2011 14th International IEEE Conference on
Intelligent Transportation Systems
Washington, DC, USA. October 5-7, 2011

Comparison of Real-Time Travel Time Estimation Using Two Distinct Approaches: Universal Kriging and Mathematical Programming

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Abstract—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. 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 mathematical programming algorithm which outperforms universal kriging approach.

I. Introduction

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.

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.

There are a large number of studies that focus on the estimation and prediction of fundamental parameters of traffic. Lin et al. [1] used occupancy (as a measure of density) to keep track of traffic conditions. However, for instance, Hong et al. [2] and Neto et al. [3] predicted traffic flow considering the fact that occupancy is subject to strong fluctuations compared to flow. Dougherty and Cobbett [4] estimated separate models for each of the three fundamental traffic parameters.

Besides the fundamental traffic parameters briefly mentioned above, travel time is another important traffic parameter, which is defined as "the required time to traverse two fixed points along a highway, freeway or urban arterial" [5]. The concept of travel time, which is easily comprehensible, provides a common measure of performance to engineers, planners, administrators, decision makers as well as general public. It has the same meaning in all transportation systems. Moreover, once it is compared to the free flow travel time, it can easily be understood as a measure of traffic congestion.

According to "Travel Time Data Collection Handbook" [6], data required to estimate travel time can be obtained through loop detectors, test vehicles, license plate matching techniques (automatic vehicle identification, AVI) and ITS probe vehicle techniques. All of the detection technologies except the one based on loop detectors provide direct measurement of travel time ([7]- [9]).

Transportation networks are usually equipped with loop detectors that collect flow, spot speed and occupancy data. There have been a number of excellent studies that use loop data for the estimation of prediction of travel time. For example, Coifman [10] developed a model to measure 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. [11] extended this study for the data collected by single loop detectors. Petty et al. [12] 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 consider traffic data and signal timings simultaneously. Skabardonis and Geroliminis [13] and Liu and Ma [14] developed models based on loop detector data and signal timing information to estimate arterial travel time.

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 have become more prominent. Travel time on urban networks is not only a function of flow and speed at a given point, but also the synthesis of free flow travel time and other factors such as signal timing and delays at intersections. Hence, loop detector based arterial travel time estimations do not provide necessary information needed to

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estimate arterial travel times. Thus, probe vehicles are widely used to close this information gap ([6], [15] and [16]).

There have also been attempts made to forecast travel time using AVI data collected by electronic toll collection systems. Chien and Kuchipudy [17] used the data collected by road side terminals installed on roadway. Vehicles with electronic toll tags are identified by road side terminals and passage times are recorded. This set-up can be described as an 'open' toll system where toll plazas are located on the main roadway so that all drivers pay the same average toll fee. When the electronic toll reader identifies vehicles on the main highway, the system becomes similar to other AVI-based systems found in the literature. However, 'closed' toll systems, where the toll fee is based on the distance travelled along the network and toll booths are located on the on and off-ramps, are only discussed by few researchers [18]-[22]. Among these studies, Ohba et al. [18] dealt with a single origin destination pair only. Faouzi et al. [19] 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. [20] used the historical average of particular OD travel times to estimate the new ones. Soriguera et al. [21] developed a simple fusion algorithm to convert OD travel time to single-section travel times and Soriguera et al. [22] improved this work by incorporating a data filtering algorithm and by extending their algorithm.

The aim of this paper 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.

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.

II. Experimental Set-up and Data Description

Empirical data used in this paper are based the data obtained from New Jersey Turnpike (NJTPK), a closed system toll road that collects tolls through a traditional ticket system as well as an electronic toll collection system used in NJ since 2002. An aggregated version of the electronic toll data (15 min) is used in this paper. Note that travel times are obtained by the median value of the vehicles that traveled between particular origin and destination points in 15 minutes time interval. More detailed aggregation levels (e.g. 5min) have been tried; however, due to low path demand level accurate results could not be obtained. The study area is narrowed down to links between Exits 13A and 8, which is composed of 8 interchanges. The average travel time between the farthest ends of the study area is 30 min.

