Dynamic Travel Time Prediction with Real-Time and Historic Data

Steven I-Jy Chien[1] and Chandra Mouly Kuchipudi[2]

Abstract: Travel time prediction has been an interesting research area for decades during which various prediction models have been developed. This paper discusses the results and accuracy generated by different prediction models developed in this study. The employed real-time and historic data are provided by the Transportation Operations Coordinating Committee, which collected them using road side terminals (RST) installed on the New York State Thruway. All the tagged vehicles equipped with EZ pass are scanned by RSTs, while dynamic information (e.g., vehicle entry times and associated RST numbers) are recorded. The emphasis of this study is focused on modeling real-time and historic data for travel time prediction. Factors that would affect the prediction results are explored. The Kalman filtering algorithm is applied for travel time prediction because of its significance in continuously updating the state variable as new observations. Results reveal that during peak hours, the historic path-based data used for travel-time prediction are better than link-based data due to smaller travel-time variance and larger sample size.

DOI: 10.1061/(ASCE)0733-947X(2003)129:6(608)

CE Database subject headings: Travel time; Forecasting; Intelligent transportation systems; Data analysis; Models.

Introduction

The ability to accurately predict future link travel times in transportation networks is a critical component for many intelligent transportation systems (ITS) applications, such as in-vehicle route guidance systems (RGS) and advanced traffic management systems (ATMS). Travel time in an urban traffic environment is highly stochastic and time-dependant due to random fluctuations in travel demands, interruptions caused by traffic control devices, incidents, and weather conditions. It has been increasingly recognized that for many transportation applications, estimates of the mean and variance of travel times significantly affect the accuracy of prediction.

With the development of the Advanced Travelers Information Systems (ATIS), short-term travel time prediction is becoming increasingly important (Chien and Chen 2001a,b). As the key input for dynamic RGS, travel time information enables the generation of the shortest path (or alternative paths) connecting the current locations and destinations, besides suggesting directions dynamically in case of congestions or incidents.

There has been much research contributing to the field of travel time prediction. In the context of prediction methodologies, various time series models (Oda et al. 1990; Anderson et al. 1994; Al-Deek et al. 1998) and artificial neural network models (Park et al. 1998; Rilett and Park 1999) have been developed. In the context of input data source, most previous studies (Oda 1990; Roden 1996; Al-Deek et al. 1998; Pant et al. 1998; D'Angelo et al. 1999) used ''indirect'' travel time data (e.g., volume, occupancy, and speed), while travel time was estimated by a function of these parameters. Even though the general relation among these parameters has been explored widely, the specific coefficients in the function are most likely site specific. Moreover, this general relation may not be consistent for saturated flow condition. Thus using speed, volume, and occupancy data to calculate travel time could lead to inaccuracies.

Travel time data can be obtained through various traffic surveillance devices (e.g., loop detectors, microwave detectors, radars, etc.), though it is not realistic to have the roadway network completely covered by detectors. With the development of wireless technologies, the data has been more reliably collected and transmitted than ever. More importantly these devices can be set up on the roadways with minimal hardware using nonsophisticated communication and installation.

The objective of this research is to develop dynamic models that can efficiently predict travel times with real-time and historic data. Several travel time prediction models (Chien and Chen 2001a,b) have been successfully developed with simulated data generated by CORSIM, a corridor traffic simulator developed by the Federal Highway Administration (FHWA). These models are further enhanced here to predict the travel times with real-time and historic data collected on the New York State Thruway (NYST).

Data Collection Methodology

The study site is located on the eastbound NYST between the interchange of the NYST and New Jersey Garden State Parkway (GSP) to the Tappan Zee Bridge, a 10.57 mil (=17 km) network, with eight on-ramps and five off-ramps. It stretches out north from the Hillsdale Toll Plaza on the GSP to the NYST. Along the

[1]Associate Professor, Dept. of Civil and Environmental Engineering, New Jersey Institute of Technology, Newark, NJ 07102. E-mail: chien@adm.njit.edu

[2]Programmer, TIDE Center, New Jersey Institute of Technology, Newark, NJ 07102. E-mail: cmk2@njit.edu

Note. Discussion open until April 1, 2004. Separate discussions must be submitted for individual papers. To extend the closing date by one month, a written request must be filed with the ASCE Managing Editor. The manuscript for this paper was submitted for review and possible publication on February 14, 2002; approved on January 24, 2003. This paper is part of the ***Journal of Transportation Engineering***, Vol. 129, No. 6, November 1, 2003. ©ASCE, ISSN 0733-947X/2003/6-608–616/$18.00.

Downloaded 05 Mar 2010 to 143.107.252.1. Redistribution subject to ASCE license or copyright; see http://pubs.asce.org/copyright

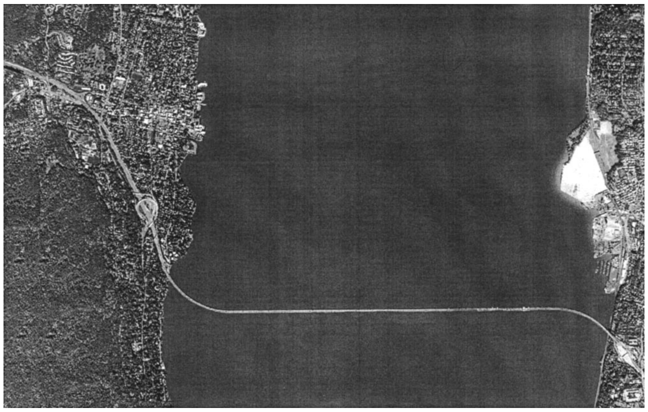


Fig. 1. Aerial photograph of the study site

NYST it extends east from the Spring Valley Toll Plaza to the Tarrytown Toll Plaza (the Tappan Zee Bridge). The data used in this study is a subset of the data acquired using the RST. Fig. 1 shows the aerial photograph of the studied segment of the NYST. Fig. 2 shows the configuration of RST on the study site as a node-link diagram. The locations of the RSTs are summarized in Table 1.

