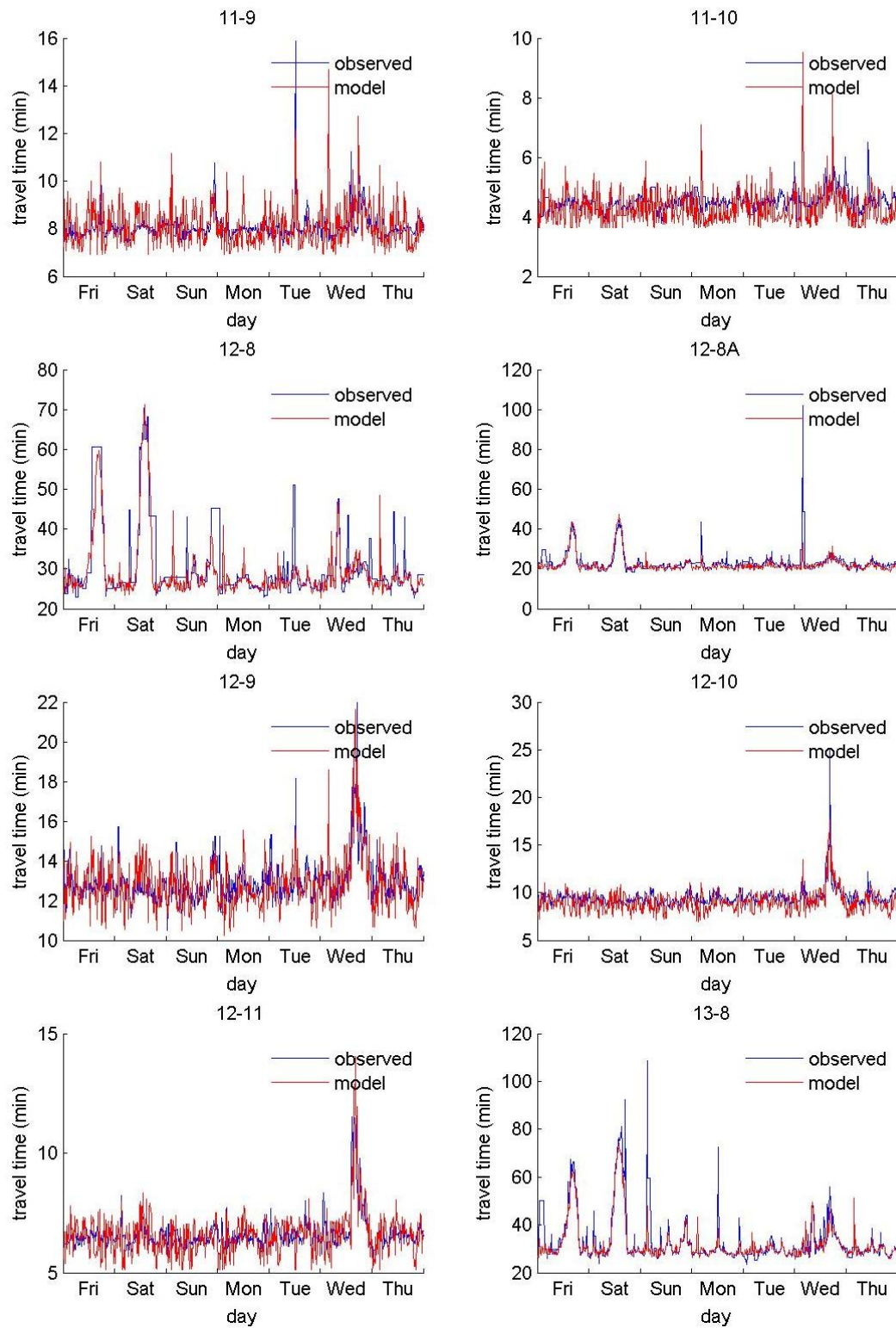


Figure 5-9 (b)- Graphical Representation of NLP Algorithm

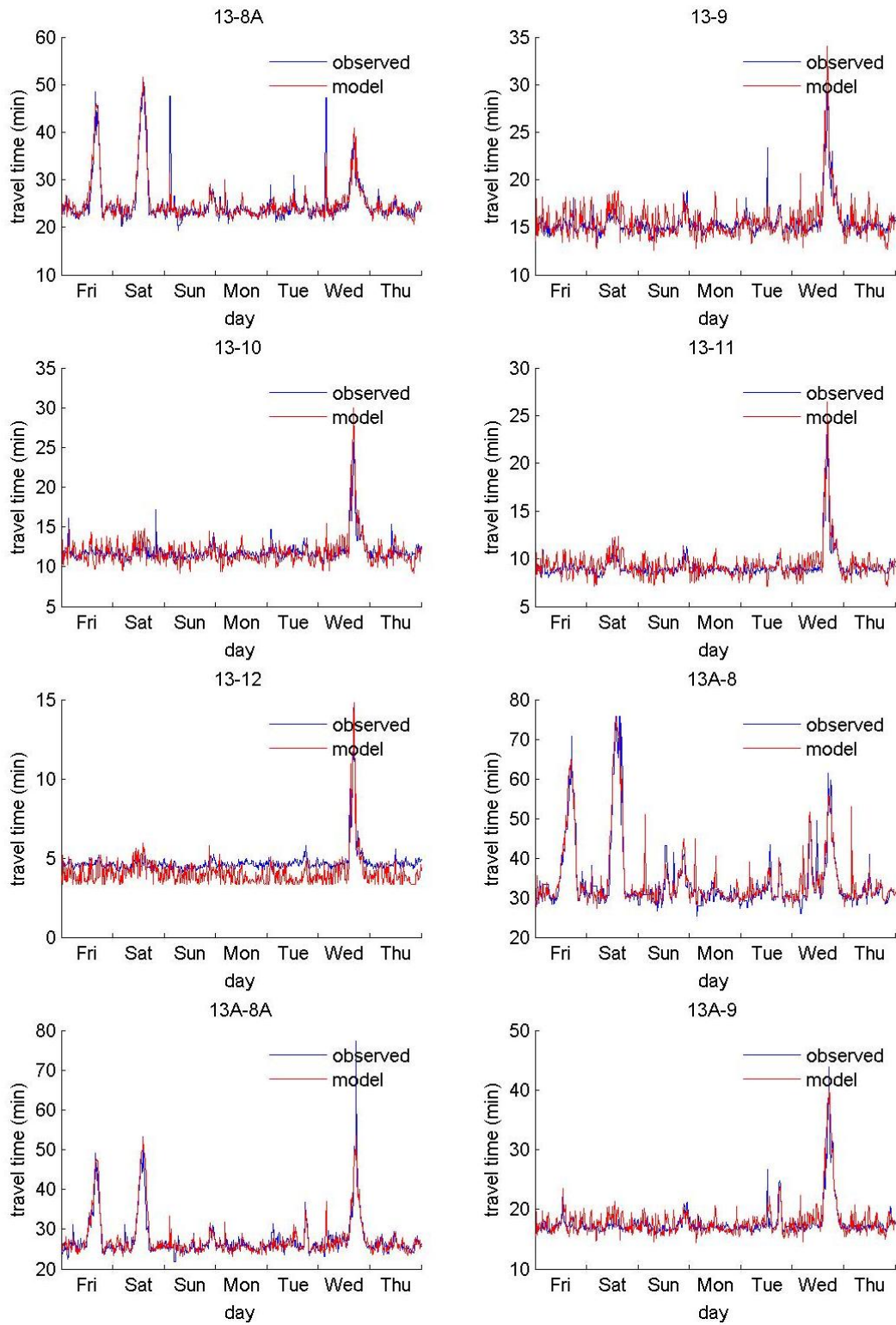


Figure 5-9 (c)- Graphical Representation of NLP Algorithm

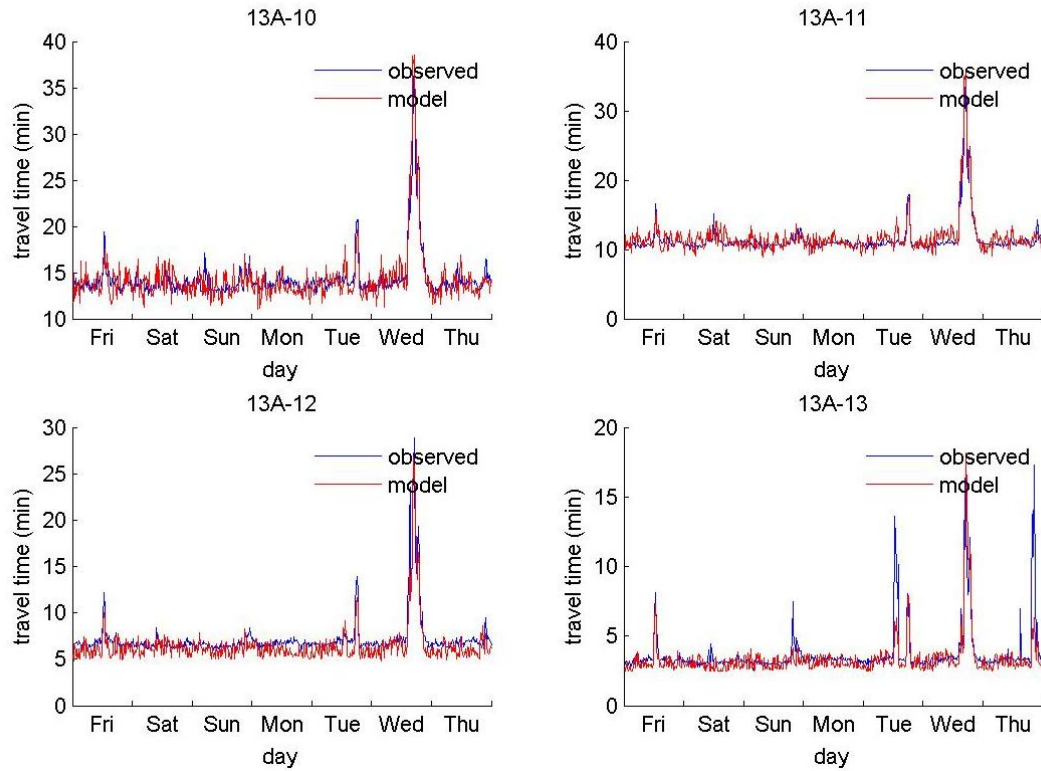


Figure 5-9 (d)- Graphical Representation of NLP Algorithm

To compute the error in travel time estimation, (11-8) pair is selected again and a detailed graphical representation of results is given in **Figure 5-10**. The error is calculated for different periods of the day and considering various demand levels. **Table 5-3** shows the estimation error generated by the algorithm. Note that peak hours are considered to be between 6am-9am and 4pm-7pm, night hours to be between 11pm-6am, and off-peak hours to be the rest. The algorithm provides accurate travel time information, with a mean absolute error of less than 8% for all the cases. As mentioned before, due to low demand in night hours, proposed algorithm gives slightly worse results. However, considering the value of travel time information, one should focus on

the periods of the day where traffic demand is high and traveler information system is really needed.

Obtained error values in **Table 5-3** are calculated for several demand patterns associated with OD pair. However, the particular travel time on OD route is actually affected by the traffic conditions and demand on the main trunk. As the travel time indicates the congestion level on the roadway, it is possible to detect non-recurrent or recurrent congested periods and to measure the performance of the algorithm under such conditions. **Table 5-4** provides the error committed by the algorithm under recurrent and non-recurrent congestion.

From the results given in **Table 5-3** and **Table 5-4**, it can be concluded that NLP algorithm provides accurate enough estimations under free-flowing and congested conditions. Note that errors are computed based on measured itinerary travel times, and, as mentioned before, these measurements can be themselves under the influence of outlier travelers. NLP algorithm is capable of capturing rapidly changing traffic conditions, as observed in non-recurrent traffic conditions given in **Table 5-4**, as well as recurrent and free-flowing conditions. The mean absolute error of travel time estimations for recurrent and non-recurrent traffic conditions ranges from 0.02 to 0.06, which proves the robustness of the developed methodology.

