Comparison of Two Novel Travel Time Estimation Techniques Based on Probe Vehicle Data: Kriging versus Non-linear Programming Based Approaches

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ABSTRACT

This study proposes and compares two novel approaches for estimating link travel times using data collected by an electronic toll collection system deployed on a closed roadway 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, readers are not located on the mainline, but instead on the ramps. Aside from the fact that the special configuration of the readers can present an important challenge in terms of accuracy of the estimates, the demand level associated with particular OD pairs is not always enough to obtain accurate average travel times. This study proposes two distinct statistical and mathematical programming based approaches to estimate link travel times, and studies pros and cons of each approach in terms of the accuracy of travel time estimates given the existing the infrastructure of the road system.
INTRODUCTION

Real-time estimates of traffic conditions are needed by operators of transportation facilities as well as travelers. Besides the fundamental traffic parameters (flow, speed and density), 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” (1). The concept of travel time has a couple of advantages over the other traffic parameters:

- It 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.
- Once it is compared to the free flow travel time, it can easily be understood as a measure of traffic congestion.

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:

\[
V_t = \frac{1}{m} \sum_{i=1}^{m} V_i
\]

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:

\[
V_t = \frac{m}{\sum_{i=1}^{m} \left( \frac{1}{V_i} \right)}
\]

Transportation 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 (2). Double loop detectors provide speed measurement, which is necessary to calculate travel time (3). There is a large number of studies that studied the estimation of travel times using loop detector data. For example, Coifman (4) developed a model to directly 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 and Krishnamurthy (5) extended this study for the data collected by single loop detectors. Petty et al. (6) 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. Liu and Ma (7) developed a model based on both loop detector data and signal timing information to estimate arterial travel time. Traffic data taken from detectors can also be used to acquire needed information through simulation models. Chien et al. (8) calibrate their simulation model with the speed data detected by the acoustic sensors, and they treat the link travel times generated by the model as actual travel times.

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 estimate arterial travel times. Thus, probe vehicles are widely used to close this information gap (9-12). Considering the fact that travel time estimations can be based on both spot and space mean speeds Chu et al. (13) fuses loop detector and probe vehicle data using an adaptive kalman filter. Another major research direction related to probe vehicles is determining required sample size; Chen and Chien (14) developed a heuristic approach to determine the minimum number of probe vehicles.

There have also been attempts made to forecast travel time using AVI data collected by electronic toll collection systems. Chien and Kuchipudy (15) 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 (16-20). Among these studies, Ohba et al. (16) dealt with a single origin destination pair only. Faouzi et al. (17) 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. (18) used the historical average of particular OD travel times to estimate the new ones. However, only Soriguera et al. (19) and Soriguera et al. (20) discussed travel time estimation problem that arises from the specific configuration of closed toll highways. Soriguera et al. (19) developed a simple fusion algorithm to convert OD travel time to single-section travel times and Soriguera et al. (20) 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 an 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.

**PROBLEM STATEMENT**

Automatic vehicle identification (AVI) systems record the exact times at which vehicles cross the detector location. A special version of AVI based data collection systems is a closed toll road with an electronic toll collection system. New Jersey Turnpike, Pennsylvania Turnpike, and New York Thruway are examples of such closed tollways. This kind of electronic toll collection system records entry and exit times and locations of each vehicle.

A straightforward approach is to use these measurements of vehicles that travel between consecutive junctions. However, this approach would not work well in real-time in the case of closed toll highways because of the limited number of observations for each relatively short time intervals that can be between 5 to 15 minutes. The volume of traffic between consecutive junctions in a closed highway system is quite low compared to through traffic. Travelers do not usually prefer toll highways for short distance trips. Furthermore, an estimation based on single section measurement only, would be biased
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by the experience of those vehicles. However, travel time estimation should incorporate through traffic as well.

The configuration of closed toll highways presents 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, 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 paths. 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 path 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. Third, long distance travel time measurement reflects the past conditions on the roadway, and a projection based on that misses the effect of rapidly changing traffic conditions on the roadway.

Toll collection system provides the data once the vehicle left the roadway network. Hence, this type of travel time measurement reflects the past conditions 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. For example, a long distance traveler may experience free flow travel time; however, an accident might have occurred on the first link of the path after the traveler crosses it. In such a case, travel time information taken from the system would not reflect the current conditions in the network. Hence, the information delay can be quite problematic under rapidly changing traffic conditions.

The algorithms presented in this study estimates link travel times, in which the information delay is minimum, without reducing the amount of available data.