When an EZ Pass equipped vehicle passes an RST, the reader antenna radiates a signal to interrogate the vehicle's electronic identification device (RF tag). The vehicle equipped with the RF tag then responds by transmitting its tag identification number (tag ID). Each RST receives signals containing information like tag ID, detection time, location, and lane position. This information is recorded and then forwarded to the Operations Information Center (OIC) located at Jersey City, New Jersey. The tag ID is immediately encoded at the OIC to a random number to ensure anonymity of the motorist. This surveillance data are acquired 24 h a day. The data are then fed into the database as MS-Access files. The data collected from February 27, 1996 to March 4, 1996 and March 12, 1996 to March 18, 1996, used in this study, are shown in the Table 2.

Data Processing

In order to reduce the data processing cost (in terms of computation time) and improve the data quality, the collected raw data are processed by a developed computer program that can generate the required details for developing the proposed predictive models. These data include vehicle travel times, average speeds, standard deviations of travel times, and traffic volumes between successive readers, which can then be organized on a reader-to-reader (for all sets of successive readers) and time-to-time basis for all the specific time intervals. If an interval of 5 min were chosen for instance, there would be 288 intervals (in a 24 h time period). All of the above-mentioned data are calculated and organized separately for each pair of the consecutive readers.

Filtering Biased Data

When the data are organized on a reader-to-reader and time-to-time basis, there could be some vehicles showing abnormal characteristics (e.g., dwelling on the roadside for a long time) compared to other vehicles. For instance, in the current experiment from reader 113 (Exit No. 14, Spring Valley Nanuet) to 116 (Exit No. 13S) in a period of 150 min, vehicles exhibiting relatively long or short travel times are found. These data may result in biased estimation of average travel time in some time intervals, and thus are improper input for the proposed prediction model (could reduce accuracy). The technique employed to remove these data is to entertain only an allowable difference between the travel times of two successive vehicles. When the travel time of a

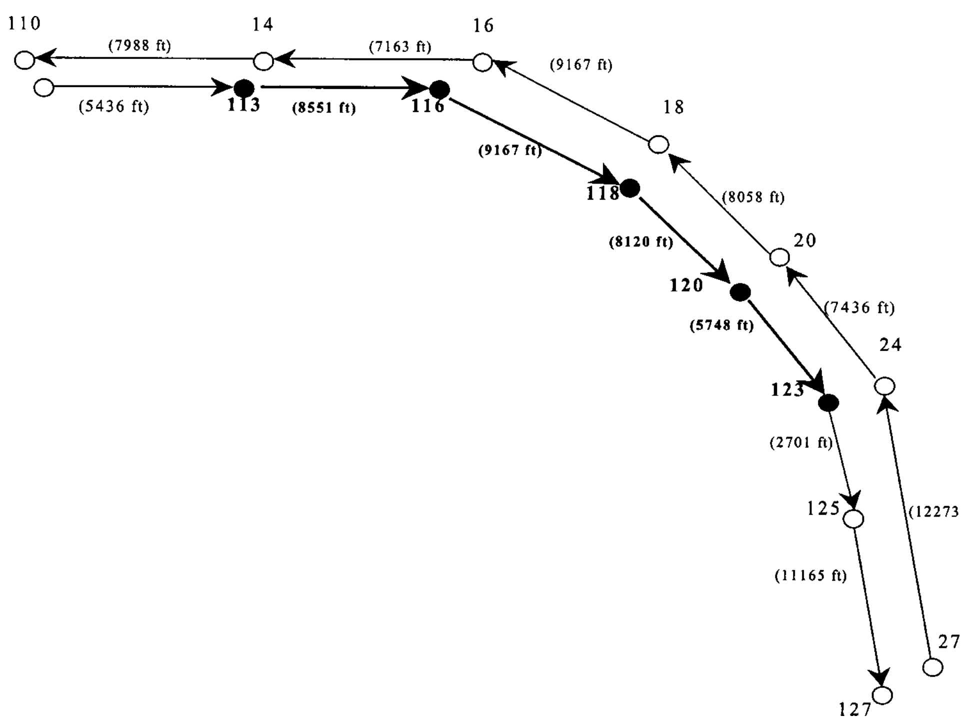


Fig. 2. Road side terminal numbers and locations on the study site

Downloaded 05 Mar 2010 to 143.107.252.1. Redistribution subject to ASCE license or copyright; see http://pubs.asce.org/copyright

Table 1. Description of Roadside Terminals and Antenna Locations

Reader	Description	Physical location of antenna	Mile post	Direction being read
113	Exit No. 14 "Rte 59, Spring Valley Nanuet"	Under sign	MP 22.5	NB main line and off-ramp
116	Exit No. 13S; Exit No. 13N	Under pass and under sign and off-ramp	MP 21.3	NB/SB
118	Conrail Bridge	Underpass	MP 19.5	NB/SB
120	Unlabeled underpass	Underpass	MP 17.9	NB/SB
123	"Tappan Zee Bridge" sign	Under sign	MP 16.9	SB

Note: NB: Northbound, SB: Southbound, 1 mil=16 km.

vehicle between two particular readers is calculated, it is compared with the average travel time of its leading vehicles traveling on the same link in the same time interval. A vehicle record is discarded if the travel time of the vehicle is highly deviated from the average link travel time (e.g., 50% higher or lower than the average travel time in that particular link).