III. Mathematical Programming Approach

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

$$\begin{aligned} t_{s(i,j)} &= t_{i,j} - t_{ent(i)} - t_{ext(j)} \\ &= t_{i,i+1} + t_{i+1,i+2} + \cdots + t_{j-1,j} \end{aligned} \quad (1)$$

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

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 (1) could be rewritten as:

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

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 main trunk and it is not possible to acquire such data. One way of solving this problem could be the use of average link travel times, identified through the examination of one year of historical data. According to average travel times, links that can be reached in one time-step can be identified and incorporated in the equation.

Considering itinerary 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 itinerary travel times. The objective of the fusion is to identify single section travel times that are compatible with all the itinerary travel times measured. Such a problem can be modeled as nonlinear programming (NLP) problem;

$$\min \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} (t_{s(i,j)}^{(p)} - \hat{t}_{i,i+1}^{(p-\Delta t_{i+1,j})} - \hat{t}_{i,i+2}^{(p-\Delta t_{i+2,j})} - \dots - \hat{t}_{j-1,j}^{(p)})^2 \quad (3)$$

$$s.t. \quad \hat{t}_{i,i+1}^{m} \geq \frac{l_{i,i+1}}{V_{\max(i,i+1)}} \quad i = 1,2 \dots, n-1 \; and \; \forall m \quad (4)$$

$$0.8 \leq \frac{\hat{t}_{i,i+1}^{(m)}}{\hat{t}_{i,i+1}^{*(m)}} \leq 1.2 \quad i = 1,2,\dots,n-1 \; and \; \forall m \neq p \quad (5)$$

where n is the number of interchanges on the roadway, $\hat{t}_{i,i+1}^{(p)}$ is the travel time estimation in current time interval p 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 and $\hat{t}_{i,i+1}^{*(m)}$ is the link travel time estimated previously. Equation (3) is the objective function that attempts to minimize the difference between the measured travel times and the ones constructed by the addition of estimated link travel times. Equation (4) is a constraint on the estimated 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. Equation (5) compares the link travel times of the previous time interval that are calculated in the current time interval and in previous interval. It basically attempts to create travel time estimates that are consistent with the ones calculated in the previous time interval (t-15). The specific range used in Eq. (5) is computed through trial-and-error process, and it introduces the dependence of travel times on past values. 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 will be dependent on a number of past values. Hence, updating or employing past travel time values within a certain range would help us to produce better travel time predictions in the future.

IV. UNIVERSAL KRIGING

In order to compare the proposed mathematical programming approach with a relatively recent statistical estimation technique we have adopted universal kriging. 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 [24]. 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.

Miura [23] 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 on small scaled real time applications is investigated. 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. Note that each link travel time (OD pairs with successive interchanges) would 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 same value for input points and interpolate them for unobserved locations. Therefore, even though they are measured, single section travel time values (link travel times) cannot be inputted 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 trend and remove it from the data. 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 expose the trend. Fig. 1 which shows travel time data for some trips in NJTPK, clearly indicates that there is a significant trend in both vertical and horizontal directions.

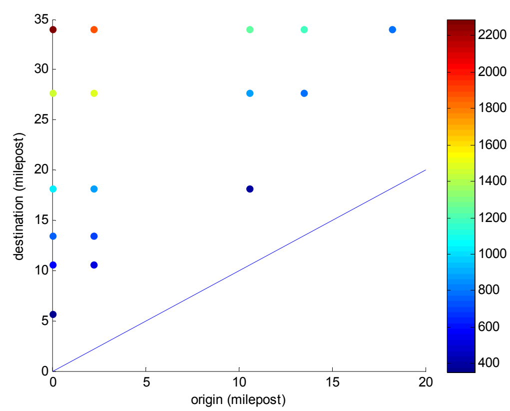

Fig. 1 Travel Time (s) Data on Two Dimensional Space

The estimation of travel time by universal kriging is described here following the notation from Cressie [24]. 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:

$$z(\boldsymbol{s}) = \beta f(\boldsymbol{s}) + \delta(\boldsymbol{s}) \quad (6)$$

where *f(s)* is the drift function, distance between origin and destination, β is the generalized least squares (GLS) coefficient and δ(**s**) is a zero-mean function of residual time and has the following properties:

$$E(\delta(\boldsymbol{s})) = 0 \quad (7)$$

$$Cov(\delta(\boldsymbol{s}), \delta(\boldsymbol{s}+\boldsymbol{h})) = C(\boldsymbol{h}) \quad (8)$$

where **h** is an arbitrary two dimensional vector and C(**h**) is the covariogram function. A random variable satisfying Eq. (7) and (8) is called second-order stationary. This implies that δ(**s**) has a constant mean for all **s** ϵ D and its covariance function is independent of the vector **s**.