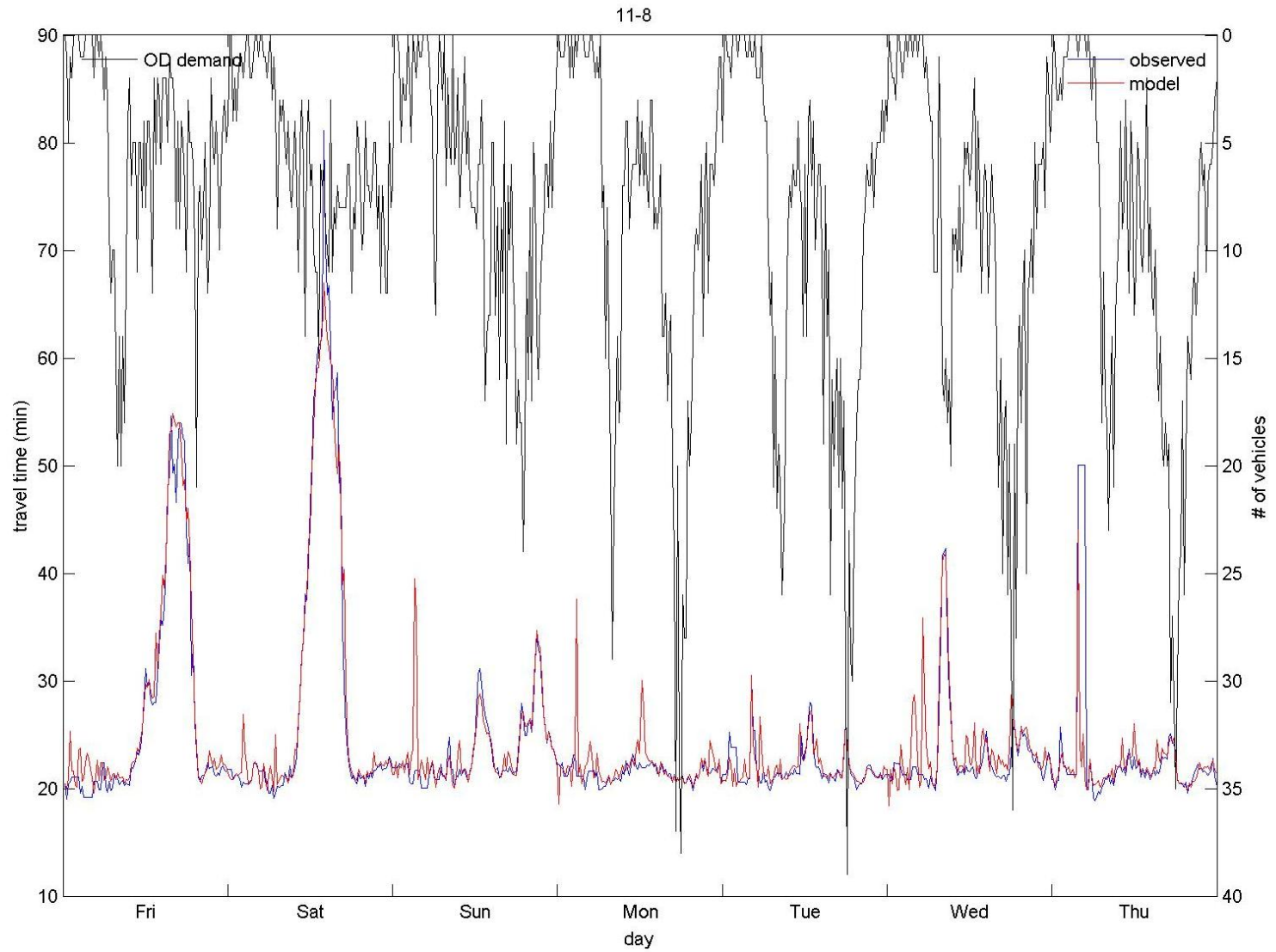


Figure 5-10- NLP Results for (11,8) Travel Times

Table 5-3 - Accuracy of NLP Algorithm for Different Periods of the Day

Test Day	Period of the Day	Travel Time Absolute Error	
		Mean (min)	Relative
weekdays	Peak Hours	0.87	0.03
	Off-Peak Hours	0.80	0.03
	Night Hours	1.32	0.06
weekend	6am-12pm	0.51	0.02
	0am-6am	0.80	0.04
7/24/2009 <i>Friday</i>	Peak Hours	1.92	0.05
	Off-Peak Hours	1.02	0.03
	Night Hours	1.22	0.06
7/27/2009 <i>Monday</i>	Peak Hours	0.23	0.01
	Off-Peak Hours	0.85	0.04
	Night Hours	1.68	0.08
7/28/2009 <i>Tuesday</i>	Peak Hours	0.43	0.02
	Off-Peak Hours	0.60	0.03
	Night Hours	1.06	0.05
7/29/2009 <i>Wednesday</i>	Peak Hours	1.29	0.05
	Off-Peak Hours	0.92	0.04
	Night Hours	1.70	0.08
7/30/2009 <i>Thursday</i>	Peak Hours	0.47	0.02
	Off-Peak Hours	0.65	0.03
	Night Hours	0.90	0.03

Table 5-4 - Accuracy of NLP Algorithm under Congestion

Test Day	Period of the Day	Traffic Condition	Travel Time Absolute Error	
			Mean	Relative
7/24/2009	11.00-20.00	Non-recurrent	2.60	0.06
7/25/2009	09.30-20.00	Non-recurrent	2.74	0.05
7/26/2009	11.00-16.00	Recurrent	0.75	0.03
7/26/2009	18.00-23.00	Recurrent	0.51	0.02
7/29/2009	06.30-09.00	Recurrent	1.08	0.04

5.3 Extended NLP Algorithm (P2)

5.3.1 Link Assignment

In the basic algorithm, a naive approach of average link travel times is used to reconstruct path travel time. However, during non-recurrent or recurrent congestion, where traffic conditions are highly stochastic, link travel times can quickly increase.. To consider such effects, link travel times estimated in the previous time interval can be used to determine the interval in which links are traversed. Path travel times can then be reconstructed based on this assumption. Note that more than two time intervals need to be incorporated in this application when congested traffic conditions are present on the roadway.

There are few assumptions made for constructing new assignment matrices:

- Vehicles are assumed to reach the destination point at the end of the current interval.
- Although in some cases it takes more than one time interval for travelers to cross a single section or only a part of the link is traversed in the current interval, links are assigned to a single time interval.

The algorithm to construct the assignment matrices can be described as follows:

1. Determine the number of time intervals, n , required to traverse the longest path using the sum of the link travel times calculated at the end of the previous time interval. Ceiling value of the sum divided by interval length provides the number of intervals needed. Note that the intervals are numbered starting from the current period towards the previous ones.
2. For each OD pair, determine the origin point i and the destination point j .

3. Assign the last link of the path $(j - 1, j)$ to the current time interval $(m = 1)$ no matter what its travel time value is.
4. For time intervals m from 1 to n , and for interchanges k from $j - 1$ to $i + 1$, do the following:
 - Calculate the sum of the link travel times between the destination point and the interchanges k and $k - 1$ using (Equation 5.20) and (Equation 5.21), respectively. To determine the time interval to which the link between the interchanges k and $k - 1$ is assigned, compute the ceiling value of the sums divided by interval length (e.g. 15 minutes).

$$\hat{t}_{k,j}^{p-1} = \sum_{r=k}^{j-1} \hat{t}_{r,r+1}^{p-1} \quad (5.20)$$

$$\hat{t}_{k-1,j}^{p-1} = \sum_{r=k-1}^j \hat{t}_{r,r+1}^{p-1} \quad (5.21)$$

- If the ceiling value of $\hat{t}_{k,j}^{p-1}$ is equal to m , assign the link $(k - 1, k)$ to the interval m .
- If the ceiling value of $\hat{t}_{k-1,j}^{p-1}$ is equal to $m + 1$ and of $\hat{t}_{k,j}^{p-1}$ is equal to m , then calculate the times spent in these two intervals traversing the section and assign the link $(k - 1, k)$ to the interval in which more time is spent.
- If the ceiling value of $\hat{t}_{k-1,j}^{p-1}$ is greater than $m + 1$ and of $\hat{t}_{k,j}^{p-1}$ is equal to m , then assign the link $(k - 1, k)$ to the interval $m + 1$.

By the algorithm described above, $S_{n_l * n_{OD}}$ matrix is computed for each time interval needed. So P2 can be written as:

$$\min ||\mathbf{t}_s^{(p)} - \sum_{m=0}^{n-1} \hat{\mathbf{t}}^{(p-m)} * S^{p-m} || \quad (5.22)$$

$$s. t. \quad \hat{t}_{i,i+1}^{(p)} \geq \frac{l_{i,i+1}}{v_{\max(i,i+1)}} \quad for \forall i \quad (5.23)$$

$$0.8 \leq \frac{\hat{t}_{i,i+1}^{(m)}}{\hat{t}_{i,i+1}^{*(m)}} \leq 1.2 \quad for \forall i \text{ and } \forall m \quad (5.24)$$

Note that the above problem is solved only for observed travel times. If the itinerary set has no data, then it is not included in the problem.

5.3.2 Results

Three interval lengths are considered to apply the extended algorithm. 5, 10 and 15 min. 5 min. is considered to be the minimum updating frequency to follow the traffic conditions that would evolve quickly (i.e. incident conditions); however, the estimations may be subject to fluctuations. Besides, the proposed algorithm may not be suitable to work with finer resolutions because of both the demand levels and outliers' effects. 15 minutes is considered to be the maximum time interval acceptable to track the traffic conditions in a real-time application.

Note that observed path travel times change for each time interval selection, because in each selection different vehicles traveling in that particular itinerary and reaching their destination in time interval " p " are used.

To compute the error in travel time estimation, OD pair (11-8) is selected. Observed travel times will be compared with travel times resulting from extended NLP algorithm. Travel time estimates are not the simple addition of the link travel times at the current interval, but they are reconstructed by building the most likely trajectory.

Graphical representations of results and path demand levels are presented in **Figure 5-11**, **Figure 5-12** and **Figure 5-13** for 15min, 10 min and 5 min applications respectively. The decrease in the interval length leads to a decrease in OD demand level. Although a detailed filtering algorithm is applied to remove the outliers, observed travel times in 5 min application are still subject to outliers' effect and they exhibit a high variation throughout the week due to low demand level. However, both 15 minute and 10 minute intervals have enough number of trips to obtain accurate average path travel times.

Link travel time estimates which are calculated using observed path travel times show high variation in 5 minute application, while 15 minute and 10 minute updating intervals reduce the fluctuations in the estimates. Despite this, 15 min application produces unnecessary jumps in travel time estimates during nighttime, which can be observed in *Sunday*, *Monday* and *Wednesday* nights. On the other hand, 10 min application does not produce such jumps. Regarding this aspect, 10 min can be seen as compromise interval length that is long enough to have proper demand level and short enough to produce accurate travel time estimates.

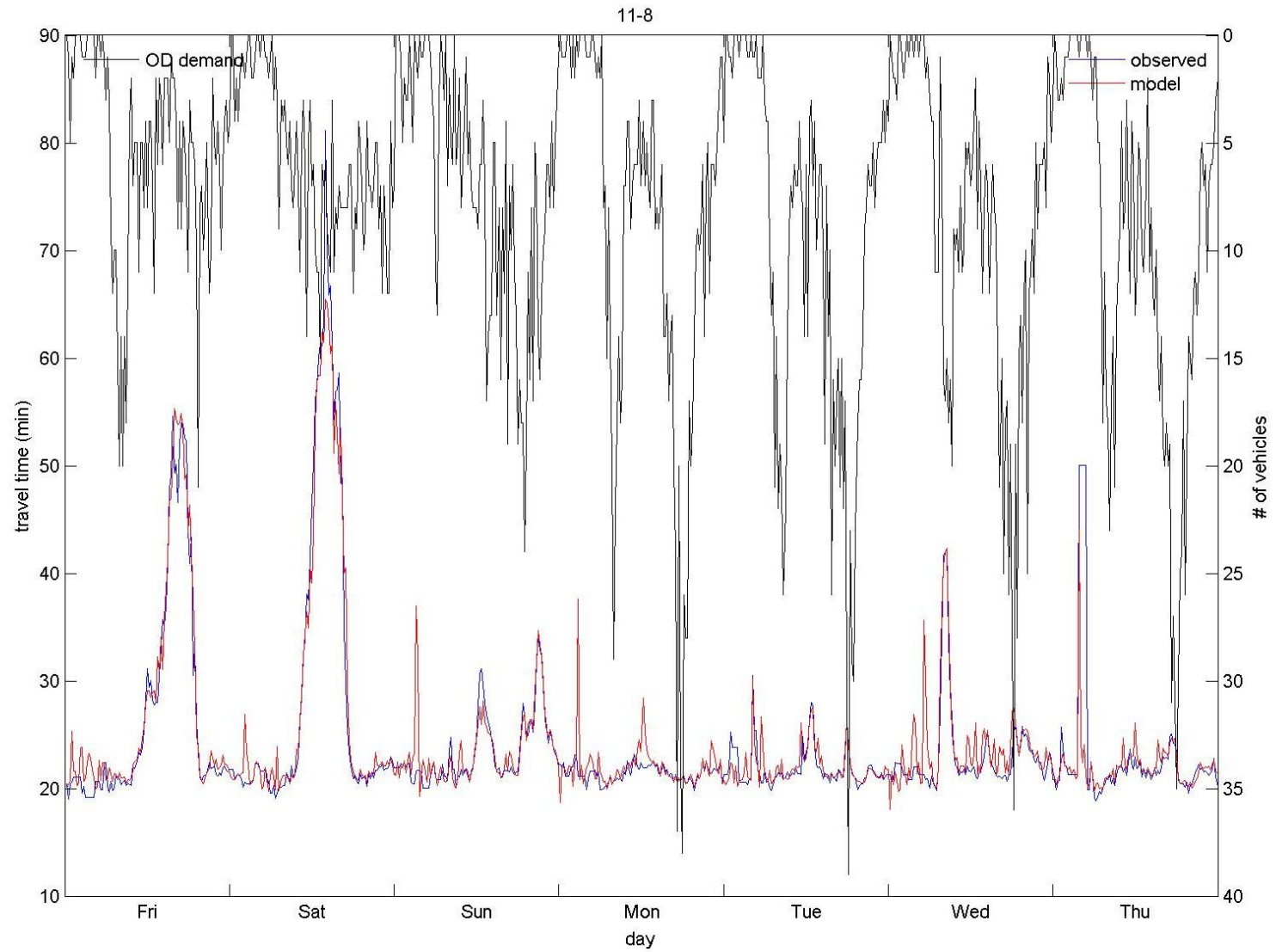


Figure 5-11- Extended NLP Results for (11,8) Travel Times (15 min)

