Paper No. 03-2750

Predicting Travel Times for the South Jersey Real-Time Motorist Information System

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A dynamic travel-time prediction model was developed for the South Jersey (southern New Jersey) motorist real-time information system. During development and evaluation of the model, the integration of traffic flow theory, measurement and application of collected data, and traffic simulation were considered. Reliable prediction results can be generated with limited historical real-time traffic data. In the study, acoustic sensors were installed at potential congested places to monitor traffic congestion. A developed simulation model was calibrated with the data collected from the sensors, and this was applied to emulate traffic operations and evaluate the proposed prediction model under time-varying traffic conditions. With emulated real-time information (travel times) generated by the simulation model, an algorithm based on Kalman filtering was developed and applied to forecast travel times for specific origin–destination pairs over different periods. Prediction accuracy was evaluated by the simulation model. Results show that the developed travel-time predictive model demonstrates satisfactory performance.

The impact of traffic congestion, continuously one of the major problems in various transportation systems, may be alleviated by providing timely and accurate traffic information to motorists. Motorists thus could avoid congested routes by using alternative routes or changing departure times. Advanced travel information systems (ATISs) have been deployed for this purpose in many places in the United States. This study, sponsored by New Jersey Department of Transportation (DOT), developed a dynamic travel-time prediction system for a potential traveler information system in southern New Jersey.

The Walt Whitman and Ben Franklin Bridges connect Camden County in the southern region of New Jersey to the city of Philadelphia, Pennsylvania. Traffic originating in South Jersey mainly uses NJ-55, NJ-42, Interstate 76, and Interstate 676. Congestion points scattered over the roadways and at toll plazas during different periods increase travel-time variations for road users.

From historic observation, it is known that the toll plazas on both bridges were congested before introduction of the E-Z Pass system. In addition, northbound NJ-42 to the Walt Whitman Bridge and the point at which NJ-42 intersects with southbound NJ-168 are congested during the morning peak period. Traffic conditions will worsen over time because of the growing population. Other congestion points in the morning peak of the study site are mainly caused by traffic merging from Interstate 295 and NJ-55 to NJ-42 before entering the Ben Franklin Bridge.

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An effective and real-time traffic advisory system that can advise motorists to use less-congested routes is desirable. For example, motorists can be advised to take less-congested bridges to Philadelphia. If the total travel time through the Ben Franklin Bridge to Philadelphia exceeds a certain threshold, use of the Walt Whitman Bridge is cost-effective for time. Variable message signs could direct traffic with the message Delay at Ben Franklin Bridge or Use Walt Whitman Bridge. Predicted travel-time information could be transmitted to drivers who have telecommunications equipment (e.g., aviation system, cell phone, beepers) to help in their route-choice decision.

The focus for this study is development of a dynamic model to predict path travel times for the South Jersey real-time motorist information system.

LITERATURE REVIEW

An intelligent transportation system (ITS) combines electronic, computer, and communication technologies with applications of transportation theory and can collect, restore, process, and transmit traffic information for transportation-management use. ATISs, a core component of ITSs, rely on modern technology (e.g., wireless communication) to predict and disseminate reliable information for motorists. Most traffic-management systems rely on historic and real-time traffic data to determine appropriate traffic-control and diversion plans. The performance of these systems, however, may be constrained because of weak predictive capabilities. The most useful information for route choices is accurate predicted travel times and delay information. Motorists, in the absence of predicted information, implicitly project travel times on the basis of their experience. Therefore, short-term predictions of what traffic conditions are likely to be in a few minutes (e.g., 5 min into the future) are needed for both traffic-management and traveler information systems. In-vehicle route guidance systems are significantly popular in advanced transportation management and information systems (ATMISs). With recent advances in communication and information technology, real-time traffic routing has emerged as a promising approach for ATMIS. As soon as traffic conditions change, a more reliable routing plan can be generated with consideration of predicted traffic information rather than current conditions alone.

Travel-time estimation and prediction have received much attention. In previous studies, probe vehicles (*1*) and geographic information system (GIS) technology (*2*) were applied to estimate travel time. Some prediction models were developed by using historic traffic data (*3*), while others relied on real-time traffic information (*4*). Development of electronic and communication technologies can improve the capacity of traffic surveillance systems and the accuracy of prediction methods. The fundamental input of predictive models is real-time and historic information, for which emphasis was placed on the relationship between travel time and flow or occupancy (*5*). However, the restrictions of those models remain. For example, the fitted traffic distribution should be appropriately defined corresponding to different ratios of variance to mean to make the predicted results consistent with real-world conditions (*6*).