The variogram model plays a crucial role in the interpolation of unobserved locations, however there is no strong agreement on how to build it for trended data. In case of the existence of a clear trend, residuals can be used to estimate the variogram. Residuals that would satisfy Eq. (7) and (8), can be calculated using generalized least squares (GLS). However, GLS estimator cannot be obtained before building the covariance matrix, which is based on the correlation between residuals. Many researchers have proposed solutions to this dilemma. For example, Cressie [24] showed that the bias due to the use of ordinary least squares (OLS) estimator, instead of GLS estimator, in the calculation of residuals is not important when there is adequate number of observations.

Define the OLS residuals:

$$\boldsymbol{R} = \boldsymbol{Z} - \boldsymbol{X}(\boldsymbol{X}'\boldsymbol{X})^{-1}\boldsymbol{X}'\boldsymbol{Z} \tag{9}$$

where **X** is n x p matrix whose (i,j)th element is $f_{j,j}(\mathbf{s_i})$ and **Z** is n x 1 vector whose (i)th element is $z(\mathbf{s_i})$. In this study, $f_{i,1}(\mathbf{s_i})=1$ and $f_{i,2}(s_i)$ is the distance between origin and destination, which compose the elements of the linear regression equation with an intercept, as seen in equation (6).

Fig. 2 shows residuals of travel time data, after the removal of the trend. The residuals of travel time values are going to be used for the determination of the variogram and covariogram, in other words to construct the correlation structure of the data.

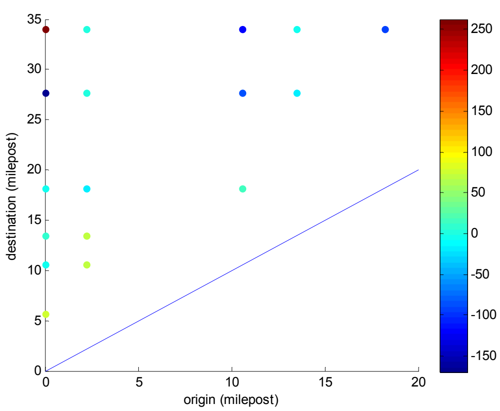

Fig. 2 Travel Time (s) Data After Removal of Trend

The variogram estimator is:

$$2\hat{\gamma}(h) = \sum_{i=1}^{n-h}(R(i+h) - R(i))^2/(n-h) \tag{10}$$

The covariogram estimator is then:

$$C(\boldsymbol{h}) = C(\boldsymbol{0}) - \hat{\gamma}(\boldsymbol{h}) \tag{11}$$

where $C(\boldsymbol{0})$ is equal to the sill value of the semivariogram, $\hat{\gamma}(.)$ (the value of semivariogram at very large **h**).

Since the spatial structure of travel time data is now independent of any direction and covariogram satisfies Eq. (7) and (8), 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: $n(h) = \begin{cases} 0 & if\ ||h|| = 0 \\ 1 & otherwise \end{cases}$
- Gaussian Model: $g(h,a) = 1 - \exp\left(\frac{-3||h||^2}{a^2}\right)$

The semivariogram model can then be written as follows:

$$\gamma(h) = \propto_1 * n(h) + \propto_2 * g(h, \propto_3) \tag{12}$$

where α_1, α_2 and α_3 are the parameters that will be determined using the least squares estimation method to minimize the error between theoretical and empirical semivariogram curves shown in Fig. 3. Empirical semivariogram values are calculated using the residuals presented in Fig. 2.