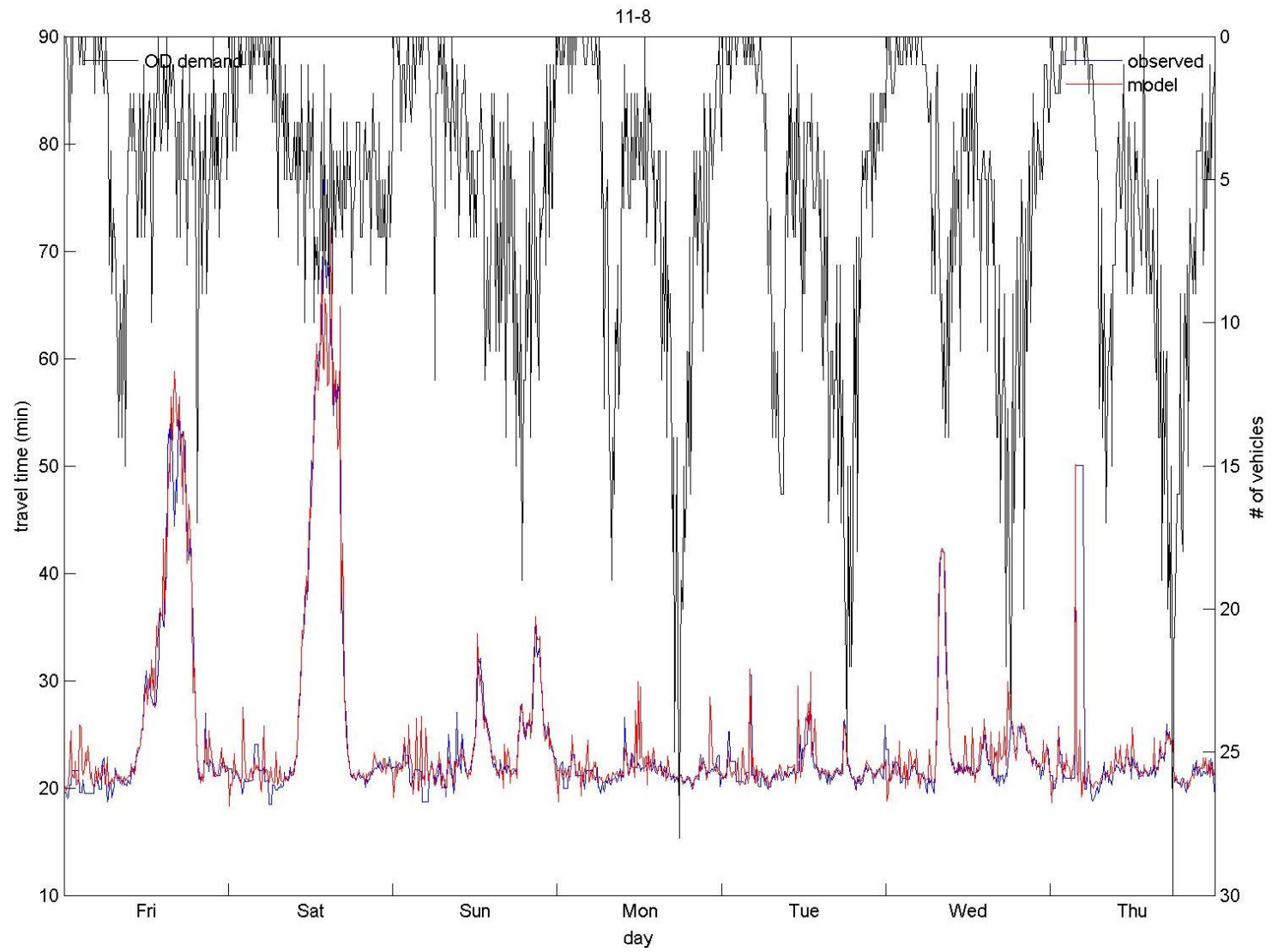


Figure 5-12- Extended NLP Results for (11,8) Travel Times (10 min)

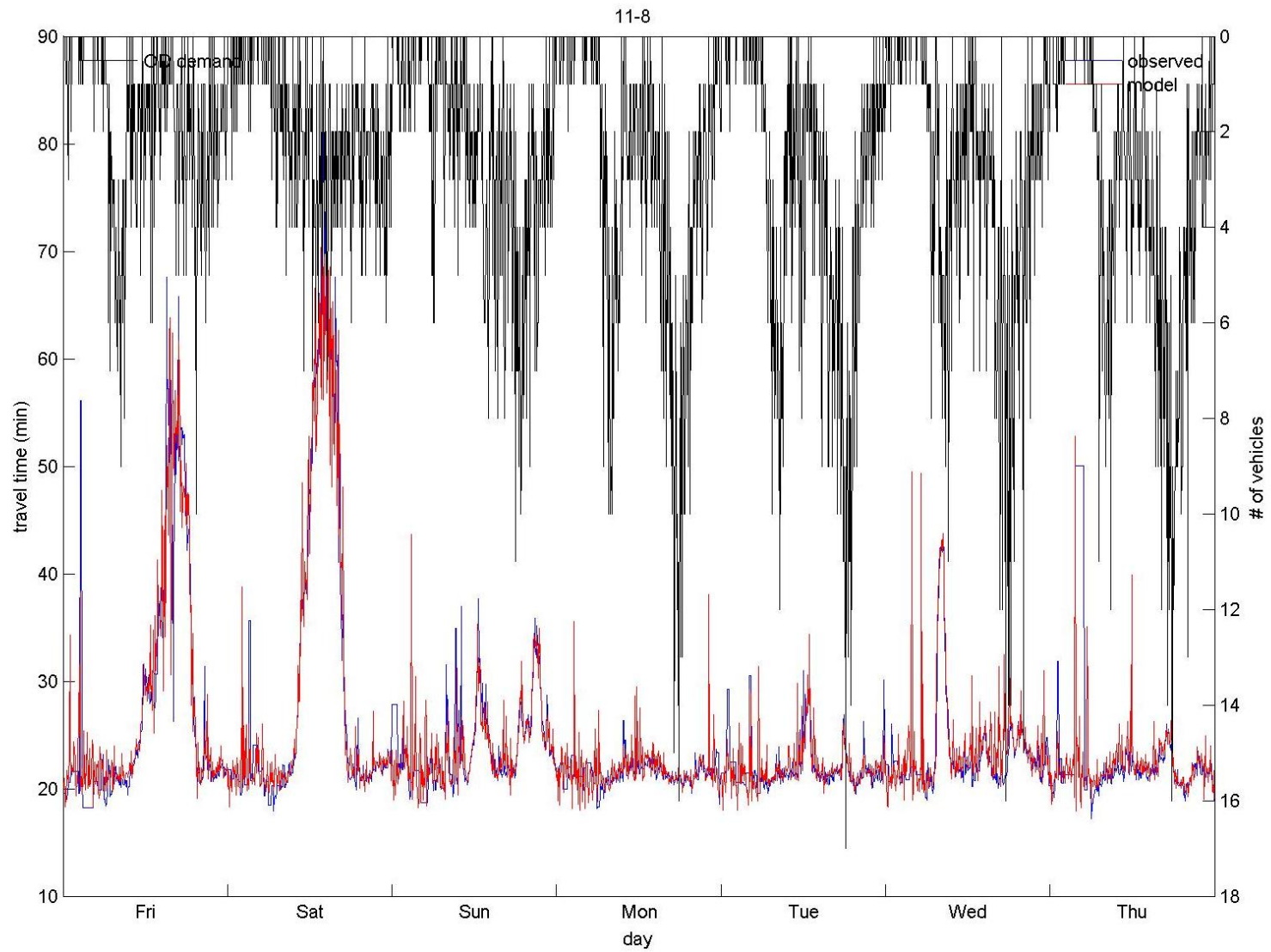


Figure 5-13- Extended NLP Results for (11,8) Travel Times (5 min)

To evaluate the performance of the algorithm for different updating intervals, the travel times to compare must be of the same nature. That means observed travel times to compare must have the finest resolution. For this purpose, itinerary travel times that result from the travelers that reach their destination in 5 min time interval are compared with travel time estimates obtained from 5, 10 and 15 min applications.

The error is calculated for different periods of the day and considering various demand levels. **Table 5-5** shows the estimation error generated by the algorithm throughout the week. All three updating intervals provide accurate travel time estimates, with a mean absolute error of less than 11%, 8% and 7% for 15 min, 10 min and 5 min applications respectively.

Obtained error values in **Table 5-5** are calculated for several demand patterns associated with OD pair. However, the particular travel time on OD route is actually affected by the traffic conditions and demand on the main trunk. As the travel time indicates the congestion level on the roadway, it is possible to detect non-recurrent or recurrent congested periods and to measure the performance of the algorithm under such conditions. **Table 5-6** provides the errors committed by the algorithms under recurrent and non-recurrent congestion. For moderate recurrent congestion, all updating intervals provide similar results; mean absolute errors are less than 5%, 4% and 4% for 15 min, 10 min and 5 min intervals respectively. However, for non-recurrent congestion long intervals are not capable of tracking rapidly changing traffic conditions as well as 5 min interval. Mean absolute errors are less than 13%, 12% and 11% for 15 min, 10 min and 5 min applications respectively.

Table 5-5 - Accuracy of Extended NLP Algorithm for Different Updating Intervals

		15 min.		10 min.		5 min.	
		Travel Time Absolute Error		Travel Time Absolute Error		Travel Time Absolute Error	
Test Day	Period of the Day	Mean (min)	Relative	Mean (min)	Relative	Mean (min)	Relative
weekdays	Peak Hours	1.04	0.04	1.14	0.04	1.18	0.05
	Off-Peak Hours	1.08	0.04	1.05	0.04	1.07	0.04
	Night Hours	1.93	0.08	1.38	0.06	1.31	0.06
weekend	6am-12pm	1.83	0.05	1.84	0.05	1.76	0.05
	0am-6am	1.93	0.09	1.44	0.06	1.16	0.05
7/24/2009 <i>Friday</i>	Peak Hours	2.47	0.07	2.58	0.08	2.56	0.07
	Off-Peak Hours	2.00	0.06	1.70	0.05	1.71	0.05
	Night Hours	2.42	0.08	2.34	0.07	1.72	0.06
7/27/2009 <i>Monday</i>	Peak Hours	0.33	0.02	0.41	0.02	0.45	0.02
	Off-Peak Hours	0.98	0.04	1.05	0.05	0.80	0.04
	Night Hours	1.72	0.08	1.31	0.06	1.50	0.07
7/28/2009 <i>Tuesday</i>	Peak Hours	0.59	0.03	0.50	0.02	0.62	0.03
	Off-Peak Hours	0.87	0.04	1.02	0.04	0.90	0.04
	Night Hours	1.94	0.09	1.36	0.06	1.13	0.05
7/29/2009 <i>Wednesday</i>	Peak Hours	1.36	0.06	1.79	0.08	1.70	0.07
	Off-Peak Hours	0.92	0.04	0.87	0.04	1.10	0.05
	Night Hours	2.32	0.11	1.01	0.05	1.48	0.07
7/30/2009 <i>Thursday</i>	Peak Hours	0.49	0.02	0.48	0.02	0.63	0.03
	Off-Peak Hours	0.80	0.04	0.68	0.03	0.92	0.04
	Night Hours	1.35	0.05	0.99	0.04	0.85	0.03

Table 5-6 - Accuracy of Extended NLP Algorithm under Congestion for Different Updating Intervals

			15 min.		10 min.		5 min.	
			Travel Time Absolute Error		Travel Time Absolute Error		Travel Time Absolute Error	
Test Day	Period of the Day	Traffic Condition	Mean	Relative	Mean	Relative	Mean	Relative
7/24/2009	11.00-20.00	Non-recur	5.29	0.13	4.92	0.12	4.53	0.11
7/25/2009	09.30-20.00	Non-recur	3.87	0.07	3.87	0.07	3.71	0.07
7/26/2009	11.00-16.00	Recurrent	1.35	0.05	1.10	0.04	1.07	0.04
7/26/2009	18.00-23.00	Recurrent	0.84	0.03	0.82	0.03	0.82	0.03
7/29/2009	06.30-09.00	Recurrent	1.05	0.03	1.14	0.04	0.82	0.03

Since travel times used to compare with estimated results are aggregated for 5 minute intervals, it is quite normal to have the best numerical performance with 5 minute updating interval. However, this is not the only performance measure that must be taken into account. As a real time information system, the algorithm is supposed to provide travel time values that are consistent with neighboring periods. While 15 min and 10 min applications of the algorithm produce consistent travel time estimates, 5 min application cannot handle the fluctuations in travel time estimates.

Figure 5-14 provides a closer look to the graphical results of the algorithm behavior in moderate recurrent and non-recurrent congestion. For free-flowing conditions, all three algorithms provide similar results, an updating interval of 15 min would be the best choice in this case considering the demand level. However, this long interval is not capable of tracking all rapid changes in the roadway, particularly the congestion onset in incident related conditions (e.g. *Friday* and *Saturday*), and it may miss peak of the travel time curve for some congested conditions (e.g. the first peak on *Sunday*). On the other hand, an updating interval of 5 min adapts itself to every single change in observed itinerary travel times and produces unacceptable fluctuations in travel time estimates for both recurrent and non-recurrent conditions. Therefore, updating interval of 10 min can be selected as compromising solution; 10 min interval is long enough to have proper demand level and short enough to respond to rapid changes in the network.