A sound travel-time predictive model can accurately forecast freeway travel time in real time. Many previous studies focused on predicting travel times, which can be broadly categorized into the time series models (*7*), the nonparametric regression method (*8*), and artificial neural networks (ANN) (*9*). In those models, the flow pattern was formulated mathematically. However, the choices of probabilistic distribution and time structure of the flow pattern contribute the prediction errors. Thus, the ratio of variance to mean of the observed flow is an effective indicator for selecting the probabilistic distribution of the traffic flow (*6*). To develop a dynamic prediction model that can perform well under different traffic conditions, a method for distinguishing between recurrent congestion and nonrecurring congestion was developed (*10*), and it can be applied to identify current traffic conditions and then perform appropriate prediction models.

These models, mostly autoregressive integrated moving average model (ARIMA) type Box–Jenkins time series models (*11*), assume that travel-time prediction is a point process, and they use purely statistical techniques to identify the stochastic nature in the observed data. Available statistic models, such as ARIMA and regression models, cannot capture the dynamics of traffic conditions and employ historic traffic patterns to predict current-day trends. Therefore, the accuracy of these algorithms depends on the similarity between the trend of the historic data used for the determination of the parameters and the actual measurements. Applications of fuzzy logic and neural networks were applied to incorporate flexible reasoning and capture nonlinear relationships between link-specific detector data and travel times (*12*). Although the algorithms that use only current-day measurements are more responsive to current traffic variations, inherent time lags characterize prediction with those algorithms. The Kalman filtering algorithm was first applied to predict 15-min volume in urban networks (*13*). Unlike off-line algorithms that use only historic data for prediction, the Kalman filtering uses adaptive parameters responsive to dynamic conditions. The advantage of this method is that it can update the adaptive parameter to make the predictor reflect the traffic fluctuation quickly.

ANNs can be applied for prediction when the functional form that relates traffic measurements to predicted value is not available (*9*). The performance of the predictive ANNs substantially depends on the network structure, including the input–output specifications and the training samples. Although the selection of input and output values for a given network may be less difficult than the determination of an appropriate functional form, no robust theory is available that can determine the best training procedure for a given problem. Compared with the Kalman filtering algorithm, prediction of travel time with ANNs may be less accurate if the future traffic patterns are not in the training samples. A study found two disadvantages in the use of ANNs: the length of time needed to learn the training data, and the trial-and-error procedure used to find the optimum architecture (*14*).

A new approach for prediction of travel time along a corridor that considers both real-time data and historic data is proposed. The time-varying data (e.g., travel times) are derived from speed data collected by the sensors. In this study, sensors were installed at potential congested places to monitor traffic operations. A calibrated simulation model is proposed to emulate traffic operations for the study site, and then the time-varying traffic information can be generated. With the travel times collected from the sensors and the simulation model, the Kalman filtering algorithm is applied to forecast the travel times.

DATA COLLECTION

The data needed for developing a simulation model can be classified into two categories: geometric data and traffic data. The geometric data were collected from the construction plans of the study site, including the lengths of links, the number of lanes, the radius of the curvature, and the grade percentage and superelevation. Most geometric data were collected from the construction plans of the study site, while other data were obtained from the straight-line diagram available at www.state.nj.us/transportation/framed/stright.htm. In addition, the GIS database at the New Jersey Institute of Technology contains roadway pavement and inventory information of the study area, by which the accurate layout and related geometric information can fill the gaps that cannot be found from the construction plans. The aerographic maps taken by the satellite are applied to verify the image of the study site.

Five acoustic sensors were installed in designated locations within the study site, as shown in Table 1, to collect traffic data, including traffic volumes, speeds, and truck volumes. The collected traffic data were applied for calibrating a developed simulation model. Sensor 1 measured the traffic on northbound NJ-42 at the start point of the studied network. The sensor was located 50 ft ahead of the ramp from the junction of NJ-55 and NJ-42, a potential congestion point in the network. Sensor 2 collected traffic data on northbound Interstate 76, where the traffic is fed by northbound Interstate 295 and diverges to northbound Interstate 76. Sensor 3 monitored the traffic condition ahead of the toll plaza on the Walt Whitman Bridge. All traffic from

TABLE 1 Sensor Locations

Sensor No.	Position	Nearby Node No.
1	50 feet upstream of conjunction of Route 55 and Route 42	893
2	15 feet upstream of conjunction of Route 295 and Route 76	811
3	Downstream right after ramp from Route 130 to Route 76	740
4	Downstream of ramp to Morgan Street on Route 676	658
5	50 feet downstream of ramp from M.L.K Blvd to Route 676	565

NOTE: All these sensors are located on northbound Routes 42, 76, and 676.

northbound Interstate 76 and westbound NJ-130 merged at this location. Sensor 4 measured traffic conditions on northbound Interstate 676 between the two bridges, while Sensor 5 collected traffic data on northbound Interstate 676 as it merges into the Ben Franklin Bridge, where the traffic from westbound NJ-30 and Linden Avenue merge. Traffic under worst-case conditions extends to the Martin Luther King Boulevard exit at downtown Camden and farther to the south. Worst-case conditions occur on Sunday evening and Monday morning during summer as traffic returns from shore areas to the metropolitan area. The sensor is thus located 0.5 mi from the dead end to gauge congestion. Drivers to Philadelphia can opt for the Walt Whitman Bridge if the congestion on northbound Interstate 676 is severe.