TRAVEL TIME ESTIMATION METHODOLOGY

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

$$t_{lj} = t_{ent(i)} + t_{i,i+1} + t_{i+1,i+2} + \cdots + t_{j-1,j} + t_{ext(j)}$$  \hspace{1cm} (3)

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 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 electronic toll collection (ETC) data, a constant entry/exit time can be identified for each junction.
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Service times are more or less constant for the vehicles equipped with electronic toll tag readers, while the travelers that receive a traditional ticket which is collected at the exit toll booth, are subject to queue time. Considering a constant acceleration/deceleration and the distance of the ramp from the mainline (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 1), 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.

![FIGURE 1- Schematic of a typical toll road section (adapted from Soriguera et al. (21))](image)

Assumption of constant entrance/exit times would also work in the case of congestion along the mainline. 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. Note that toll plaza configurations of the NJ Turnpike have some lanes dedicated to the EZ-Pass users. 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.

As entrance and exit times for vehicles equipped with electronic tag readers are assumed constant, Equation (3) can be rewritten as:

\[ t_{s(i,j)} = t_{i,j} - t_{ent(i)} - t_{ext(j)} = t_{i,i+1} + t_{i+1,i+2} + \cdots + t_{j-1,j} \]  

(4)

Two travel time estimation methods based on universal kriging and mathematical programming are proposed to estimate single section travel times using the available data from the electronic toll collection system.
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 (22). 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 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, 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. 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, and it should be removed from the dataset.

The estimation of travel time by universal kriging is described here following the notation from Cressie (22). Let \( D \) be a fixed subset of two dimensional space where each point represents a single journey. An arbitrary point in the space \( s \in D \) that consists of a pair of origin and destination has the following travel time model:

\[
z(s) = \beta f(s) + \delta(s)
\]

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

\[
E(\delta(s)) = 0
\]

\[
\text{Cov}(\delta(s), \delta(s + h)) = C(h)
\]

where \( h \) is an arbitrary two dimensional vector and \( C(h) \) is the covariogram function. A random variable satisfying Equations (6) and (7) is called second-order stationary. This implies that \( \delta(s) \) has a constant mean for all \( s \in D \) and its covariance function is independent of the vector \( s \).

The correlation structure in kriging algorithm is represented by the variogram model, and it 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 Equations (6) and (7), 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 (22) 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:

\[
R = Z - X(X'X)^{-1}X'Z
\]
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where $X$ is an $n \times p$ matrix whose $(i,j)$th element is $f_{i,j}(s_i)$ and $Z$ is an $n \times 1$ vector whose $(i)$th element is $z(s_i)$. In this study, $f_{i,1}(s_i)=1$ 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 (5).

Using the residuals, variogram estimator is defined as:

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

Covariogram estimator is then:

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

where $C(0)$ 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 Equations (6) and (7), 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 can then be written as follows:

$$\gamma(h) = \alpha_1 * n(h) + \alpha_2 * g(h, \alpha_3)$$

where $\alpha_1$, $\alpha_2$ and $\alpha_3$ are the parameters that will be determined using the least squares estimation method to minimize the error between theoretical and empirical semivariogram curves. FIGURE 2 presents an example of the procedure explained above; a) travel time values in the imaginary origin-destination space, b) residuals after the removal of the trend, c) discrete semivariogram values and the continuous model fitted on them.
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Let $s_i$ be the two dimensional origin-destination vector of $i$th trip and $z(s_i)$ be the associated travel time. The estimated travel time for an arbitrary $s$, unobserved origin-destination pair, $\hat{Z}(s)$ is the weighted mean of $z(s_i)$.

$$\hat{Z}(s) = \sum_{i=1}^{n} \lambda_i z(s_i)$$  \hspace{1cm} (12)

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

$$\lambda = \{c + X(X'\Sigma^{-1}X)^{-1}(X'\Sigma^{-1}c)\}'\Sigma^{-1}$$  \hspace{1cm} (13)

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

$$\hat{Z}(s) = \lambda z$$

$$= \hat{\beta}_{gls}f(s) + c'\Sigma^{-1}(z - \hat{\beta}_{gls}X)$$  \hspace{1cm} (14)

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

$$\hat{\beta}_{gls} = (X'\Sigma^{-1}X)^{-1}X'\Sigma^{-1}z$$  \hspace{1cm} (15)

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.
Non-Linear Programming (NLP) Based Travel Time Estimation

Equation (3) 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 traverses a particular section. If this information is available, Equation (3) can be rewritten as:

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

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. Therefore, link travel times estimated in the previous time interval can be used to reconstruct path travel times or to identify the time intervals in which links are traversed. OD-Link matrix, whose rows represent OD pairs and whose columns represent links, can then be constructed. In the following matrices, an exemplary roadway segment, that consists of 8 junctions, 7 links and 28 OD pairs is used. It is assumed that the whole roadway section can be traversed in two time steps. If the link is reachable in the current time period for the corresponding OD trip, the first matrix contains 1. If the link is reachable in two time periods, then the second matrix contains 1.

\[
S_{\text{OD}}^{p} = \begin{bmatrix}
2-1 & 3-2 & 4-3 & 5-4 & 6-5 & 7-6 & 8-7 \\
2-1 & 1 & 0 & 0 & 0 & 0 & 0 \\
3-1 & 1 & 1 & 0 & 0 & 0 & 0 \\
3-2 & 0 & 1 & 0 & 0 & 0 & 0 \\
4-1 & 1 & 1 & 0 & 0 & 0 & 0 \\
4-2 & 0 & 1 & 1 & 0 & 0 & 0 \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
8-6 & 0 & 0 & 0 & 0 & 0 & 1 \\
8-7 & 0 & 0 & 0 & 0 & 0 & 1
\end{bmatrix}
\]

\[
S_{\text{OD}}^{p-1} = \begin{bmatrix}
2-1 & 3-2 & 4-3 & 5-4 & 6-5 & 7-6 & 8-7 \\
2-1 & 0 & 0 & 0 & 0 & 0 & 0 \\
3-1 & 0 & 0 & 0 & 0 & 0 & 0 \\
3-2 & 0 & 1 & 0 & 0 & 0 & 0 \\
4-1 & 0 & 0 & 1 & 0 & 0 & 0 \\
4-2 & 0 & 1 & 1 & 0 & 0 & 0 \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
8-6 & 0 & 0 & 0 & 0 & 0 & 0 \\
8-7 & 0 & 0 & 0 & 0 & 0 & 0
\end{bmatrix}
\]

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:

\[
\begin{align*}
\min & \quad ||t_\Sigma - \sum_{m=0}^{k-1} \hat{t}^{(p-m)} * S^{p-m} || \\
\text{s.t.} & \quad \hat{t}_{i,i+1}^{(m)} \geq \frac{l_{i+1}}{v_{\max(i,i+1)}} \quad \text{for } \forall i \text{ and } \forall m
\end{align*}
\]
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\[
0.8 \leq \frac{t_i^{(m)}}{\hat{t}_{i,i+1}^{(m)}} \leq 1.2 \quad \text{for } \forall i \text{ and } \forall m \neq p
\]  

(19)

where

- \( t_i^{(p)} \) is the vector of path (OD) travel times at the time interval \( p \),
- \( \hat{t}^{(p)} \) is the vector of link travel time estimates for time interval \( p \),
- \( k \) is the number of time intervals needed to reconstruct longest path,
- \( n \) is the number of interchanges in the roadway,
- \( t_i^{(m)} \) is the travel time estimate for the link between interchanges \( i \) and \( i+1 \),
- \( l_{i,i+1} \) is the length of the link,
- \( V_{\text{max}}(i,i+1) \) is the maximum speed assumed on the link,
- \( \hat{t}_{i,i+1}^{(m)} \) is the link travel time estimated previously.

Equation (17) is the objective function that attempts to minimize the difference between the measured travel times and the ones reconstructed by estimated link travel times. Equation (18) 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 (19) compares the link travel times that are calculated in the current time interval and in previous time intervals. For instance, to reconstruct the path travel times in the time period \( p+1 \), link travel times that belong to the time period \( p \) will be needed. Hence, link travel times will be estimated more than once. Regarding this aspect, Equation (19) basically attempts to create travel time estimates that are consistent with the ones calculated previously. The specific range used in Equation (19) 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.

The problem is represented in matrix form. However, note that path travel time is not incorporated in the programming problem, if there is no demand associated with it, which can happen particularly in the nighttime.

**CASE STUDY**

Empirical data used in this paper are 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. The study area is narrowed down to links between Exits 13A and 8, which is composed of 8 interchanges (FIGURE 3).
Only one interval length is considered to apply the kriging algorithm; namely, 15 minute. It is considered to be the maximum time interval acceptable to track the traffic conditions in a real-time application.