Based on the data collected from 6:30 to 9:30 a.m. on February 27, 1996, the average travel time distributions before and after removing the biased data are demonstrated in Fig. 3. Significant differences between estimated average travel times with original and filtered data are observed, especially during intervals 13, 21, 26, 28, 32, 33, and 34. Mean travel times of 103.5 and 93.85 s and standard deviations of 219.42 and 22.66 s are found, respectively, with original and filtered data.

A computer program has been developed for this experiment to model and process the collected data. The data for the experiment are restored into two MS-access files, each containing 1 week of data. Structured *Query* Language (SQL) commands are used to initially split the data into individual files each containing 24 h data. These files are then fed to the program, which in turn processes the data and populates the results into separate text files.

The results generated from the raw data include

Table 2. Format of the Data Used in the Study

Tag	Date	Time (a.m.)	Reader
E0C10803F90A12000000	Tuesday March 12	6:30:00	118
E0C1080302C812000000	Tuesday March 12	6:30:00	123
E0C10804950012000000	Tuesday March 12	6:30:00	125
E0C10803E79012000000	Tuesday March 12	6:30:00	123
E0C1080481AA12000000	Tuesday March 12	6:30:00	24
E0C10803CA0012000000	Tuesday March 12	6:30:00	125
E0C10803FA0412000000	Tuesday March 12	6:30:01	123
E0C1080451D812000000	Tuesday March 12	6:30:01	125
E0C10804678E12000000	Tuesday March 12	6:30:01	123
E0C10803077E12000000	Tuesday March 12	6:30:01	125
E0C10803C5DE12000000	Tuesday March 12	6:30:01	120
E0C108037CE612000000	Tuesday March 12	6:30:01	216
E0C108030DD212000000	Tuesday March 12	6:30:01	111
E0C108045DEC12000000	Tuesday March 12	6:30:01	118
E0C108035F0212000000	Tuesday March 12	6:30:01	123
E0C1080518FA12000000	Tuesday March 12	6:30:02	120
E0C108064D4A12000000	Tuesday March 12	6:30:02	28
E0C10804203612000000	Tuesday March 12	6:30:02	125
E0C10803A5F012000000	Tuesday March 12	6:30:02	123
E0C10803CEA812000000	Tuesday March 12	6:30:02	125
E0C1080306A212000000	Tuesday March 12	6:30:02	120

- All Vehicle Data: A record of all the vehicles between the selected pair of readers. Information includes vehicle IDs, travel times, and speeds between a particular set of readers (including biased vehicle information).
- A Time-based Data: Volumes, average travel times, average speeds, and standard deviations of travel times for all vehicles are calculated for each time interval throughout the day. In this study a 5 min time interval is used. Thus the program produces the above data for 288 time intervals, as we have 24 h data in each input data file.
- Average Travel Time of Probe Vehicles: Some of the vehicles are selected randomly and processed from each interval based on a specified percentage, to interpret as probe vehicle data, used in the developed prediction algorithms.

Limitations of Real-Time Data

The following situations have been observed when real-time data are applied to predictive models.

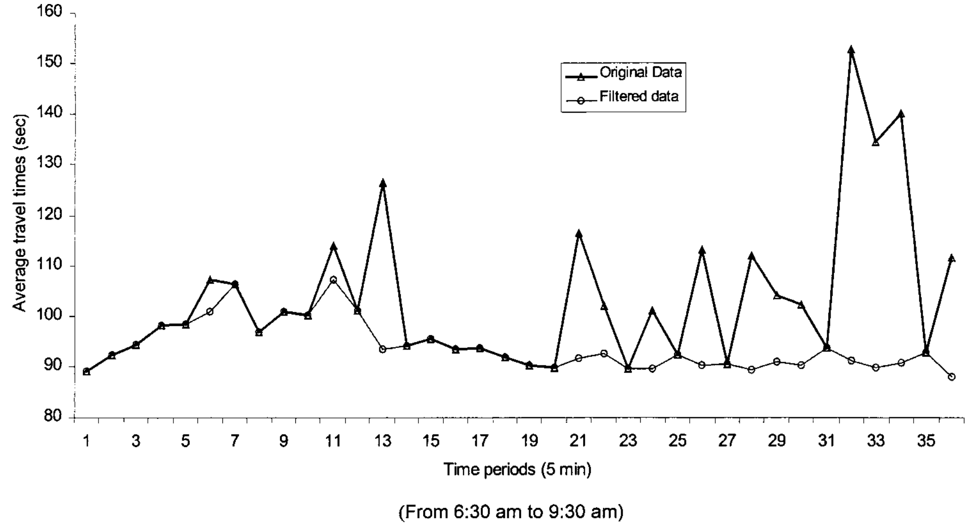
- Higher standard deviation of properties like travel times in consecutive time periods. This would affect the accuracy of the model by introducing rapid deviations of traffic properties from real-world situations in particular time intervals.
- Reader information missing over time intervals, resulting in fallacious data for prediction. Data with partial or missing reader information are naturally unrealistic for prediction involving those particular readers in the time intervals they are missing.
- No tagged vehicles operating in off-peak hours. This would limit the feasible time intervals of the experiment to a particular range. Since when a short time interval (e.g., 5 min) is chosen, some intervals in off-peak hours may not capture any tagged vehicle information.

The problem of deviation is taken care of by using aggregated historic data. The biased data are discarded and the situation for no vehicles operating in off-peak hours is applied with the average travel time of the previous time interval. Models based on real-time data may have the above-mentioned tasks required to surmount the data hazards, but they have proved to be more robust and pragmatic.