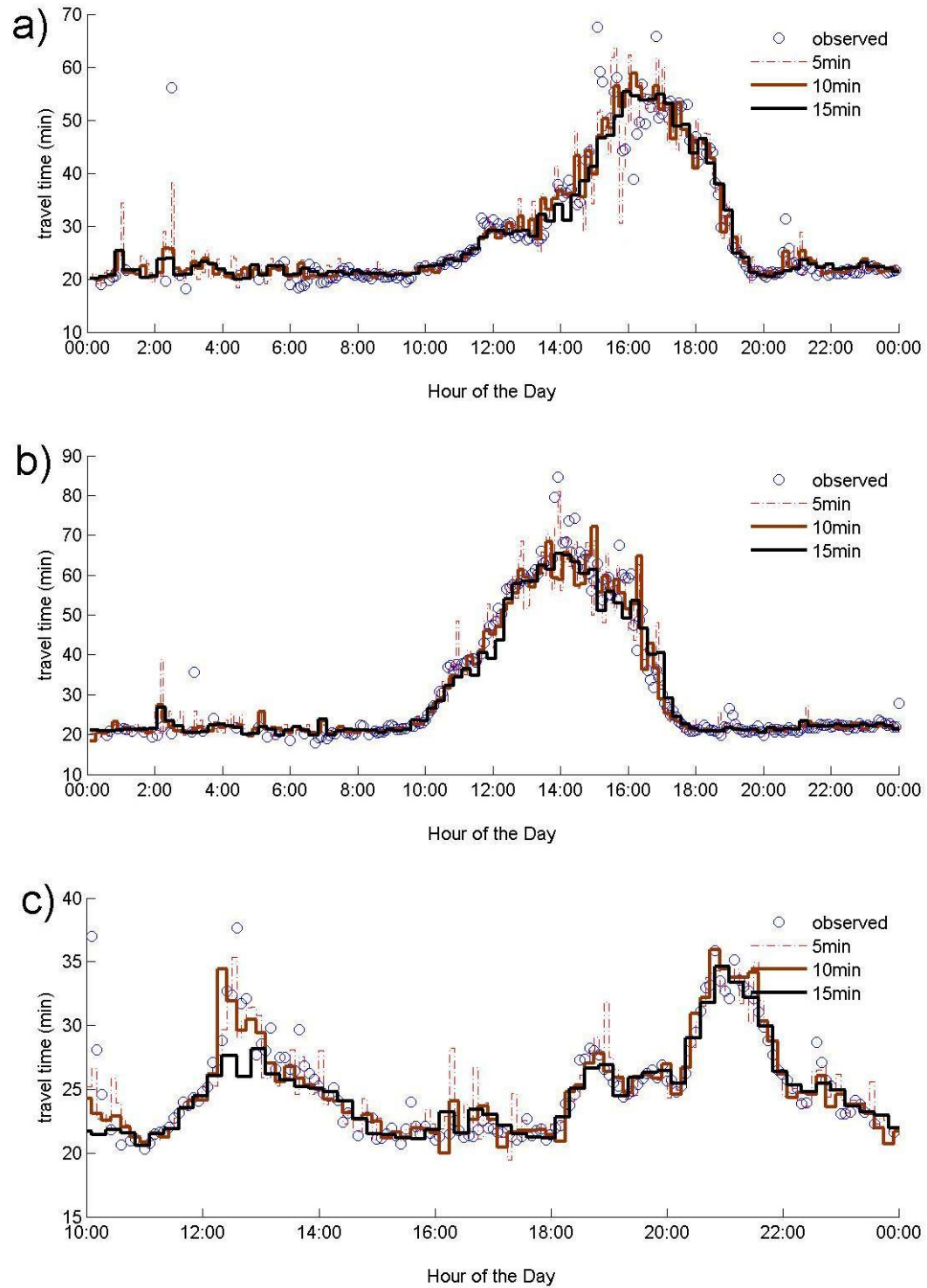


Figure 5-14 -Extended NLP Results for Different Updating Intervals (a) Incident Related Congestion (7/24/2009, Friday), (b) Incident Related Congestion (7/25/2009, Saturday), (c) Moderate Congestion (7/26/2009, Sunday)

5.4 Comparison of Algorithms

5.4.1 Comparison of Kriging and NLP

Kriging algorithm, developed as geostatistical technique, is used in this study to estimate single-section travel times, based on the values of other itinerary travel times. Travel time values represented in the imaginary two-dimensional space are interpolated for the unobserved origin-destination points. However, kriging algorithm returns the exact same value for observed locations; therefore, single-section travel time measurements cannot be incorporated in the analysis. This reduces the amount of data available to the study. Another disadvantage of the kriging algorithm is that the proposed methodology is not able to take the information delay into account. Direct measurement techniques, such as electronic toll collection system used in this study, provides travel time information once the vehicle reached the point where the detectors are located. Hence, especially travel times associated with long itineraries give information based on the past conditions of the roadway. Although a small network, like the one used in this study, does not suffer from this drawback, it may bring some important problems to a larger network application.

Proposed NLP model attempts to minimize the difference between the measured trip travel times and summation of corresponding link travel times for all the links between a given OD pair. To take the information delay into account, time lag between links is incorporated in the model. Once the interval in which traveler traversed the section is identified, the trip travel time is reconstructed by the addition of the link travel times associated with the relevant time interval. Clearly, NLP model can be improved

depending on the data source and the application area. The developed algorithm can be applied to larger networks that consist of multiple roadways with an appropriate connection matrix and maybe with a shortest path algorithm. This approach can allow us to deal with probe vehicle data which become highly available in the last years through the use of GPS devices.

The results of kriging and NLP algorithms clearly show that NLP outperforms kriging. In all cases considered in **Table 5-1** to **Table 5-4**, NLP algorithm provides better results. Considering also the advantages of NLP algorithm in terms of flexibility and temporal capability, NLP is a better method to deal with the estimation problem.

5.4.2 Comparison of Basic and Extended NLP

Numerical errors provided in **Table 5-5** and **Table 5-6** are based on 5 min aggregated travel time observations. However, to compare 15 min applications of basic and extended NLP algorithms, both results must be compared with travel time observations that have the same resolution. Hence, extended NLP errors are recalculated for 15 min of aggregated observations and the comparison is presented in **Table 5-7** and **Table 5-8**.

Table 5-7 - Comparison of Basic and Extended NLP (15 min)

Test Day	Period of the Day	<i>Basic</i> Travel Time Absolute Error		<i>Extended</i> Travel Time Absolute Error	
		Mean (min)	Relative	Mean (min)	Relative
weekdays	Peak Hours	0.87	0.03	0.84	0.03
	Off-Peak Hours	0.80	0.03	0.80	0.03
	Night Hours	1.32	0.06	1.34	0.06
weekend	6am-12pm	0.51	0.02	0.53	0.02
	0am-6am	0.80	0.04	1.25	0.04
7/24/2009 <i>Friday</i>	Peak Hours	1.92	0.05	1.89	0.05
	Off-Peak Hours	1.02	0.03	1.08	0.04
	Night Hours	1.22	0.06	1.22	0.06
7/27/2009 <i>Monday</i>	Peak Hours	0.23	0.01	0.23	0.01
	Off-Peak Hours	0.85	0.04	0.76	0.04
	Night Hours	1.68	0.08	1.69	0.08
7/28/2009 <i>Tuesday</i>	Peak Hours	0.43	0.02	0.37	0.02
	Off-Peak Hours	0.60	0.03	0.55	0.03
	Night Hours	1.06	0.05	1.13	0.05
7/29/2009 <i>Wednesday</i>	Peak Hours	1.29	0.05	1.25	0.05
	Off-Peak Hours	0.92	0.04	0.90	0.04
	Night Hours	1.70	0.08	1.75	0.08
7/30/2009 <i>Thursday</i>	Peak Hours	0.47	0.02	0.45	0.02
	Off-Peak Hours	0.65	0.03	0.68	0.03
	Night Hours	0.90	0.03	0.87	0.03

Table 5-8 - Comparison of Basic and Extended NLP (15 min) under Congestion

Test Day	Period of the Day	Traffic Condition	<i>Basic</i> Travel Time Absolute Error		<i>Extended</i> Travel Time Absolute Error	
			Mean	Relative	Mean	Relative
7/24/2009	11.00-20.00	Non-recurrent	2.60	0.06	2.42	0.06
7/25/2009	09.30-20.00	Non-recurrent	2.66	0.06	2.39	0.05
7/26/2009	11.00-16.00	Recurrent	0.75	0.03	0.75	0.03
7/26/2009	18.00-23.00	Recurrent	0.51	0.02	0.50	0.02
7/29/2009	06.30-09.00	Recurrent	1.08	0.04	1.05	0.03

Basic (P1) and extended NLP (P2) formulations provide similar results regarding the numerical errors. For free-flowing conditions, link assignment process works in the same manner in both algorithms, which generates similar results. For recurrent and non-recurrent congestions, extended algorithm is expected to modify the link assignment process and to produce better results. **Table 5-8** shows that the performance of extended algorithm under non-recurrent congestion is better than that of basic algorithm. However, more importantly, considering the information delay and the link assignment process, extended algorithm is better suited to deal with changing traffic conditions on the roadway. Therefore, extended algorithm results with 10 min of updating interval will be used as the basis of the prediction models that will be studied next.

Chapter 6 Travel Time Prediction

The majority of the studies that focus on traffic state prediction problem evaluated the performance of their models under "normal" traffic conditions. However, the prediction problem becomes quite unnecessary under typical traffic conditions, because traffic parameters take more or less a constant value in case of such conditions. Hence, this study considers both typical and atypical traffic conditions to evaluate the performance of prediction models.

The main objective of this study is to perform short-term travel time forecasts and compare the prediction performance of a parametric model, ARIMA, a recently developed non-parametric model, SVR, and a commonly used non-parametric model, ANN.

6.1 ARIMA

6.1.1 Model Definition

A time series $\{x_t\}$ is an $ARIMA(p, d, q)$ process if the d th differences of the time series are an $ARMA(p, q)$ process. If the differenced series $y_t = (1 - \mathbf{B})^d x_t$, then $\theta_p(\mathbf{B})y_t = \phi_q(\mathbf{B})w_t$. Now, differenced time series can be substituted by the original time series;

$$\theta_p(\mathbf{B})(1 - \mathbf{B})^d x_t = \phi_q(\mathbf{B})w_t \quad (6.1)$$

where

θ = autoregressive parameter polynomial

ϕ = moving average parameter polynomial

B = backshift operator defined by $B^a w_t = w_{t-a}$ and a the order of backshift operator
(number of time steps)

$$\theta_p(z) = 1 - \theta_1 z - \dots - \theta_p z^p$$

$$\phi_q(z) = 1 - \phi_1 z - \dots - \phi_q z^q$$

w_t = white noise

The parameters p and q represent autoregressive and moving average polynomial orders, respectively. The parameter d represents the order of differencing. "AR" refers to autoregressive part of the model and deal with regression on past values. "MA" refers to moving average part of the model and involves regression on the past random deviations.

ARIMA models can be applied to the time series that are weakly stationary or that can be made weakly stationary through differencing. If the expected value of the time series is the same for all t and the covariance between any two observations in the series is independent of t and dependent only the lag between the observations, then the series is considered to be weakly stationary (Box and Jenkins, 1976).

Because of the cyclical pattern of traffic conditions, first-order differencing might not be sufficient to transform the data into a stationary series. The daily patterns of traffic flow, for example, are quite similar for weekdays, while weekend patterns are apparently different. Therefore, to deal with traffic flow prediction, data should be differenced

using 1 week lag to make it stationary. If travel time is somehow proportional to the demand on the roadway, same analogy can be applied to travel time prediction process. However, travel time does not necessarily show a strong proportionality with the demand, especially for roadways where volume/capacity ratio is low. If this kind of seasonality is detected in travel time series, seasonal ARIMA can also be used to predict future values.

6.1.2 ARIMA Model Fitting

ARIMA model fitting has been first implemented by the methodology developed by Box and Jenkins (1976). In their approach, model orders are estimated using ACF (auto-correlation function) and PACF (partial auto-correlation function) plots. Although this technique is still useful and relevant, increased computing power makes it possible to try out a wide range of models to fit to data and to choose a best-fitting model using an appropriate information criterion such as Akaike (AIC) and Bayesian (BIC) information criteria. Once a best fitting model has been found, the correlogram of the residuals should be verified as white noise.

Forecast package developed in *R* by Hyndman and Khandakar (2008) is used in this study to estimate the model orders and coefficients.

For non-seasonal data, the package determines the first-order differencing order based on successive KPSS unit root tests (Kwiatkowski et al., 1992). The original series is tested for a unit root, if the result is significant, differenced series is tested for a unit root, and so on. The procedure is stopped when the first insignificant result is obtained.

For seasonal data, for any seasonal frequency $m > 1$, the package implements Canova-Hansen test (Canova and Hansen, 1995) to determine whether seasonal differencing is needed or not.

After testing the seasonal frequency, first-order differencing parameter d is identified based on KPSS unit root tests applied to the seasonally differenced series or the original series. Then, it proceeds to select the other model orders (p and q , if there is no seasonality) by minimizing the AIC.

Applying the above procedure to 7 single-section travel times obtained through 10 minute application of extended NLP algorithm leads to ARIMA models presented in **Table 6-1**. ARIMA models are trained with 14 weeks of data (04/17/2009-07/23/2009) and seasonality is not observed in any of them. Travel times on the considered links are not highly affected by the cyclical demand peaks, since the roadway is able to handle high traffic volumes observed during peak hours. On the other hand, it is largely affected by special events which impose an unexpected volume of traffic to the roadway and random events such as accidents.

Table 6-1 - ARIMA Model Orders

Link	p	d	q
8A-8	4	1	2
9-8A	3	1	3
10-9	2	1	2
11-10	2	1	3
12-11	1	1	3
13-12	2	1	2
13A-13	3	1	2

6.1.3 Multivariate ARIMA

In addition to the univariate ARIMA model, an ARIMA model which includes a congestion indicator variable is employed (multivariate ARIMA). Any time series model, including ARIMA, is based on the past values within the time window considered. Therefore, the reaction of them to rapidly changing traffic conditions can be quite problematic. To address the delay problem, a dummy variable that would signal unexpected conditions in the network can be used.