Three interval lengths are considered for the NLP algorithm; 5, 10 and 15 minutes. 5 minutes is considered to be the minimum updating interval to follow the traffic conditions that would evolve quickly (e.g. incident conditions). The proposed algorithm may not be suitable to work with finer resolutions finer than 5 minutes because of both the demand level and outliers' effects. Note that observed path travel times change for each time interval selection, because in each selection different vehicles traveling in that particular path and reaching their destination in time interval "p" are used.

Proposed algorithms are tested using one week of data between 7/24/2009 and 7/30/2009. To compute the error in travel time estimation, OD pair (11-8) is selected. Travel time estimates, obtained from the proposed models, are not the simple addition of the link travel times at the current interval, but they are reconstructed by building the most likely trajectory. On the other hand, observed path travel times are computed using only the vehicles that travel between Exit 11 and 8. Note that path travel time associated with OD pair (11-8) is not included in Equation (17) for the purpose of error calculation.

Graphical representations of results and path demand levels are presented in FIGURE 4. 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.
FIGURE 4- Results for the Path (11,8) (a) Kriging (15 min), (b) NLP (15 min), (c) NLP (10 min), (d) NLP (5 min)
Comparison of Kriging and NLP based estimation

To compare the performance of kriging and NLP based estimation algorithms, travel time observations that result from 15 minutes updating interval are used. Numerical errors are computed for both different periods of the day (with different demand levels) and for atypical conditions observed on the roadway. TABLE 1 presents the performance of two algorithms.

TABLE 1 (a)- Comparison of Kriging and NLP

<table>
<thead>
<tr>
<th>Test Day</th>
<th>Period</th>
<th>Kriging 15 min. Travel Time Absolute Error</th>
<th>NLP 15 min. Travel Time Absolute Error</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean (min)</td>
<td>Relative Mean</td>
<td>Mean (min)</td>
</tr>
<tr>
<td>weekdays</td>
<td>Peak Hours</td>
<td>3.03</td>
<td>0.11</td>
</tr>
<tr>
<td></td>
<td>Off-Peak Hours</td>
<td>1.89</td>
<td>0.08</td>
</tr>
<tr>
<td></td>
<td>Night Hours</td>
<td>4.51</td>
<td>0.20</td>
</tr>
<tr>
<td>weekend</td>
<td>6am-12pm</td>
<td>2.53</td>
<td>0.08</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1.63</td>
<td>0.08</td>
</tr>
<tr>
<td>7/24/2009</td>
<td>Peak Hours</td>
<td>6.03</td>
<td>0.16</td>
</tr>
<tr>
<td>7/25/2009</td>
<td>Off-Peak Hours</td>
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<td>0.07</td>
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<td></td>
<td>Night Hours</td>
<td>2.21</td>
<td>0.11</td>
</tr>
<tr>
<td>7/27/2009</td>
<td>Peak Hours</td>
<td>1.93</td>
<td>0.09</td>
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<tr>
<td>7/28/2009</td>
<td>Off-Peak Hours</td>
<td>1.45</td>
<td>0.07</td>
</tr>
<tr>
<td></td>
<td>Night Hours</td>
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<td>7/29/2009</td>
<td>Peak Hours</td>
<td>3.79</td>
<td>0.13</td>
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<td>7/30/2009</td>
<td>Off-Peak Hours</td>
<td>1.94</td>
<td>0.09</td>
</tr>
<tr>
<td></td>
<td>Night Hours</td>
<td>6.96</td>
<td>0.33</td>
</tr>
<tr>
<td>7/31/2009</td>
<td>Peak Hours</td>
<td>1.51</td>
<td>0.07</td>
</tr>
<tr>
<td>8/01/2009</td>
<td>Off-Peak Hours</td>
<td>1.84</td>
<td>0.09</td>
</tr>
<tr>
<td></td>
<td>Night Hours</td>
<td>4.34</td>
<td>0.15</td>
</tr>
</tbody>
</table>