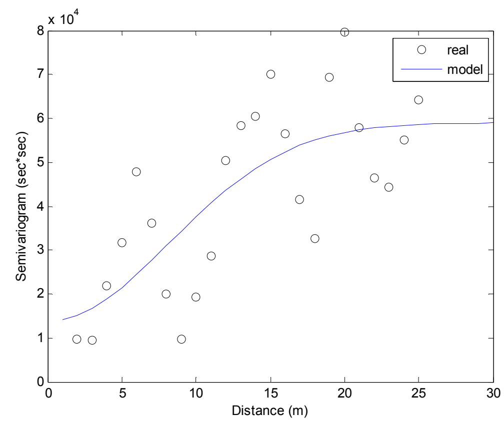

Fig. 3 Semivariogram

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 for an arbitrary **s**, unobserved origin-destination pair, $\hat{Z}(\boldsymbol{s})$ is the weighted mean of $z(\mathbf{s_i})$.

$$\hat{Z}(\boldsymbol{s}) = \sum_{i=1}^{n} \lambda_i\, z(\boldsymbol{s_i}) \tag{13}$$

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

$$\boldsymbol{\lambda} = \{\boldsymbol{c} + \boldsymbol{X}(\boldsymbol{X}'\Sigma^{-1}\boldsymbol{X})^{-1}(x - \boldsymbol{X}'\Sigma^{-1}\boldsymbol{c})\}'\Sigma^{-1} \tag{14}$$

where $\mathbf{c}=(C(\mathbf{s}-\mathbf{s_1}),....,C(\mathbf{s}-\mathbf{s_n}))'$, Σ is n x n matrix whose (i,j)th element is $C(\mathbf{s_i}-\mathbf{s_j})$ and x is the travel time associated with arbitrary **s** vector calculated by generalized least squares estimator. Estimated travel time value of $\hat{Z}(\boldsymbol{s})$ can be also written as the following:

$$\begin{aligned}\hat{Z}(\boldsymbol{s}) &= \boldsymbol{\lambda z} \\ &= \hat{\beta}_{gls} f(\boldsymbol{s}) + \boldsymbol{c}'\Sigma^{-1}(\boldsymbol{z} - \hat{\beta}_{gls}\boldsymbol{X})\end{aligned} \tag{15}$$

where $\mathbf{z}=\{z(\mathbf{s_1}),...,z(\mathbf{s_n})\}$ and GLS estimator $\hat{\beta}_{gls}$ is:

$$\hat{\beta}_{gls} = (\boldsymbol{X}'\Sigma^{-1}\boldsymbol{X})^{-1}\boldsymbol{X}'\Sigma^{-1}\boldsymbol{z} \tag{16}$$

Following methodology should be repeated at the end of each time period; 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 reducing the amount of available 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 interchanges, they cannot be incorporated in the kriging equations. Since the demand level between consecutive interchanges is quite low, this can be seen as a minor 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.

V. Results

To illustrate estimation errors by both approaches compared to observed travel times, OD pair (11-8) is selected and detailed graphical representation of travel time estimates by kriging and NLP methods are shown in Fig. 4 and Fig. 5, respectively. Note that trip travel times between OD pairs are estimated as a summation of travel times of links that constitute the path between each OD pair. In the case of multiple paths, shortest path calculated using free flow travel times between each OD pair can be used as the path that represents trips between each OD pair. For a closed system like NJ Turnpike, there is a single path between each OD pair, so such an assumption is not needed. Error is calculated for different periods of the day and various demand levels. Table 1 compares the estimation errors (mean and relative absolute travel time error) generated by two methods for different periods of the day. Table 2 provides the errors committed by two algorithms under atypical traffic conditions.

Table 1 and Table 2 clearly show that NLP outperforms kriging. Note that trip travel times are incorporated in both applications, 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. On the other hand, NLP algorithm has relatively small errors, even under low demand conditions.

VI. Conclusion

The aim of this study is to estimate travel times using toll data and to compare two approaches; universal kriging and nonlinear programming. The methodology is tested using 15 minute data obtained from an electronic toll collection system.