Path-Based and Link-Based Travel Times

Most of the existing studies (Sen et al. 1991; Anderson et al. 1994; D'Angelo et al. 1999; Chien et al. 2001a,b) compare the link-based and path-based travel times in order to check the accuracy of the prediction. The path-based travel time is recorded when a vehicle finishes a particular path, which can be deter-

Downloaded 05 Mar 2010 to 143.107.252.1. Redistribution subject to ASCE license or copyright; see http://pubs.asce.org/copyright



$\text{Mean}_{\text{original}} = 103.35$ seconds, $\text{Deviation}_{\text{original}} = 219.42$ seconds

$\text{Mean}_{\text{filtered}} = 93.85$ seconds, $\text{Deviation}_{\text{filtered}} = 22.66$ seconds

Fig. 3. Comparison of average travel times calculated from original and filtered data

mined based on the difference between the recorded times when the vehicle was entering and exiting the path. Link-based travel time is the sum of travel times of vehicles in the consecutive individual links that constitute the whole path. Both types of travel-time data are prepared as the input of the proposed predictive models and are discussed next.

Two types of link-based models are developed in the experiment. The travel time predicted by Link-based model I is calculated by simply adding the travel times predicted in all the successive links that are used to estimate the path travel times in different time intervals. The second approach is to get a progressive addition, which only does simple addition for the current travel times as long as the sum of the predicted values does not exceed the time interval (5 min in this study). Then the addition procedure goes into the next time interval and continues to add up the predicted values falling in that interval until the predicted travel time falls into the next time period and so on, this is repeated until the path destination has been reached. This value is termed the Link-based model II, and is calculated accordingly throughout the time period of the experiment.

Prediction Methodology

The Kalman filtering algorithm (Kalman 1960) has been applied in the study because it enables the prediction of the state variable (e.g., travel time) to be continually updated as a new observation becomes available. The Kalman filtering technique has been applied in many fields, but mainly in two categories: estimation and performance analysis of estimators. In this study, it is used to perform a travel time prediction based on real-time and historic information collected by RSTs. Specifically, the average travel time of tagged vehicles in each time interval is treated as the true value to predict the travel time in the next time period.

Let $x(t)$ denote the travel time at time interval t that is to be predicted, $\phi(t)$ denote the transition parameter at time interval t which is externally determined, and $w(t)$ denote a noise term that has a normal distribution with zero mean and a variance of $Q(t)$. The system model can be written as

$$x(t)=\phi(t-1)x(t-1)+w(t-1) \tag{1}$$

Let $z(t)$ denote the observation of travel time on time interval t and $v(t)$ denote the measurement error at time interval t that has a normal distribution with zero mean and a variance of $R(t)$. Since no traffic parameter other than travel time is involved, the observation equation associated with the state variable $x(t)$ is given by

$$z(t)=x(t)+v(t) \tag{2}$$

In our application, $z(t)$ is obtained from the program as the average travel time between two particular readers at time interval t. The data in the previous time step is used to obtain the transition parameter $\phi(t)$, which describes the relationship between the statuses of state variable (in this case, travel time) in two time periods. This is to assume that the pattern of travel time variation over time remains basically the same between these 2 days.

Assume that for all i, j, $E[w(i)v(j)]=0$, and let $P(t)$ denote the covariance of the estimation error at time interval t, then the filtering procedure is shown as follows:

Step 1. Initialization

Set $t=0$ and let $E[x(0)]=\hat{x}(0)$ and $E\{[x(0)-\hat{x}(0)]^2\}=P(0)$, where $\hat{x}(0)$=predicted travel time at time 0.

Step 2. Extrapolation

1. Extrapolate state estimate

$$\hat{x}(t)_-=\phi(t-1)\hat{x}(t-1)_+ \tag{3}$$

Extrapolate error covariance

$$P(t)_-=\phi(t-1)P(t-1)_+\phi(t-1)+Q(t-1) \tag{4}$$

Step 3. Kalman gain calculation

$$K(t)=P(t)_-[P(t)_-+R(t)]^{-1} \tag{5}$$

Step 4. Update

1. Update state estimate

$$\hat{x}(t)_+=\hat{x}(t)_-+K(t)[z(t)-\hat{x}(t)_-] \tag{6}$$

Update error covariance

$$P(t)_+=[I-K(t)]P(t)_- \tag{7}$$

Downloaded 05 Mar 2010 to 143.107.252.1. Redistribution subject to ASCE license or copyright; see http://pubs.asce.org/copyright