TABLE 1 (b)- Comparison of Kriging and NLP under Atypical Conditions

<table>
<thead>
<tr>
<th>Test Day</th>
<th>Period</th>
<th>Congestion</th>
<th>Kriging 15 min. Travel Time Absolute Error</th>
<th>NLP 15 min. Travel Time Absolute Error</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Mean (min)</td>
<td>Mean (min)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Relative</td>
<td>Relative</td>
</tr>
<tr>
<td>7/24/2009</td>
<td>11.00-20.00</td>
<td>High</td>
<td>6.59</td>
<td>0.14</td>
</tr>
<tr>
<td>7/25/2009</td>
<td>09.30-20.00</td>
<td>High</td>
<td>5.99</td>
<td>0.11</td>
</tr>
<tr>
<td>7/26/2009</td>
<td>11.00-16.00</td>
<td>Moderate</td>
<td>2.18</td>
<td>0.08</td>
</tr>
<tr>
<td>7/27/2009</td>
<td>18.00-23.00</td>
<td>Moderate</td>
<td>2.22</td>
<td>0.08</td>
</tr>
<tr>
<td>7/29/2009</td>
<td>06.30-09.00</td>
<td>Moderate</td>
<td>5.74</td>
<td>0.16</td>
</tr>
</tbody>
</table>

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The results show that NLP based estimation clearly outperforms kriging based estimation. In all cases considered in TABLE 1, 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.

**Comparison of Updating Intervals in NLP based estimation**

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 large jumps.

To evaluate the performance of NLP 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, path 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 for atypical conditions separately. TABLE 2 shows the estimation error generated by the algorithm. For the defined periods of the day, 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. 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 highly and moderately congested periods and to measure the performance of the algorithm under such conditions. 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. For highly congested periods, mean absolute errors are less than 13%, 12% and 11% for 15 min, 10 min and 5 min applications respectively.

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 produces fluctuating results, which are not consistent with neighboring time periods.

FIGURE 5 provides a closer look to the graphical results of the algorithm behavior under atypical conditions. 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 highly and moderately congested conditions. Therefore, updating interval of 10 min can be selected...
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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.

### TABLE 2 (a) - Comparison of Updating Intervals

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

### TABLE 2 (b) - Comparison of Updating Intervals under Atypical Conditions

<table>
<thead>
<tr>
<th>Test Day</th>
<th>Period of the Day</th>
<th>Congestion</th>
<th>Mean</th>
<th>Rel.</th>
<th>Mean</th>
<th>Rel.</th>
<th>Mean</th>
<th>Rel.</th>
</tr>
</thead>
<tbody>
<tr>
<td>7/24/2009</td>
<td>11.00-20.00</td>
<td>High</td>
<td>5.29</td>
<td>0.13</td>
<td>4.92</td>
<td>0.12</td>
<td>4.53</td>
<td>0.11</td>
</tr>
<tr>
<td>7/25/2009</td>
<td>09.30-20.00</td>
<td>High</td>
<td>3.87</td>
<td>0.07</td>
<td>3.87</td>
<td>0.07</td>
<td>3.71</td>
<td>0.07</td>
</tr>
<tr>
<td>7/26/2009</td>
<td>11.00-16.00</td>
<td>Moderate</td>
<td>1.35</td>
<td>0.05</td>
<td>1.10</td>
<td>0.04</td>
<td>1.07</td>
<td>0.04</td>
</tr>
<tr>
<td>7/26/2009</td>
<td>18.00-23.00</td>
<td>Moderate</td>
<td>0.84</td>
<td>0.03</td>
<td>0.82</td>
<td>0.03</td>
<td>0.82</td>
<td>0.03</td>
</tr>
<tr>
<td>7/29/2009</td>
<td>06.30-09.00</td>
<td>Moderate</td>
<td>1.05</td>
<td>0.03</td>
<td>1.14</td>
<td>0.04</td>
<td>0.82</td>
<td>0.03</td>
</tr>
</tbody>
</table>
FIGURE 5 - 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)
CONCLUSION

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. To break down path travel times into link travel times, universal kriging and mathematical programming (NLP) algorithm is developed. Results showed that NLP clearly outperforms universal kriging, and updating interval of 10 min provides the best results for the interested highway. It is long enough to have proper demand level and short enough to respond to rapid changes in the network. 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 and to track the traffic conditions on the roadway.

Future research is needed to extend the application area. Mathematical programming model presented in this study can be modified according to the needs in a larger application. For example, very long trips (e.g. trips whose free flow travel time is more than 30 minutes) should not be incorporated in link travel time estimation. In this study, path travel times are decomposed based on trajectory reconstruction. The algorithm may end up with inaccurate trajectory reconstruction for long trips, because the longer the trip is, the harder it is to track the vehicles on the network. Therefore, inputs should be limited to short and moderately long trips.

Future research may also consider data fusion with other sources, such as loop detectors and GPS devices. Travel time prediction based on the link travel time estimates presented in this study is also an important area for further research.

ACKNOWLEDGEMENT

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REFERENCES


Yildirimoglu M., Ozbay K.