In case of a special or unexpected event (e.g. incident), it is intuitively known that traffic flow does not follow its typical pattern. Although in our case mainline traffic flow data is not available, exit toll counts can be used to detect the unexpected conditions in the network.

7 toll plazas that are located at the end of 7 considered links are incorporated in this analysis. Average exit toll counts are calculated for each toll plaza and for each period in the day using 14 weeks of 10-min toll counts data. Since daily traffic flow patterns are quite different for weekdays and weekend, they are classified in two separate groups.

Another parameter that can be used to detect the unexpected conditions in the network is link travel time. Under rapidly changing conditions, travel times show an upward or downward trend, while they take more or less a constant value under 'normal' conditions. Therefore, the slope of the linear regression line obtained using 4 past travel time values is used as the trend parameter.

Note that each link is attributed to the toll plaza located at its end. Putting them together, an indicator that signals congestion onset is turned on if all the following conditions apply:

- Exit toll count in the current period is less than 75% of the average toll count that corresponds to the same period (weekday and weekend separately).
- Travel time trend is greater than 0.
- Link travel time in the current period is greater than 150% of free flow link travel time.

Figure 6-1 shows travel time values of the link between Exit 9 and 8A for two successive days. Red dots represent the periods where the congestion indicator is turned on. The indicator detects the second peak almost at its starting point, while it misses the small peak on the first day. Another problem with the indicator is false alarm. Although there is not any significant change in traffic conditions, indicator may give a false alarm and push travel time predictions upwards.

Multivariate ARIMA model orders are shown in **Table 6-2**.

Table 6-2 - Multivariate ARIMA Model Orders

Link	p	d	q
8A-8	2	1	2
9-8A	3	1	3
10-9	2	1	4
11-10	3	1	3
12-11	1	1	3
13-12	2	1	2
13A-13	3	1	3

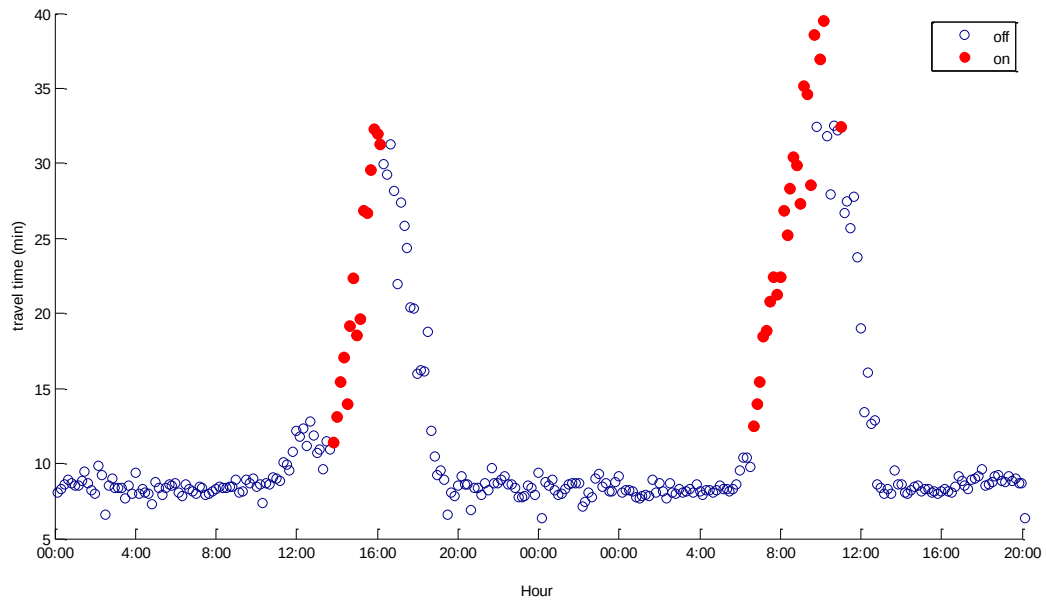


Figure 6-1 - Performance of Congestion Indicator

6.2 Support Vector Regression

6.2.1 Model Definition

The basic idea in SVR is to map the input space into a high dimensional feature space via nonlinear transformation and to implement linear regression in the high dimensional feature space that corresponds to nonlinear regression in the input space.

Given a training dataset $x_i \in \mathcal{R}^n, i = 1, \dots, l$ where l corresponds to the size of training data and $y_i = \pm 1$ class labels, SVM will find a nonlinear mapping function Φ , a hyperplane direction w and a constant b such that $f(x) = w * \Phi(x) + b \geq 0$ for positive examples and $f(x) = w * \Phi(x) + b \leq 0$ for negative examples. Despite the absence of such a linear function in the input space to decide the class labels, an optimal hyperplane

which can do that in the high dimensional space can be obtained through SVM classification.

SVM classification can be extended to regression problems. Given a training dataset which is the same as the one in the classification problem, but which has target values $y_i \in \mathcal{R}$ for $i = 1, \dots, l$. SVR estimating function is then;

$$f(x) = w * \Phi(x) + b \quad (6.2)$$

The goal in parameter estimation is to minimize the regression risk;

$$R_{reg}(f) = C \sum_{i=1}^l \Gamma(f(x_i) - y_i) + 0.5 \|w\|^2 \quad (6.3)$$

where C is a user-defined constant, Γ is a cost function and vector w can be rewritten with the use Lagrange multipliers α_i and α_i^* ;

$$w = \sum_{i=1}^l (\alpha_i - \alpha_i^*) \Phi(x_i) \quad (6.4)$$

Estimating function can be rewritten by substituting Eq. (6.4) into Eq. (6.2):

$$f(x) = \sum_{i=1}^l (\alpha_i - \alpha_i^*) (\Phi(x_i) * \Phi(x)) + b \quad (6.5)$$

$$= \sum_{i=1}^l (\alpha_i - \alpha_i^*) k(x_i, x) + b \quad (6.6)$$

In Eq. (6.6), the dot product is replaced by kernel function, which is required to map the data into a high dimensional feature space without knowing the transformation Φ . Some common kernel functions are shown in

Table 6-3.

Table 6-3 - Common Kernel Functions

Kernel	Function
Linear	x^*y
Polynomial	$[(x^*x_i)+1]^d$
Radial Basis Function (RBF)	$\exp\{-\gamma x-x_i ^2\}$

ε -insensitive loss function is used in this study:

$$\Gamma(f(x) - y) = \begin{cases} |f(x) - y| - \varepsilon, & \text{for } |f(x) - y| > \varepsilon \\ 0, & \text{otherwise} \end{cases} \quad (6.7)$$

By minimizing the regression risk, model parameters can be obtained;

$$\min \frac{1}{2} \sum_{i=1}^l \sum_{j=1}^l (\alpha_i^* - \alpha_i)(\alpha_j^* - \alpha_j)k(x_i, x_j) - \sum_{i=1}^l \alpha_i^*(y_i - \varepsilon) - \alpha_i(y_i + \varepsilon)$$

subject to (6.8)

$$\sum_{i=1}^l (\alpha_i - \alpha_i^*) = 0, \quad \alpha_i, \alpha_i^* \in [0, C]$$

The constant C is a penalty parameter which determines the generalization level of the model. That is, larger C assigns higher penalties to errors and the regression is trained to minimize the error with lower generalization. While C gets smaller, the model tolerates higher errors and becomes less complex.

Support Vector Regression can be applied without knowing the transformation, but there are couple of parameters that should be tried out to determine the best SVR model; constant C, kernel type and tube ε .

6.2.2 Model Implementation

Several combinations of model parameters have been experimented, and SVR model with a linear kernel function, $\varepsilon=0.01$ and $C=1000$ has been considered to be the best. LibSVM 3.1 software kit has been used in this study and a window size of 4 has been assigned to all 7 links.

6.3 Artificial Neural Networks

Neural networks is a computational approach that is inspired by biological neural networks and is based on pattern recognition techniques. Even if the underlying relation between dependent and independent variables is not clear, the ability of neural networks to address uncertainty and nonlinearity makes it useful for working with databases with large noise.

The most widely applied neural network methodology is back-propagation (BP). The topology of the network is shown in **Figure 6-2**. A back-propagation neural network consists of nodes, connection weights, transfer function and a structure composing them. In the topological structure, nodes are joined together by connections that have varying strength; each connection has a weight associated with it. A neural network has one input layer, one or more hidden layers and one output layer.

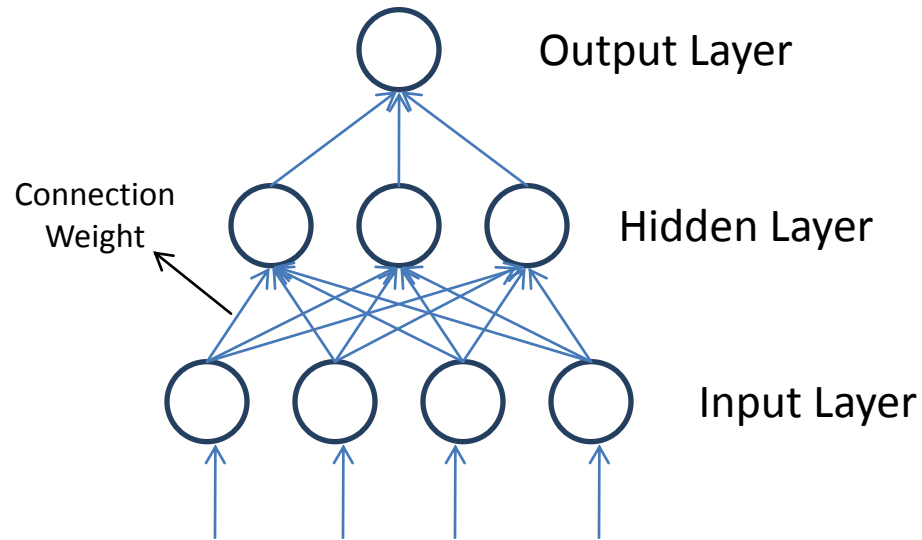


Figure 6-2 - Topological Structure of Neural Network

BP networks accept the inputs at the input layer, pass the weighted input values to the hidden layer, then process and transfer them to the output layer. BP neural network learns connection weights using a training dataset. The model without knowing any explicit functional form a priori, maps the input space to the output space by identifying the relationships of the nodes within the structure.

Large number of nodes at the hidden layer may lead to a more accurate model, while it increases the computation cost. However, Park and Rilett (1999) report no significant improvement with larger number of nodes. Therefore, 10 nodes and 4 input time steps are used in this study. Note that univariate time series (i.e. 4 past travel time values) is used to implement NN model.

MATLAB Neural Networks toolbox has been used to conduct the study.

6.4 Results and Analysis

To compare the performance of models, mean absolute percentage error is utilized as follows:

$$MAPE(\%) = \frac{1}{n} \frac{|y_i - \hat{y}_i|}{y_i} * 100 \quad (6.9)$$

where y_i is actual travel time, $\hat{y}_i$ is predicted travel time, n is number of predictions. To compare the forecasts by different methods, a simple average of APE values or frequency of APE values within certain range can be used as diagnostic measure.

For each of 7 link travel times, the first 14 weeks of data are utilized to train the models and one week of 10 min travel time data are used for model testing, which brings a total of 1008 observations ($24*6*7$). Once one-step ahead prediction models are identified, they are used to predict two-step and three-step ahead travel time values. In other words, one-step ahead prediction is incorporated in the time window to calculate two-step ahead prediction, and so on. The prediction accuracy of the models is assessed with two different approaches or two different scenarios, which are described below.

6.4.1 General Performance

In the first approach, general performance of the models is evaluated. The whole testing set is used to evaluate the performance of models. **Table 6-4**, **Table 6-5** and **Table 6-6** present the forecasting performance of the models for one-step, two-step and three-step ahead predictions respectively. Comparing four different models, they all have

Table 6-4 - Forecasting Performance - One-Step Ahead

Link	ARIMA	SVR	ANN	ARIMA ^c
8A-8	12.7	12.1	12.7	13.1
9-8A	6.6	6.5	6.2	6.6
10-9	8.4	8.2	8.3	8.4
11-10	14.1	13.2	14.0	14.3
12-11	13.6	13.2	13.6	13.6
13-12	13.9	13.4	13.8	13.9
13A-13	19.0	18.2	18.5	18.9
Average	12.6	12.1	12.4	12.7

Table 6-5 - Forecasting Performance - Two-Step Ahead

Link	ARIMA	SVR	ANN	ARIMA ^c
8A-8	15.0	14.0	15.2	15.3
9-8A	7.7	7.3	6.9	7.7
10-9	8.7	8.5	8.6	8.8
11-10	14.5	13.5	14.3	14.6
12-11	14.5	14.0	14.4	14.5
13-12	14.8	14.2	14.8	14.8
13A-13	20.7	19.4	20.1	20.6
Average	13.7	13.0	13.5	13.7

Table 6-6 - Forecasting Performance - Three-Step Ahead

Link	ARIMA	SVR	ANN	ARIMA ^c
8A-8	16.8	15.2	17.1	17.2
9-8A	8.6	8.0	7.5	8.6
10-9	8.9	8.6	8.7	9.0
11-10	14.7	13.7	14.4	15.0
12-11	14.9	14.3	14.7	14.9
13-12	15.3	14.7	15.1	15.4
13A-13	21.5	19.8	20.9	21.3
Average	14.4	13.5	14.1	14.5

similar prediction accuracy, but SVR has the best overall prediction accuracy with an average MAPE of 12.1%, 13% and 13.5% for one, two and three steps ahead predictions respectively.