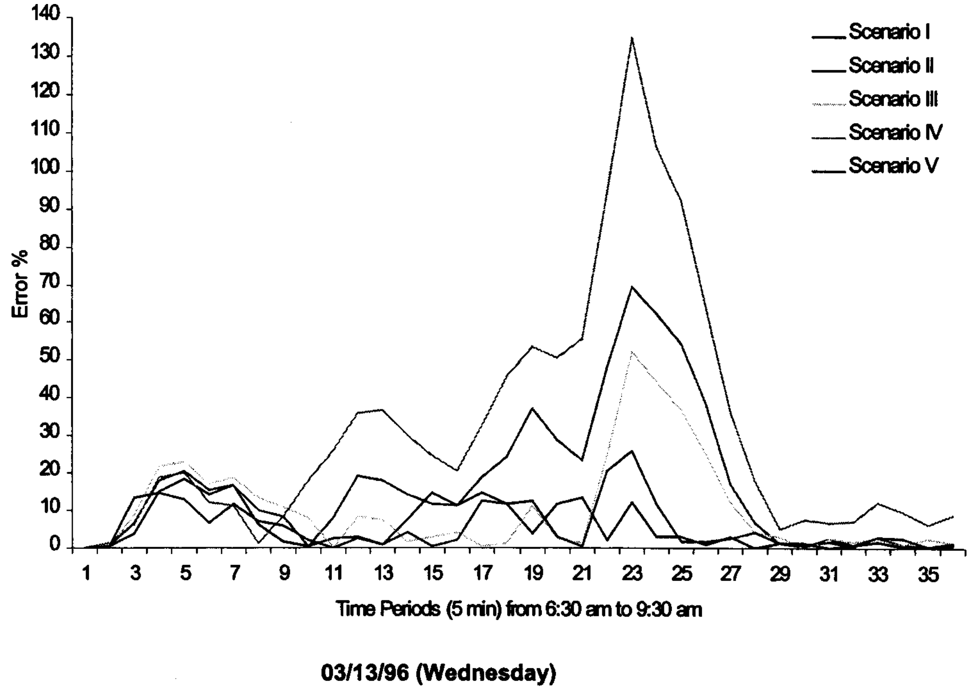


Fig. 4. Comparison of prediction errors for five scenarios

Step 5. Next iteration

Let $t = t + 1$ and go back to step 2 until the preset time period ends.

Experiment

As shown in Fig. 2, the freeway segment from node 113 (Exit No. 14, Spring Valley Nanuet) to 123 (near Exit No. 10) is chosen as the experimental path on which travel times of tagged vehicles are recorded. We use all tagged vehicle data to produce true average travel time, while 10% of all tagged vehicles are randomly selected as probe vehicles. Particularly, at peak periods at least 10% probe vehicles are needed to ensure accurate estimates (Chien et al. 2001a). A 5 min interval is chosen for the short-term travel time prediction, which means that travel time is predicted every 5 min. Within each interval, the travel time is indeed a continuous variable, for the purpose of prediction we consider it as a discrete variable. Appropriate sample size collected in each interval is a significant factor that affects the accuracy of the prediction. The sample size used in this study is much higher than the required size discussed in a previous study (Chien et al. 2001b) to avoid insufficient samples collected during off-peak hours.

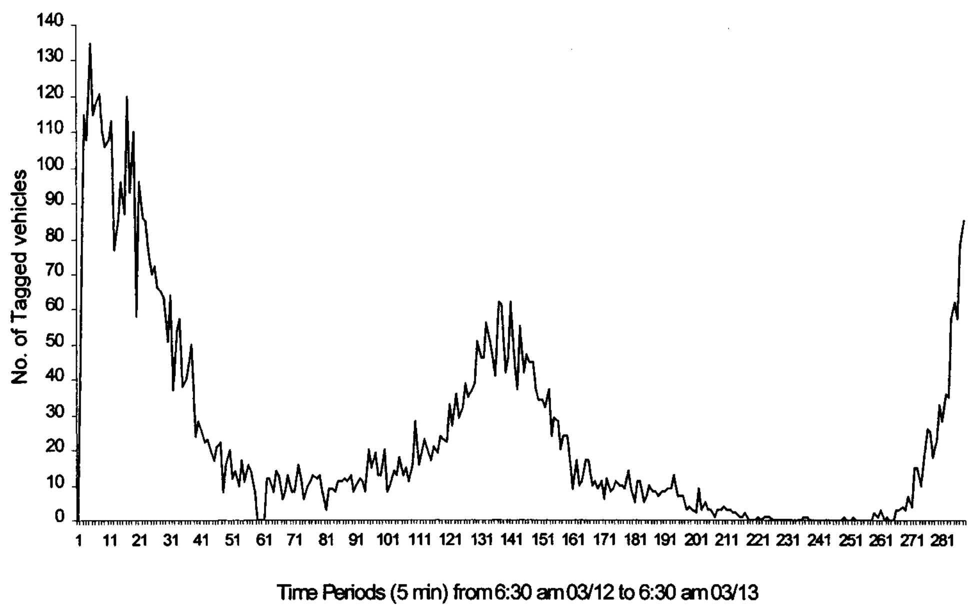


Fig. 5. Distribution of tagged vehicles on 12 March, 1996 (Tuesday)

Downloaded 05 Mar 2010 to 143.107.252.1. Redistribution subject to ASCE license or copyright; see http://pubs.asce.org/copyright

Aggregate Historic Data

Prediction models need a historical seed as a basis to adapt to the traffic conditions going to exist at the time of prediction. Providing it with the conditions that prevailed on the same path at a previous time period is rather a comprehensive idea. The historic data collected on the same path is contemplated as historic seed in the current experiment. However, the idea is only nearly safe, unless unbiased historic data are generated. Information may be biased due to situations specific to an individual vehicle or a driver that are inevitable. The speed distribution for the study site on consecutive days is analyzed and found to be inconsistent in some time intervals. A test has been conducted to check the speed consistency on consecutive weekdays, and on the same days in different weeks.

Vehicle speeds have been found for all time intervals throughout the day and for all sets of readers. It is observed that speeds on different days exhibit divergent characteristics, and hence the assumption that consecutive weekdays would have similar traffic conditions is unjustified. Also the travel time distributions on the same days for different weeks are not similar to each other. Therefore using daily average travel times as historic data is unreliable.

Thus the appropriate method for this study is either using aggregated historic data or the data collected from the previous time interval (e.g., using data collected 5 min earlier). Applying the previous time interval data would apparently be the better pick, but this method may suffer from practical inavailability of data, depending on traffic volume and the length of time interval for the experiment.

A test has been conducted to check whether the enhancement by using aggregate historic data is practically attainable. Prediction accuracy analysis is conducted by comparing actual and predicted travel times in the following five scenarios.

Based on available data provided by the Transportation Operations Coordinating Committee five scenarios applied for different historic seeds are developed for evaluating prediction accuracy.

Scenario I: Average travel times of four weekdays from 27 February, 1996 to 1 March, 1996 (from Tuesday to Friday).

Scenario II: Average travel times of three weekdays 27 February, 1996, 28 February, 1996, and 29 February, 1996.