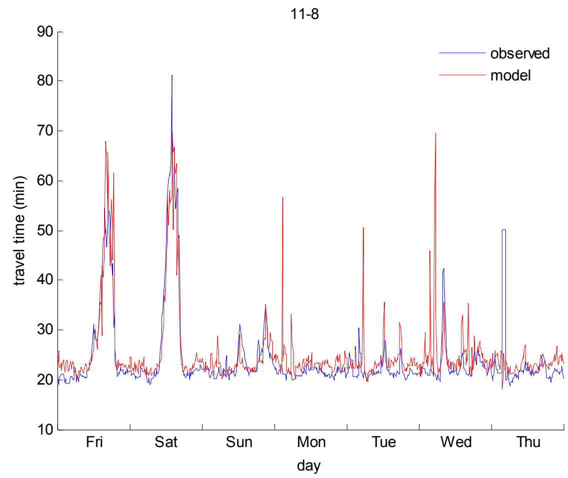

Fig. 4 Kriging Results

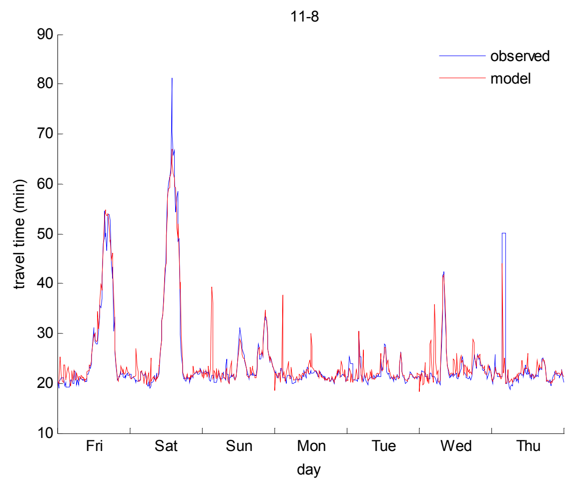

Fig. 5 NLP Results

The most important disadvantage of the kriging algorithm is that it 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 readers are located. Hence, especially travel time measurements of long trips are based on the past conditions of the roadway, which weakens the assumption of instantaneous travel time. Although a small network does not suffer from this drawback, it may cause important problems in a larger network application where delays can be considerable.

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.

TABLE 1 KRIGING & NLP RESULTS

Test Day	Period	Kriging Abs. Error Mean (min)	Kriging Rel.	NLP Abs. Error Mean (min)	NLP Rel.
w/days	Peak	3.03	0.11	0.87	0.03
	Off-Peak	1.89	0.08	0.8	0.03
	Night	4.51	0.2	1.32	0.06
w/end	6am12pm	2.53	0.08	1.14	0.03
	0am-6am	1.63	0.08	1.79	0.08
Fri	Peak	6.03	0.16	1.92	0.05
	Off-Peak	2.12	0.07	1.02	0.03
	Night	2.21	0.11	1.22	0.06
Mon	Peak	1.93	0.09	0.23	0.01
	Off-Peak	1.45	0.07	0.85	0.04
	Night	4.97	0.24	1.68	0.08
Tue	Peak	1.88	0.09	0.43	0.02
	Off-Peak	2.03	0.09	0.6	0.03
	Night	3.76	0.17	1.06	0.05
Wed	Peak	3.79	0.13	1.29	0.05
	Off-Peak	1.94	0.09	0.92	0.04
	Night	6.96	0.33	1.7	0.08
Thu	Peak	1.51	0.07	0.47	0.02
	Off-Peak	1.84	0.09	0.65	0.03
	Night	4.34	0.15	0.9	0.03

TABLE 2 KRIGING & NLP RESULTS UNDER ATYPICAL TRAFFIC CONDITIONS

Test Day	Period of the Day	Congestion	Kriging Abs. Error Mean	Kriging Rel.	Basic NLP Abs. Error Mean	Basic NLP Rel.
Fri	11.00-20.00	High	6.59	0.14	2.60	0.06
Sat	09.30-20.00	High	5.99	0.11	2.66	0.06
Sun	11.00-16.00	Moderate	2.18	0.08	0.75	0.03
Sun	18.00-23.00	Moderate	2.22	0.08	0.51	0.02
Wed	06.30-09.00	Moderate	5.74	0.16	1.08	0.04

In the future proposed NLP model can be improved to better respond to rapid changes in traffic conditions depending on the availability of data and the characteristics of the application area. Assumption of average link travel times for the lag can be replaced with an adaptive procedure that reflects time-dependent fluctuations.

ACKNOWLEDGEMENTS

This study was partially funded by a grant from New Jersey Department of Transportation (NJDOT). Their support is both acknowledged and appreciated. The contents of this paper reflect the views of the authors who are responsible for the facts and the accuracy of the data presented herein. The contents of the paper do not necessarily reflect the official views or policies of the funding agencies.

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