6.4.2 Atypical Traffic Conditions

The prediction problem becomes highly important under unexpected traffic conditions. Therefore, the prediction performance of the models is evaluated for the periods where travel times under non-recurrent congestion conditions are observed.

Figure 6-3 shows estimated and one-step ahead predicted values for the links 8A-8, 9-8A and 13A-13. Notice that for the links 8A-8 and 9-8A, ARIMA and MARIMA react faster and dissipates later than non-parametric models namely, SVR and NN. However, the addition of congestion indicator does not bring any significant improvement to ARIMA predictions of the links 8A-8 and 9-8A. On the other hand, for the link 13A-13, congestion indicator helps ARIMA improve its performance and pushes the predictions towards the observed values. However, NN captures the peak travel time values better than both types of ARIMA models (**Figure 6-3 (g)-(h)**). Besides, all the models have relatively inadequate performance during congestion onset and dissipation, because their predictions are all based on the past values within the time window that do not signal the severity of the unexpected event. This becomes quite problematic in case of short duration congestion, which is shown in **Figure 6-3 (c), (d), (g) and (h)**.

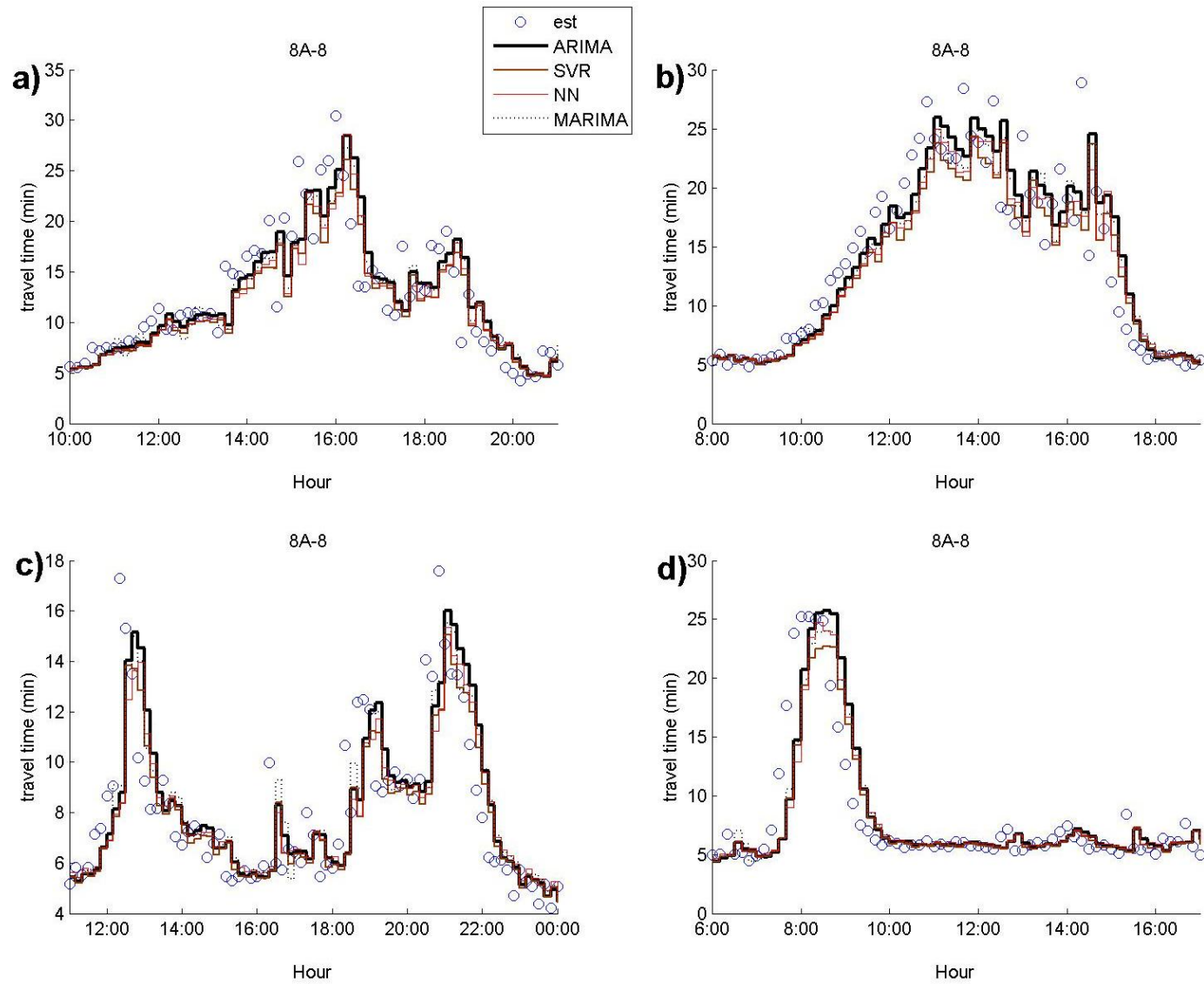


Figure 6-3 - Estimated vs Predicted Values a.7/24/2009, b.7/25/2009, c.7/26/2009, d.7/29/2009

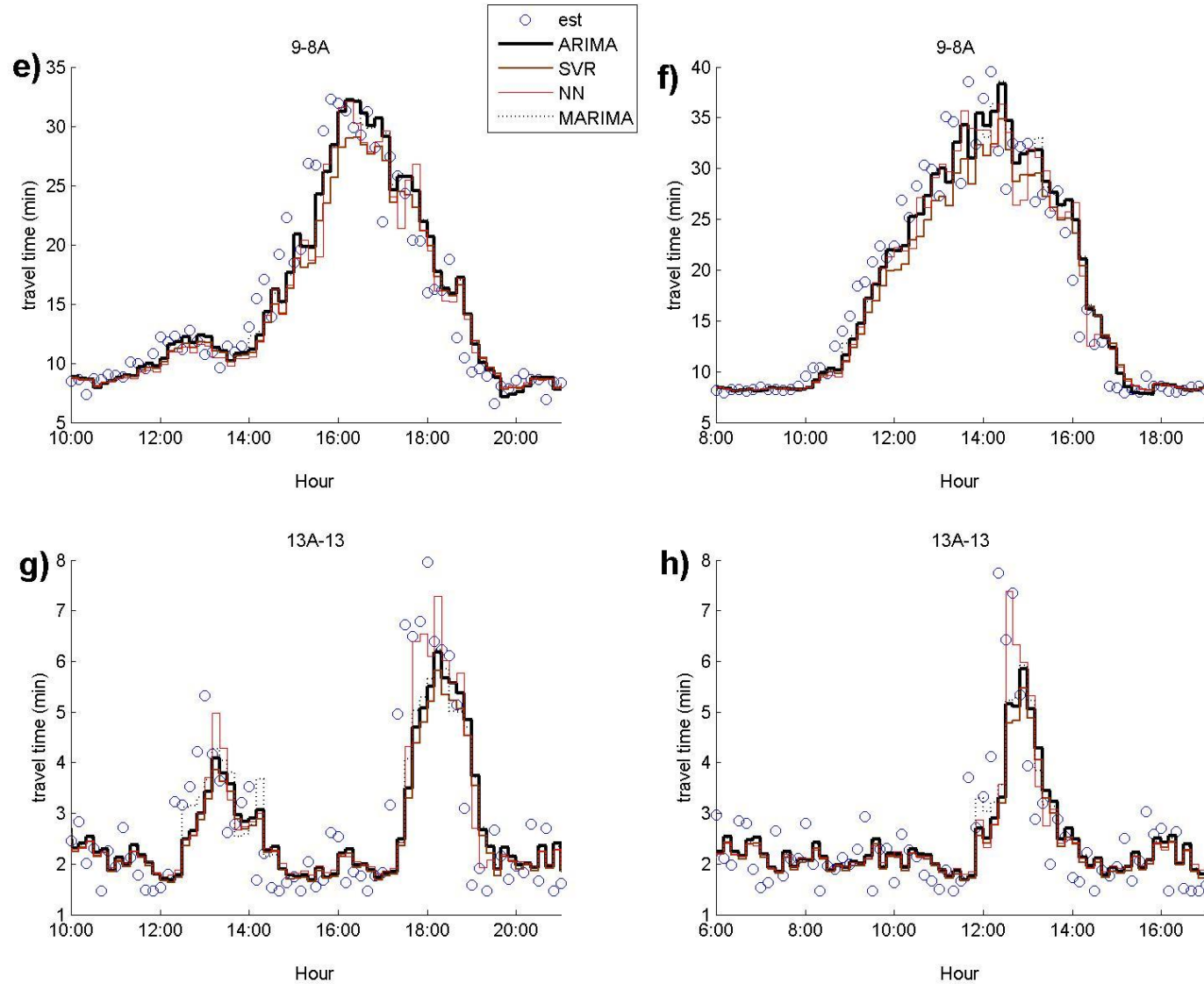


Figure 6-3 - Estimated vs Predicted Values e.7/24/2009, f.7/28/2009, g.7/26/2009, h.7/24/2009

Table 6-7 to **Table 6-9** show the MAPE values of each model for each link under moderate or high congestion. For all prediction horizons considered in this study, ARIMA model exhibited the best overall performance, which is described as the weighted average of MAPE values by congestion duration.

The most significant difference in MAPE values is observed for the link 13A-13, on 7/28/2009, between 17.00 and 19.30. NN clearly outperforms all other models which are not able to catch the extreme values, as shown in Error! Reference source not found. (h).

Note that atypical traffic conditions are not commonly observed in the training dataset of the link 13A-13. Since models are not specifically trained for atypical traffic conditions, model parameters are estimated to produce accurate results under free flowing conditions rather than atypical traffic conditions. On the other hand, congestion is more likely to occur on the links 8A-8 and 9-8A (based on the visual observations on training dataset), and training dataset includes many examples of it.

Table 6-7 to **Table 6-9** indicate that ARIMA has the best overall performance for the links 8A-8 and 9-8A. However, NN provides the best results for the link 13A-13. Therefore, ARIMA can be considered as the best overall option, if the training dataset has examples of atypical traffic conditions, for which a time series model is actually needed. However, if the training dataset is mainly composed of uncongested conditions, non-parametric regression techniques, especially NN, have better performance than ARIMA.

Table 6-7 - Forecasting Performance - One-Step Ahead

Test Day	Period	Congestion	Link	ARIMA	SVR	ANN	MARIMA
7/24/2009	11.00-20.00	high	8A-8	17.9	18.2	18.5	18.5
	11.00-20.00	high	9-8A	11.7	12.1	12.5	11.6
	11.30-13.30	moderate	13A-13	28.6	27.7	26.7	26.3
7/25/2009	09.30-18.00	high	8A-8	15.7	15.8	16.0	17.0
	09.30-18.00	high	9-8A	11.5	13.3	12.5	11.4
7/26/2009	11.00-16.00	moderate	8A-8	10.5	10.7	11.9	10.5
	18.00-23.00	moderate	8A-8	13.2	13.3	14.8	13.1
7/28/2009	12.00-14.30	moderate	13A-13	24.5	24.3	24.2	24.3
	17.00-19.30	moderate	13A-13	35.7	35.8	24.0	34.4
7/29/2009	7.00-10.00	high	8A-8	23.2	21.6	22.9	22.5
Average				16.2	16.6	16.3	16.3

Table 6-8 - Forecasting Performance - Two-Step Ahead

Test Day	Period	Congestion	Link	ARIMA	SVR	ANN	MARIMA
7/24/2009	11.00-20.00	high	8A-8	22.1	22.9	22.8	22.4
	11.00-20.00	high	9-8A	15.0	16.0	15.7	14.9
	11.30-13.30	moderate	13A-13	40.3	38.4	33.3	34.8
7/25/2009	09.30-18.00	high	8A-8	20.7	21.8	20.7	21.3
	09.30-18.00	high	9-8A	15.5	17.9	16.5	15.6
7/26/2009	11.00-16.00	moderate	8A-8	15.6	15.7	17.1	15.8
	18.00-23.00	moderate	8A-8	18.2	18.7	21.1	18.6
7/28/2009	12.00-14.30	moderate	13A-13	31.6	30.5	30.1	32.2
	17.00-19.30	moderate	13A-13	45.0	47.8	36.5	45.7
7/29/2009	7.00-10.00	high	8A-8	37.2	34.4	36.8	35.9
Average				21.7	22.5	21.8	21.7

Table 6-9 - Forecasting Performance - Three-Step Ahead

Test Day	Period	Congestion	Link	ARIMA	SVR	ANN	MARIMA
7/24/2009	11.00-20.00	high	8A-8	25.5	26.4	25.8	25.7
	11.00-20.00	high	9-8A	18.9	19.9	20.1	18.8
	11.30-13.30	moderate	13A-13	46.0	42.9	42.9	42.9
7/25/2009	09.30-18.00	high	8A-8	26.3	28.5	26.4	27.8
	09.30-18.00	high	9-8A	15.5	22.5	20.3	20.1
7/26/2009	11.00-16.00	moderate	8A-8	17.5	17.7	19.3	21.0
	18.00-23.00	moderate	8A-8	23.0	23.7	25.8	27.0
7/28/2009	12.00-14.30	moderate	13A-13	35.5	33.3	32.1	37.4
	17.00-19.30	moderate	13A-13	57.9	54.8	47.9	52.7
7/29/2009	7.00-10.00	high	8A-8	47.2	44.4	48.0	49.6
Average				25.9	27.2	26.6	27.4

In addition to the advantageous explicit structure of ARIMA model, under rapidly changing traffic conditions it has overall better performance than the two non-parametric methods namely, SVR and NN. Although ARIMA exhibits the least accurate prediction performance under normal conditions, considering its performance under unexpected traffic conditions and its explicit model structure, ARIMA can be selected as the most appropriate model to deal with the travel time prediction problem, if the training set includes examples of atypical conditions.