Scenario III: Average travel times of two weekdays 27 February, 1996 and 28 February, 1996.

Scenario IV: Average travel times on 27 February, 1996.

Scenario V: Travel times in the previous time interval on 12 March, 1996.

Fig. 4 shows the comparison of errors in predicted travel times under the five scenarios. From the figure, it is evident that using aggregate data for four weekdays (scenario I) and the previous time interval data (scenario V) would yield better results compared to that in other scenarios. The prediction error is inadmissible in the peak hours of the day for the rest of the historic data. Exceptionally high error percentages under scenario IV in peak periods are found, which can be attributed to special cases like traffic congestion resulting in an unrealistic traffic pattern on that particular day. Hence both types of data, aggregate data of four weekdays and previous time interval data, are suggested for predicting travel times. Data were aggregated according to the relevant time intervals to form the final historic seed to be fed to the predictive model. The model is finally implemented by predicting travel time on 12 March, 1996 (Tuesday) using an aggregated four-weekday data (historic data), and the data collected from the previous time interval.

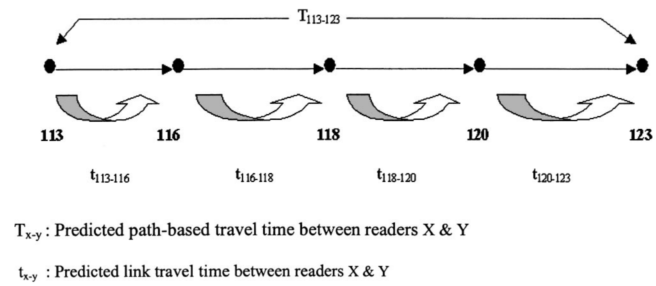


Fig. 6. Configuration for path- and link-based travel times

The distribution of tagged vehicles on 12 March, 1996 (Tuesday) is observed and shown in Fig. 5. The data on any particular day starts with the vehicle information from 6:30 a.m. on a certain day to 6:30 a.m. the next day. The curve is a combination of two normal distribution curves pertaining to two peak periods in a day. The morning peak starts from 6:30 a.m. and ends at 9:30 a.m. The next peak period starts at 4:30 p.m. and ends at 7:00 p.m.

Results and Analysis

The model is implemented with the acquired data and predicted path-based and link-based travel times are discussed. The vehicle's entering and exiting times are recorded when the vehicle is detected by the first reader (i.e., reader 113) and the last reader (e.g., reader 123). The time difference is treated as the path travel time of the vehicle. The link-based travel time of vehicles in the network is calculated (based on models I and II) by adding up the travel times in the links that constitute the path. The intermediate

Table 3. Prediction Error Indices with Different Predictive Models

Model	$MARE_{MPH}$	$MARE_{NPH}$	$MARE_{OPH}$	$RRSE_{MPH}$	$RRSE_{NPH}$	$RRSE_{OPH}$
(a) Using historic data						
Path-based	0.056718	0.072711	0.066792	0.088738	0.111908	0.124628
Link-based (I)	0.088412	0.021479	0.048831	0.145578	0.027154	0.074772
Link-based (II)	0.092652	0.021569	0.048743	0.155497	0.02693	0.074585
(b) Using previous time interval data						
Path-based	0.05637	0.011722	0.034604	0.082807	0.015673	0.053027
Link-based (I)	0.049222	0.02425	0.031587	0.069396	0.026354	0.048576
Link-based (II)	0.024668	0.024507	0.031885	0.0302	0.026157	0.048727

Note: MARE: mean absolute relative error, RRSE: root relative square error, MPH: morning peak hours (6:30 to 9:30 a.m.), NPH: afternoon peak hours (4:30 to 7:00 p.m.), OPH: off peak hours (9:30 a.m. to 4:30 p.m. and 7:00 p.m. to 6:30 a.m.).

Downloaded 05 Mar 2010 to 143.107.252.1. Redistribution subject to ASCE license or copyright; see http://pubs.asce.org/copyright

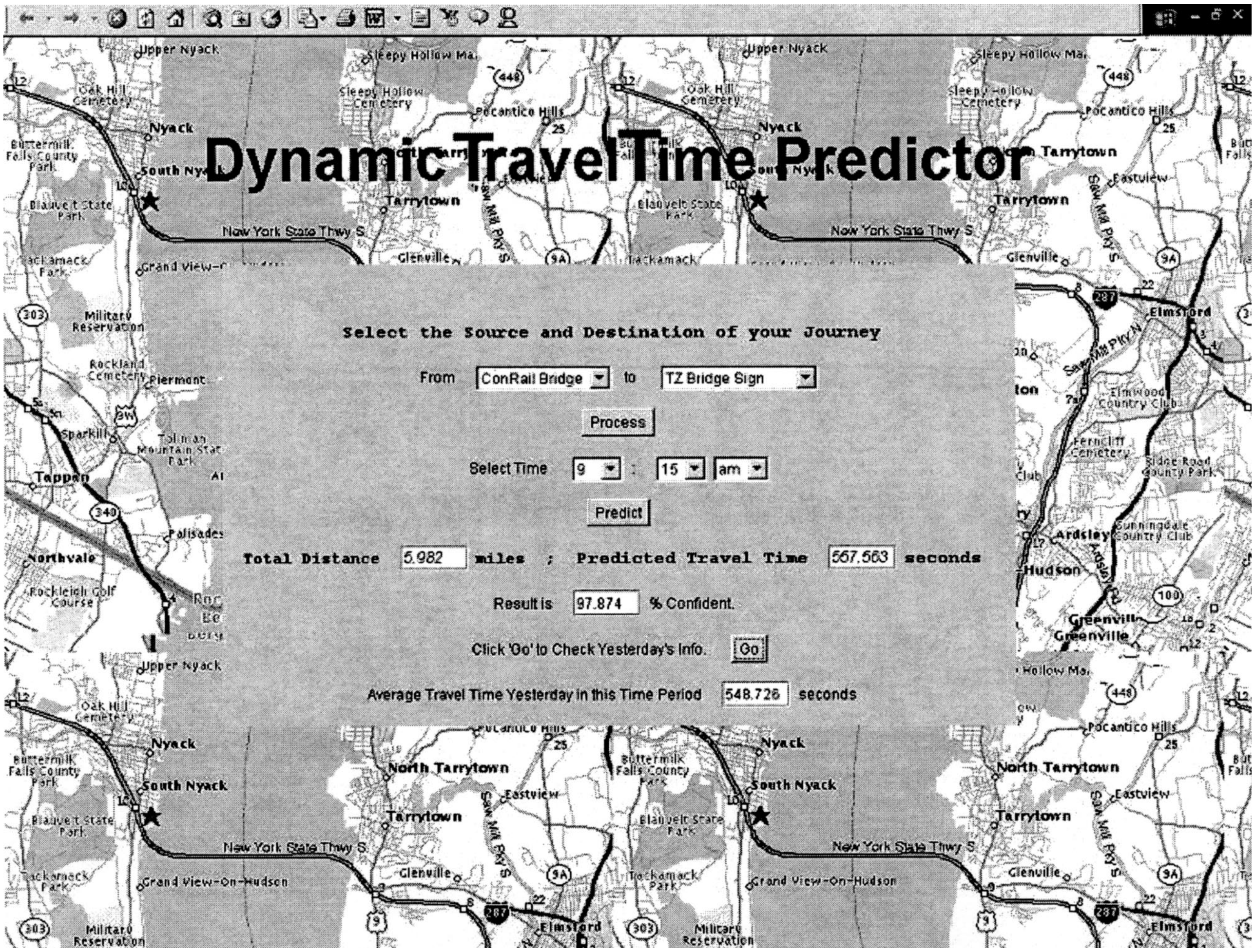


Fig. 7. Dynamic travel times predictor for the study site

links of the path considered are 113–116, 116–118, 118–120, and 120–123, as shown in Fig. 6. In other words, the path 113–123 is composed of four links stated above. The path travel time is computed as the difference between vehicles entering at node 113 and exiting at node 123, defined as $T_{113-123}$. On the other hand, the link travel time is the sum of the individual link travel times, for example $T_{113-123}=t_{113-116}+t_{116-118}+t_{118-120}+t_{120-123}$. In this analysis, two types of link-based travel times are estimated by models I and II with current and future time interval information, respectively.

The fact that travel time patterns may vary over time from day to day is acknowledged, and the experiment is conducted using both four-weekday average historic data and previous time interval data.

Prediction error indices such as mean absolute relative error (MARE) and root relative square error (RRSE) are computed with Eqs. (1) and (2), respectively.

$$\text{MARE}=\frac{1}{N}\sum_{t}\frac{|x(t)-\hat{x}(t)|}{x(t)} \tag{8}$$

$$\text{RRSE}=\sqrt{\frac{1}{\sum_{t}x(t)}\sum_{t}\left[\frac{x(t)-\hat{x}(t)}{x(t)}\right]^{2}x(t)} \tag{9}$$

where $x(t)$=true travel time; $\hat{x}(t)$=predicted travel time in each time interval; and N=number of samples.

To compare and analyze the prediction error indices in different time intervals, a 24 h time period is divided into three categories, the morning peak hours (MPH) from 6:30 to 9:30 a.m., afternoon peak hours (NPH) from 4:30 to 7:00 p.m., and off peak hours (OPH) from 9:30 a.m. to 4:30 p.m. and from 7:00 p.m. to 6:30 a.m. on the next day.

The error indices of prediction with four-weekday average historic data and previous time interval data are shown in Tables 3(a) and 3(b), respectively. Using predicted path-based travel times is a better choice in the morning peak with historic data. However, link-based model I performed well throughout the rest of the day. While using the previous time interval data, link-based model II performed remarkably well throughout the day, compared to the other two models. Predicted path-based travel times are reliable only when uniform traffic conditions prevail throughout the network. Congestion or an incident would affect the accuracy of the path-based model because it takes longer time for a vehicle to finish its trip. Thus the sample size of path-based travel times is reduced depending on the degree of the congestion. On the other hand, link-based models would be more sensitive to respond to travel time spikes of a link with a congestion or incident. A standard procedure should be developed to employ different models in different time periods

The comparison of error indices from Tables 3(a) and 3(b) shows that using previous time interval data is generally less er-

Downloaded 05 Mar 2010 to 143.107.252.1. Redistribution subject to ASCE license or copyright; see http://pubs.asce.org/copyright

roneous. However, the idea has some drawbacks. Using the data from the previous time interval may not always be feasible, especially if the time interval in the experiment is short. Very few travel time samples can be obtained for prediction under this situation. Predicting travel time only for the next time interval would be the primary limitation while using only data collected from the previous time interval. The advantage of using historic data over the link-based model is procurable data, allowing prediction at any given time, but at the expense of prediction accuracy under congestion situations.

Conclusions

Compared to real-world data, simulated travel-time data used in previous studies (Oda 1990; Anderson et al. 1994; Al-deek et al. 1998; Chien et al. 2001a,b) are generally ideal, but suffers impracticability. For example, the vehicle speed variation in simulated data is relatively flatter than that in real-world data. The models developed in this study have been tested successfully and were behaving reasonably well when applied to the real-world data collected from the NYST. With special treatment to the collected data (e.g., filtering out the biased data and picking the appropriate data sets as historic seeds) the developed models have been apprehended as well disciplined and robust dynamic travel-time prediction models.