Chapter 7 Conclusion

This chapter summarizes the analysis presented in the thesis and indicates the future research directions.

The primary purpose of this study is to provide accurate travel time estimates using data collected by the electronic toll collection system instead of sensors and AVI readers specifically deployed for traffic monitoring. This dual use of toll readers for travel time estimation can be an attractive approach since it eliminates additional costs of deploying and maintaining sensors. However, this approach can present an important challenge in terms of accuracy of the estimates because readers are not located on the main roadway, but instead on the ramps. In a closed toll highway, which is the main focus of this study, it is considerably easy to obtain travel times between all origin-destination pairs. By directly measuring the time taken by the vehicles to travel between certain OD pairs, electronic toll collection system provides necessary information about OD pairs. However, the demand level associated with particular OD pairs is not always enough to obtain accurate average travel times. Especially the demand between consecutive junctions can be extremely low, since travelers do not prefer using toll highways for short distance trips. Besides, considering measured trip travel times separately and providing that information as a future projection for that specific trip may cause some problems. First, although a detailed filtering algorithm is applied, collected data may be subject to outliers' effect. In addition to a filtering algorithm, there is a need for an algorithm that would correct or fuse the collected data using spatial connections of OD routes. Second, measured trip travel times do not tell us much about the location of

congestion. If trip travel time is broken down into link travel times and different itinerary travel times can be fused through an algorithm, a single estimate of link travel time (single section between consecutive junctions in a closed toll highway) can be provided.

To break down trip travel times into section travel times, two methods based on, universal kriging and mathematical programming are developed. Our results based on the real-data show that it is possible to use electronic toll data to provide accurate estimations of link travel times especially using extended mathematical programming algorithm which outperforms universal kriging approach.

The primary purpose of travel time prediction section is to perform short-term travel time forecasts and compare the prediction performance of a parametric model, ARIMA, a recently developed non-parametric model, SVR, a commonly used non-parametric model, ANN, and a multivariate ARIMA model which includes a dummy variable that indicates the unexpected conditions on the roadway. Comparing the performance of the models not only under normal traffic conditions, but also under atypical traffic conditions, their predictive behavior under different circumstances is investigated. Relatively large number of real probe vehicle data obtained from an existing electronic toll collection system, is also an important aspect of this study because most of travel time prediction studies based on probe vehicle data suffer from the small sample size of probe vehicle data.

Although SVR produces the best results under 'normal' traffic conditions, ARIMA presents a better overall performance including rapidly changing traffic conditions, which is the main interest of a real-time traveler information or traffic management system.

In this study, an indicator variable that signals unexpected conditions based on exit toll counts is incorporated in multivariate ARIMA model. Although it has a better performance than single ARIMA model for some cases, congestion indicator does not have a significant positive effect to the overall performance.

The results reveal that performance of the models is highly related with characteristics of the training set. If the training set consists of adequate number of atypical travel time observations, then ARIMA can be considered as the best model. However, when it is mainly composed of uncongested travel times, NN becomes a better option. NN, as a non-parametric regression technique, is able to produce accurate results under rapidly changing traffic conditions, even if training dataset does not have enough real-time data about atypical conditions.

Future research is needed to extend the application area. Extended mathematical programming model presented in this study can be modified according to the needs in a larger application. For example, very long trips should not be incorporated in link travel time estimation. In this study, itinerary travel times are reconstructed based on trajectory reconstruction; time period in which vehicles travel along consecutive sections is considered when trajectory based travel time is reconstructed. Then, previously estimated link travel times are updated within a certain interval for previous time intervals. Updating them within a certain interval leads to more accurate results, because, more information is used to obtain the travel time estimate. However, for very long trips, this could be problematic, because the longer the trip is, the harder it is to track the vehicles on the network. The algorithm presented in this study would probably end up with

inaccurate trajectory reconstruction for long trips. Therefore, inputs should be limited to short and moderately long trips.

Future research should focus on the prediction of rapidly changing traffic conditions. Travel time prediction under atypical conditions is the most challenging part of the problem demanded by travelers and operational agencies. Multivariate time series models that incorporate adjacent link travel times can be used to improve forecasting performance. In addition to that, if mainline detector data is available, it can be used as an additional important parameter that would signal the unexpected conditions on the network.

REFERENCES

1. Abdulhai, B., Porwal, H. and Recker, W. (1999) Short-term freeway traffic flow prediction using genetically optimized time-delay-based neural networks. UCB, UCB-ITS-PWP-99-1 (Berkeley, CA: Institute of Transportation Studies, University of California, Berkeley).
2. Ahmed, M. S. and Cook, A. R. (1979) Analysis of freeway traffic time-series data by using Box-Jenkins techniques, *Transportation Research Record*, 722, pp. 1-9.
3. Ashok, K. and Ben-Akiva, M.E. (2000) Alternative approaches for real-time estimation and prediction of time-dependent origin-destination flows, *Transportation Science*, 34(1), pp. 21-36.
4. Balke, K.N., Charara, H., Parker, R. (2005) Development of a traffic signal performance measurement system (TSPMS), Report 0-4422-2, performed in cooperation with the Texas Department of Transportation and the Federal Highway Administration.
5. Behrisch, M., Bonert, M., Brockfeld, E., Krajzewicz, D., Wagner, P. (2008) Event traffic forecast for metropolitan areas based on microscopic simulation, In Proceedings of Third International Symposium of Transport Simulation.
6. Billings, D. and Yang, J.-S. (2006) Application of the ARIMA models to urban roadway travel time prediction - a case study, In IEEE Proceedings of the International Conference on Systems, Man, and Cybernetics, Taipei, Taiwan, pp. 2529-2534.
7. Box, G.E.E., Jenkins, G.M. (1976) Time series analysis, forecasting and control. Holden-Day, Oakland.
8. Canova, F., Hansen, B.E. (1995) Are Seasonal Patterns Constant Over Time? A test for seasonal stability, *Journal of Business and Economic Statistics*, 13, pp. 237-252.
9. Castro-Neto, M., Jeong, Y.-S., Jeong, M.-K., Han, L.D. (2009) Online-SVR for short-term traffic flow prediction under typical and atypical traffic conditions, *Expert Systems with Applications*, 36, pp. 6164-6173.
10. Chen, M. and Chien, S. I. J. (2001) Dynamic freeway travel time prediction using probe vehicle data: link-based vs. path-based, In Proceedings of the Transportation Research Board 80th Annual Meeting, Washington, DC.
11. Chen, M. and Chien, S.I.J. (2000) Determining the number of probe vehicles for freeway travel time estimation by microscopic simulation, *Transportation Research Record*, 1719, pp. 61-68.
12. Cheslow, M., Hatcher, S. G. and Patel, V. M. (1992) An initial evaluation of alternative intelligent vehicle highway systems architectures. Report 92W0000063 (McLean, VA: MITRE).
13. Chien, S. I. J. and Kuchipudi, C. M. (2002) Dynamic travel time prediction with real-time and historical data, *ASCE Journal of Transportation Engineering*, 129(6), pp. 608-616.
14. Chu, L., Oh, S., Recker, W. (2005) Adaptive kalman filter based freeway travel time estimation, In Proceedings of the Transportation Research Board 84th Annual Meeting, Washington, DC.

15. Clark, S. (2003) Traffic prediction using multivariate nonparametric regression, *ASCE Journal of Transportation Engineering*, 129(2), pp. 161–168.
16. Coifman, B. (2002) Estimating travel times and vehicle trajectories on freeways using dual loop detectors, *Transportation Research Part A*, 36, pp. 351–364.
17. Coifman, B., Krishnamurthy, S. (2007) Vehicle re-identification and travel time measurement across freeway junctions using the existing detector infrastructure, *Transportation Research Part C*, 15(3), pp. 135–153
18. Cortes, C.E., Lavanya, R., Oh, J.S., Jayakrishnan, R., (2002) A general purpose methodology for link travel time estimation using multiple point detection of traffic, *Transportation Research Record 1802*, pp. 181–189.
19. Cressie, N. A. C. (1993) *Statistics for spatial data* (revised edition). Wiley, New York.
20. Dailey, D. J. (1997) Travel time estimates using a series of single loop volume and occupancy measurements, In *Proceedings of the Transportation Research Board 76th Annual Meeting*, Washington, DC.
21. Danech-Pajouh, M. and Aron, M. (1991) ATHENA: a method for short-term inter-urban motorway traffic forecasting, *Recherche Transport Securite*, 6, pp. 11–16.
22. Davis, G. A., Niham, N. L., Hamed, M. M. and Jacobson, L. N. (1991) Adaptive forecasting of freeway traffic congestion, *Transportation Research Record*, 1287, pp. 29–33.
23. Dharia, A., Adeli, H. (2003) Neural network model for rapid forecasting of freeway link travel time, *Engineering Application of Artificial Intelligence*, 16, pp. 607–613.
24. Dia, H. (2001) An object-oriented neural network approach to short-term traffic forecasting, *European Journal of Operational Research*, 131, pp. 253–261.
25. Dimitriou, L., Tsekeris, T., Stathapoulos, A. (2008) Adaptive hybrid fuzzy rule-based system approach for modeling and predicting urban traffic flow, *Transportation Research Part C*, 16, pp. 554–573.
26. Ding, A., Zhao, X., Jiao, L. (2002) Traffic flow time series prediction based on statistics learning theory, In *IEEE proceedings of 5th International Conference on Intelligent Transportation Systems*, pp. 727–730.
27. Dion, F., Rakha, H., (2006) Estimating dynamic roadway travel times using automatic vehicle identification data for low sampling rates, *Transportation Research Part B*, 40(9), pp. 745–766.
28. Dougherty, M. S. and Cobbet, M. R. (1997) Short-term inter-urban traffic forecasts using neural networks, *International Journal of Forecasting*, 13, pp. 21–31.
29. El Faouzi, N.-E, Billot, R., Bouzebda, S. (2010) Motorway travel time prediction based on toll data and weather effect integration, *IET Intelligent Transportation Systems*, 4(4), pp. 338–345.
30. El Faouzi, N.-E., Klein, L.A., De Mouzon, O. (2009) Improving travel time estimates from inductive loop and toll collection data with Dempster–Shafer data fusion, *Transportation Research Record*, 2129, pp. 73–80.

31. Florio, L. and Mussone, L. (1996) Neural network models for classification and forecasting of freeway traffic flow stability, *Control Engineering Practice*, 4(2), pp. 153–164.
32. Hamed, M. M., Al-Masaeid, H. R. and Bani Said, Z. M. (1995) Short-term prediction of traffic volume in urban arterials, *ASCE Journal of Transportation Engineering*, 121(3), pp. 249–254.
33. Head, L. K. (1995) Event-based short-term traffic flow prediction model, *Transportation Research Record*, 1510, pp. 45–52.
34. Herrera, J. and Bayen, A.M. (2008) Traffic flow reconstruction using mobile sensors and loop detector data, In Proceedings of the Transportation Research Board 87th Annual Meeting, Washington, DC.
35. *Highway Capacity Manual* (2000) (Washington, DC: Transportation Research Board, National Research Council).
36. Hong, W.-C., Dong, Y., Zheng, F., Lai, C.-Y. (2011) Forecasting urban traffic flow by SVR with continuous ACO, *Applied Mathematical Modelling*, 35, pp. 1282-1291
37. Hu, S.-R. and Chen, C.-B. (2004) Dynamic estimation of freeway origin-destination demand and travel time using extended kalman filtering algorithm, In IEEE Proceedings of International Conference on Networking, Sensing and Control, Taipei, Taiwan, pp.1329-1334.
38. Huisken, G. and van Berkum, E.C. (2003), A comparative analysis of short-range travel time prediction methods, In Proceedings of the Transportation Research Board 82th Annual Meeting, Washington, DC.
39. Hunter, T., Herring, R., Abbeel, P., Bayen, A. (2009) Path and travel time inference from GPS probe vehicle data, In NIPS Analyzing Networks and Learning with Graphs.
40. Hyndman, R.J., Khandakar, Y. (2008) Automatic time series forecasting: the forecast package for R, J Statis Software.
41. Innamaa, S. (2000) Short-term prediction of traffic situation using MLP-neural networks, In Proceedings of the 7th World Congress on Intelligent Transportation Systems, Turin, Italy.
42. Ishak, S. and Al-Deek, H. (2002) Performance of short-term time series traffic prediction model, *Journal of Transportation Engineering*, 128(6), pp. 490–498.
43. Ishak, S. and Al-deek., H., (2003) Statistical evaluation of interstate 4 traffic prediction system, *Transportation Research Record*, 1856, pp. 16-24.
44. Ishak, S. and Alecsandru, C. (2003) Optimizing traffic prediction performance of neural networks under various topological, input and traffic condition settings, In Proceedings of the Transportation Research Board 82th Annual Meeting, Washington, DC.
45. Kachroo, P., Ozbay, K., Narayanan, A. (1997) Investigating the use of kalman filtering approaches for dynamic origin-destination trip table estimation, In IEEE Proceedings of Southeastcon '97. 'Engineering new New Century' , pp.138-142.
46. Kamarianakis, Y. and Prastakos, P. (2003) Forecasting traffic flow conditions in an urban network: comparison of multivariate and univariate approaches, *Transportation Research Record*, 1857, pp. 74-84.

47. Kirby, H., Dougherty, M. and Watson, S. (1997) Should we use neural networks or statistical models for short term motorway forecasting, *International Journal of Forecasting*, 13, pp. 45–50.
48. Kwiatkowski, D., Phillips, P.C., Schmidt, P., Shin, Y. (1992) Testing the null hypothesis of stationarity against the alternative of a unit root, *Journal of Econometrics*, 54, pp. 159–178
49. Kwon, E., Coifman, B. and Bickel, P. (2002) Day-to-day travel time trends and travel time prediction from loop detector data, In Proceedings of the Transportation Research Board 81st Annual Meeting, Washington, DC.
50. Lam, S. and Toan, T. D. (2008) Short-term travel time prediction using support vector regression, In Proceedings of the Transportation Research Board 87th Annual Meeting, Washington, DC.
51. Ledoux, C. (1997) An urban traffic flow model integrating neural networks, *Transportation Research Part C*, 5(5), pp. 287–300.
52. Lee, S. and Fambro, D. B. (1999) Application of subset autoregressive moving average model for short term freeway traffic volume forecasting, *Transportation Research Record*, 1678, pp. 179–188.
53. Lieu, H. C. (2000) Traffic estimation and prediction system. *TR News*, 208, pp. 3–6.
54. Lin, P.-W., Chang, G.-L. (2007) A generalized linear model and solution algorithm for estimation of the dynamic freeway origin-destination matrix, *Transportation Research Part B*, 41(5), pp. 554–572.
55. Lin, W.-H., Lu, Q. and Dahlgren, J. (2002) A dynamic procedure for short-term prediction of traffic congestion, In Proceedings of the Transportation Research Board 81st Annual Meeting, Washington, DC.
56. Liu, H., H. J. van Zuylen, H. van Lint, and M. Salomons (2006) Predicting urban arterial travel time with state-space neural networks and kalman filters, *Transportation Research Record*, No. 1968, pp. 99–108.
57. Liu, H.X., Ma, W. (2009) A virtual vehicle probe model for time-dependent travel time estimation on signalized arterials, *Transportation Research Part C*, 17(1), pp. 11–26
58. Liu, Y., Lin, P.W., Lai, X.R., Chang, G.L., Marquess, A. (2006) Developments and applications of simulation-based online travel time prediction system: traveling to Ocean City, Maryland, *Transportation Research Record*, 1959, pp. 92–104
59. Mark, C. D., Sadek, A. W., Rizzo, D. (2004) Predicting experienced travel time with neural networks: a PARAMICS simulation study, In IEEE Proceedings of Conference on Intelligent Transportation Systems, pp. 906–911.
60. Mihaylova, L., Boel, R., Hegyi, A., (2007) Freeway traffic estimation within particle filtering framework, *Automatica*, 43(2), pp. 290–300.
61. Min, W., Wynter, L. (2011) Real-time road traffic prediction with spatio-temporal correlations, *Transportation Research Part C*, 19(4), pp. 606–616
62. Miura, H. (2010) A study of travel time prediction using universal kriging, *TOP*, 18(1), pp. 257–270.

63. Miwa, T., Tawada, Y., Yamamoto, T., Morikawa, T. (2004) En-route updating methodology of travel time prediction using accumulated probe-car data, In Proceedings of the 14th World Congress on Intelligent Transport Systems.
64. Muller, T.H.J, Miska, M.P., van Zuylen, H.J. (2005) Monitoring traffic under congestion, In Proceedings of the Transportation Research Board 82nd Annual Meeting, Washington, DC.
65. Nanthawichit, C., Nakatsuji, T., Suzuki H. (2003) Application of probe-vehicle data for real-time traffic-state estimation and short-term travel-time prediction on a freeway. *Transportation Research Record*, 1855, pp. 49–59.
66. Nikovski, D., Nishiuma, N., Goto, Y., Kumazawa, H. (2005) Univariate Short Term Prediction of Road Travel Times, In IEEE Proceedings of International Conference on Intelligent Transportation Systems, Vienna, Austria, pp. 1074–1079.
67. Ohba, Y., Ueno, H., Kuwahara, M. (2000) Travel time prediction method for expressway using toll collection system data. Proceedings of the 7th World Congress on Intelligent Systems, Turin, Italy, pp. 471-475.
68. Okutani, I. and Stephanedes, Y. J. (1984) Dynamic prediction of traffic volume through kalman filtering theory, *Transportation Research Part B*, 18(1), pp. 1–11.
69. Park, D. and Rilett, L. R. (1998) Forecasting multiple-period freeway link travel times using modular neural networks, *Transportation Research Record*, 1617, pp. 163–170.
70. Park, D., Rilett, L. R., Han, G. (1999) Spectral basis neural networks for real-time travel forecasting, *ASCE Journal of Transportation Engineering*, 125, pp.515–523.
71. Paterson, D., Rose, G. (2008) A recursive cell processing model for predicting freeway travel times, *Transportation Research Part C*, 16(4), pp. 432-445.
72. Petty, K.F., Bickel, P., Ostland, M., Rice, J., Schoenberg, F., Jiang, J., Ritov, Y. (1998) Accurate estimation of travel times from single-loop detectors, *Transportation Research Part A*, 32(1), pp. 1-17.
73. Ren, S., Bi, J., Fung, Y.F., Li, X.I., Ho, T.K. (2010) Freeway traffic estimation in Beijing based on particle filter, In IEEE Proceedings of 6th International Conference of Natural Computation, 1, pp.292-296
74. Rice, J. and van Zwet, E. (2001) A simple and effective method for predicting travel times on freeways, In IEEE proceedings of 4th International Conference of Intelligent Transportation Systems, pp. 227–232.
75. Shekhar, S., Williams, B.M. (2007) Adaptive seasonal time series models for forecasting short-term traffic flow, *Transportation Research Record*, 2024, pp. 116–125.
76. Skabardonis, A., Geroliminis, N., (2008) Real-time monitoring and control on signalized arterials, *Journal of Intelligent Transportation Systems*, 12(2), pp.64-74.
77. Smith, B. L. and Demetsky, M. J. (1994) Short-term traffic flow prediction: neural network approach, *Transportation Research Record*, 1453, pp. 98–104.
78. Smith, B. L. and Demetsky, M. J. (1996) Multiple-interval freeway traffic flow forecasting, *Transportation Research Record*, 1554, pp. 136–141.

79. Smith, B. L. and Demetsky, M. J. (1997) Traffic flow forecasting: comparison of modeling approaches, *ASCE Journal of Transportation Engineering*, 123(4), pp. 261–266.
80. Smith, B. L., Williams, B. M. and Oswald, K. R. (2002) Comparison of parametric and non-parametric models for traffic flow forecasting, *Transportation Research Part C*, 10(4), pp. 303–321.
81. Soriguera F., Thorson, L., Robuste, F. (2007) Travel time measurement using toll infrastructure, *Transportation Research Record*, 2027, pp. 99-107
82. Soriguera, F., Rosas, D., Robuste, F. (2010) Travel time measurement in closed toll highways, *Transportation Research Part B*, 44(10), pp. 1242-1267.
83. Stathopoulos, A. and Karlaftis, M. G. (2003) A multivariate state-space approach for urban traffic flow modeling and prediction, *Transportation Research Part C*, 11(2), pp. 121–135.
84. Su, H. , Zhang, L., Yu, S. (2007) Short-term traffic flow prediction based on incremental support vector regression, In *IEEE Proceedings of Third International Conference of Natural Computation*, pp. 640-645.
85. Sun, S., Zhang, C., Yu, G. (2006) A bayesian network approach to traffic flow forecasting, In *IEEE proceedings of International Conference on Intelligent Transportation Systems*, 7(1), pp. 124–132.
86. *Travel Time Data Collection Handbook* (1998) FHWA-PL–98–035, March (College Station, TX: Texas Transportation Institute, The Texas A&M University System).
87. Ulbricht, C. (1994) Multi-recurrent networks for traffic forecasting, In *Proceedings of the Twelfth National Conference on Artificial Intelligence*, 11, pp. 883–888 (Cambridge, MA: AAAI Press/MIT Press).
88. Van Arem, B., Van der Vlist, M., de Ruiter, J., Muste, M., Smulders, S. (1997) Travel time estimation in the GERDIEN project, *International Journal of Forecasting*, 13, pp.73-85.
89. Van der Voort, M., Dougherty, M. and Watson, S. (1996) Combining kohonen maps with ARIMA time series models to forecast traffic flow, *Transportation Research Part C*, 4(5), pp. 307–318.
90. Van Lint, J. W. C. (2008) Online learning solutions for freeway travel time prediction, In *IEEE proceedings of International Conference on Intelligent Transportation Systems*, 9(1), pp. 38–47.
91. Van Lint, J. W. C., Hoogendoorn, S. P. and Van Zuylen, H. J. (2002) Freeway travel time prediction with state-space neural networks: modelling state-space dynamics with recurrent neural networks, In *Proceedings of the Transportation Research Board 81st Annual Meeting*, Washington, DC.
92. Van Lint, J. W. C., Hoogendoorn, S. P. and Van Zuylen, H. J. (2003) Towards a robust framework for freeway travel time prediction: experiments with simple imputation and state-space neural networks, In *Proceedings of the Transportation Research Board 82nd Annual Meeting*, Washington, DC.
93. Van Lint, J., Hoogendoorn, S.P., van Zuylen, H.J. (2005) Accurate freeway travel time prediction with state-space neural networks under missing data, *Transportation Research Part C*, 13(5/6), pp. 347-369.

94. Vanajakshi, L. and Rilett, L.R. (2007) Support vector machine technique for the short term prediction of travel time, In IEEE Proceedings of Intelligent Vehicles Symposium, Istanbul, Turkey, pp. 600-605.
95. Vlahogianni, E. I., Golias, J. C., Karlaftis, M. G. (2003) Short-term traffic forecasting: overview of objectives and methods, *Transport Reviews*, 24(5), pp.533-557.
96. Vlahogianni, E., Karlaftis, M., Golias, J., Kourbelis, N. (2006) Pattern-based short-term urban traffic predictor, In IEEE proceedings of 9th International Intelligent Transportation Systems Conference, Toronto, Canada, pp.389-393
97. Vlahogianni, E.I., Karlaftis, M.G., Golias, J.C. (2005) Optimized and meta-optimized neural networks for short-term traffic flow prediction: A genetic approach, *Transportation Research Part C*, 13(3), pp. 211-234
98. Wang, Y., Papageorgiou, M., and Messmer, A. (2006) A real-time freeway network traffic surveillance tool, In IEEE proceedings of Transportation Control Systems Technology, 14 (1), pp. 18– 32.
99. Wang, Y., Papageorgiou, M., Messmer, A. (2005) An adaptive freeway traffic state estimator and its real-data testing-Part II: adaptive capabilities, In IEEE proceedings of 8th International Conference of Intelligent Transportation Systems, Vienna, Austria, 2005, pp. 537–542.
100. Wang, Y., Papageorgiou, M., Messmer, A. (2008) Real-time freeway traffic state estimation based on extended Kalman filter: Adaptive capabilities and real data testing, *Transportation Research Part A*, 42(10), pp. 1340-1358.
101. Wang, Y., Papageorgiou, M., Messmer, A., Coppola, P., Tzimitsi, A., Nuzzolo, A. (2009) An adaptive freeway traffic state estimator, *Automatica*, 45, pp.10-24.
102. Wilcoxon, Frank (1945) Individual comparisons by ranking methods, *Biometrics Bulletin*, 1(6), pp. 80–83.
103. Williams, B. M. (2001) Multivariate vehicular traffic flow prediction: an evaluation of ARIMAX modeling, *Transportation Research Record*, 1776, pp. 194–200.
104. Williams, B. M., Durvasula, P. K. and Brown, D. E. (1998) Urban traffic flow prediction: application of seasonal autoregressive integrated moving average and exponential smoothing models, *Transportation Research Record*, 1644, pp. 132–144.
105. Work, D.B.; Tossavainen, O.-P.; Blandin, S.; Bayen, A.M.; Iwuchukwu, T.; Tracton, K. (2008) An ensemble Kalman filtering approach to highway traffic estimation using GPS enabled mobile devices, In IEEE proceedings of Decision and Control, pp.5062-5068.
106. Wu, C.-H., Ho, J.-M., Lee, D. T. (2004) Travel-time prediction with support vector regression, In IEEE Proceedings of Intelligent Transportation Systems, 5(4), pp. 276–281.
107. Xie, Y., Zhang, Y., Ye, Z. (2006) Short-Term Traffic Volume Forecasting Using Kalman Filter with Discrete Wavelet Decomposition, In Proceedings of the Transportation Research Board 85th Annual Meeting, Washington, DC.
108. Yang, J.-S.(2005) Travel time prediction using the GPS test vehicle and Kalman filtering techniques, In Proceedings of the American Control Conference, pp. 2128- 2133

109. Yasdi, R. (1999) Prediction of road traffic using a neural network approach, *Neural Computing and Applications*, 8, pp. 135-142.
110. Yeon, J., Elefteriadou, L., Lawphongpanich, S. (2008) Travel time estimation on a freeway using discrete time markov chains. *Transportation Research Part B*, 42(4), pp. 325–338.
111. Zhang, H. M. (2000) Recursive prediction of traffic conditions with neural networks, *Journal of Transportation Engineering*, 126(6), pp. 472–481.
112. Zhang, X. and Rice, J. A. (2001) Short-term travel time prediction using a time-varying coefficient linear model, *Transportation Research Part C*, 11(3–4), pp. 187–210.
113. Zheng, W., Lee, D.-H., Shi, Q., (2006). Short-term freeway traffic flow prediction: Bayesian combined neural network approach, *Journal of Transportation Engineering*, 132 (2), 114–121.
114. Zhou, X., and Mahmassani, H. (2007) A structural state space model for real time traffic origin–destination demand estimation and prediction in a day-to-day learning framework, *Transportation Research Part B*, 41(8), pp. 823–840.