The compatibility of the model with the real-world data is essentially the most important aspect of the research. The following are some of the issues for developing prediction models using real-world data:

- Data collection methods: Real-time data can be collected in many feasible and reliable methods. Data collected with loop detectors or mobile detectors can also be used for the models developed in this study.
- Raw data refinement: Filtering biased data plays an important role in improving the accuracy of the developed models. The collected data should be initially scanned, and any biased data should be carefully filtered subject to the constraint of sample size.
- Data hazards: The collected real-time data does not usually qualify to be directly used in the developed models. The data has to be refashioned to overcome hazards, such as missing vehicle data in off-peak hours and high deviations from mean travel time, etc.
- Travel-time distribution: During the process of selecting the best historic seed for the developed models, traffic patterns and distributions should be thoroughly observed, owing to the fact that single day data could be less reliable for prediction, compared to aggregated data collected from a number of days.

Future Research

Rapid deterioration of travel conditions in many urban areas has generated a resurgent interest in more effectively managing congestion caused by traffic incidents. Effective incident management necessitates a thorough understanding of incident characteristics and better models for detecting and verifying the occurrence of incidents and for predicting the incident evolution process.

Reliable and timely detection, verification, and prediction enables effective response to incidents through adjustment of traffic control strategies and dissemination of incident information to public. The model is developed and can be accessed through the internet as Fig. 7. The model assumes the user would query predicted travel time on the present day. Thus the program switches between historic or previous time step data, picks the data set appropriate for the time selected by the user, and performs prediction with the developed models. The future focus of this research would be: (1) Investigating the evolution patterns of traffic incidents and (2) Enhancing the developed models and tools for dynamically predicting travel times under incident situations.

Acknowledgment

This study was sponsored by New Jersey Commission on Science and Technology under Grant No. 99-2042-007-20.

Notation

The following symbols are used in this paper:

$K(t)$ = kalman gain;
N = number of samples;
$P(t)$ = covariance of estimation error at time interval t;
$Q(t)$ = variance of $w(t)$ with zero mean;
$R(t)$ = variance of $v(t)$ with zero mean;
T_{x-y} = predicted path travel time for path $x-y$;
t_{x-y} = predicted link travel time for link $x-y$;
$v(t)$ = measurement error at time interval t with normal distribution;
$w(t)$ = noise term with normal distribution;
$x(t)$ = travel time at time interval t;
$\hat{x}(t)$ = predicted travel time in time interval t;
$z(t)$ = observation of travel time at time interval t; and
$\phi(t)$ = transition parameter at time interval t.

References

Al-Deek, H., D'Angelo, M., and Wang, M. (1998). "Travel time prediction with non-linear time series." *Proc., ASCE 1998 5th Int. Conf. on Applications of Advanced Technologies in Transportation*, Newport Beach, Calif., pp. 317–324.

Anderson, J., Bell, M., Sayers, T., Busch, F., and Heymann, G. (1994). "The short term prediction of link travel time in signal controlled road networks." *Proc., IFAC/IFORS 7th Symp. on Transportation Systems: Theory and Application of Advanced Technology*, Tianjin, China, pp. 621–626.

Chien, S., and Chen, M. (2001a). "Determining the number of probe vehicles for freeway travel time estimation using microscopic simulation." *Transportation Research Record 1719*, Transportation Research Board, Washington, D.C., pp. 61–68.

Chien, S., and Chen, M. (2001b). "Dynamic freeway travel time prediction using probe vehicle data: Link-based vs. path-based." *Transportation Research Record 1768*, Transportation Research Board, Washington, D.C., pp. 157–161.

D'Angelo, M., Al-Deek, H., and Wang, M. (1999). "Travel time prediction for freeway corridors." *Presented at the 78th TRB Annual Meeting (CD-ROM)*, Washington, D.C.

Kalman, R. (1960). "A new approach to linear filtering and prediction problems." *J. Basic Eng.*, 82D, 35–45.

Oda, T. (1990). "An algorithm for prediction of travel time using vehicle sensor data." *Proc., IEE 3rd Int. Conf. on Road Traffic Control*, London, pp. 40–44.

Pant, P., Polycarpou, M., Sankaranarayanan, P., Li, B., Hu, X., and Hossain, A. (1998). "Travel time prediction system (TIPS) for freeway work zones." *ASCE Proc., ICTTS'98 Conf. on Traffic and Transpor-*

Downloaded 05 Mar 2010 to 143.107.252.1. Redistribution subject to ASCE license or copyright; see http://pubs.asce.org/copyright

tation Studies, Beijing, China, pp. 20–29.

Park, D., Rilett, L., and Han, G. (1998). ''Forecasting multiple-period freeway link travel times using neural networks with expanded input nodes.'' *Proc., ASCE 1998 5th Int. Conf. on Applications of Advanced Technologies in Transportation*, Newport Beach, CA, pp. 325–332.

Rilett, L., and Park, D. (1999). ''Direct forecasting of freeway corridor travel times using spectral basis neural networks.'' *Presented at the 78th TRB Annual Meeting (CD-ROM), Transportation Research Record 1617*, Transportation Research Board, Washington, D.C., pp. 163–170.

Roden, D. (1996). ''Forecasting travel time.'' *Transportation Research Record 1518*, Transportation Research Board, Washington, D.C., pp. 7–12.

Sen, A., Liu, N., Thakuriah, P., and Li, J. (1991). ''Short-term forecasting of link travel times: A preliminary proposal.'' *ADVANCE Working Paper Series #7*.

Downloaded 05 Mar 2010 to 143.107.252.1. Redistribution subject to ASCE license or copyright; see http://pubs.asce.org/copyright