For commuters traveling from Camden to Philadelphia, two origin–destination (OD) pairs are considered. The first OD pair is from the starting point on NJ-42 of the network and ends at the Walt Whitman Bridge. The second OD pair starts from the starting point of NJ-42 and ends at the Ben Franklin Bridge. A simulation model will be developed to emulate the travel times. The travel times of the second OD pair are predicted in the case study for evaluating prediction accuracy.

Data for traffic volumes and speeds, including hourly distribution, can be obtained from the acoustic sensors installed for this project. Traffic counts such as annual average daily traffic (AADT) are collected by data stations operated by the Bureau of Transportation Data Development of NJDOT (search.panzitta.com/searches/nfgensearch.cfm).

Travel-Time Prediction Model

Travel time can be affected by such factors as traffic volume, geometric conditions, speed limits, incidents, vehicle composition, and weather condition. In real-world applications, it is quite difficult to model the relationship among these factors, especially when the traffic volume is near roadway capacity. Various techniques have been used to predict travel times, as discussed in the literature review. The Kalman filtering algorithm was chosen for the study because it allows the prediction of the state variable (e.g., travel time) to be continuously updated. This approach has been used for predicting traffic volume and for real-time demand diversion, as well as estimation of trip distribution and traffic density. In this study, this technique is used to perform travel-time prediction based on the traffic data generated by a microscopic traffic simulation, which is calibrated with data collected by acoustic sensors. The step procedure for applying the Kalman filtering algorithm to travel-time prediction is discussed in the following.

Let $x(t)$ denote the travel time at time interval t that is to be predicted, let $\phi(t)$ denote the transition parameter at time interval t that is externally determined, and let $w(t)$ 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 let $v(t)$ 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 this application, $z(t)$ is obtained from averaging the travel times reported by probe vehicles at time interval t. Historic data (e.g., travel-time data from the same period of a previous day with a similar traffic situation) are used to obtain the transition parameter $\phi(t)$, which describes the relationship between the status of state variable (in this case, travel time) in two periods. This assumes that the pattern of travel-time variation over time remains basically the same between these 2 days.

Assume that in a linear system, 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 0. Initialization:

Set $t = 0$ and let $E[x(0)] = \hat{x}(0)$ and $E\left\{[x(0) - \hat{x}(0)]^2\right\} = P(0)$

Step 1. Extrapolation:

State estimate extrapolation: $\hat{x}(t)_- = \phi(t-1)\hat{x}(t-1)_+$

Error covariance extrapolation:

$$P(t)_- = \phi(t-1)P(t-1)_+\phi(t-1) + Q(t-1)$$

Step 2. Kalman gain calculation:

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

Step 3. Update:

State estimate update: $\hat{x}(t)_+ = \hat{x}(t)_- + K(t)[z(t) - \hat{x}(t)_-]$

Error covariance update: $P(t)_+ = [I - K(t)]P(t)_-$

Step 4. Let $t = t + 1$ and go to Step 1 until the preset period ends.

Case Study

To evaluate the performance of the prediction model, a microscopic simulation model was developed with CORSIM. CORSIM has been widely applied for simulating traffic operations (*15*) and evaluating the implementation of ITS (*16*) and is one of the best microscopic models to date. Both geometric conditions and traffic-related data are required for developing the simulation model that can replicate traffic operations. The link-node diagram of the studied network is shown in Figure 1. The AADTs over the study network were collected from seven data stations, as shown in Table 2. The daily traffic data in one direction have been normalized on the basis of collected AADT and are shown in Figure 2. Compared with the traffic-count data collected from the designated sensors, the normalized daily volumes closely match the real-world traffic distribution over the study site. The hourly traffic volume distribution over time, for example, at Sensor 1, as shown in Figure 3, is derived from the traffic distribution detected by the installed acoustic sensors and AADT collected by the data stations.

Traffic operations from 6:00 to 10:00 a.m. of the studied site are simulated by considering time-varying traffic volumes. With the speed data detected by the acoustic sensors, the simulation model is calibrated by fine-tuning parameters shown in Table 3, including car-following sensitivity factor, lane-change parameters, and desired free-flow speed to reflect the realistic traffic operations.

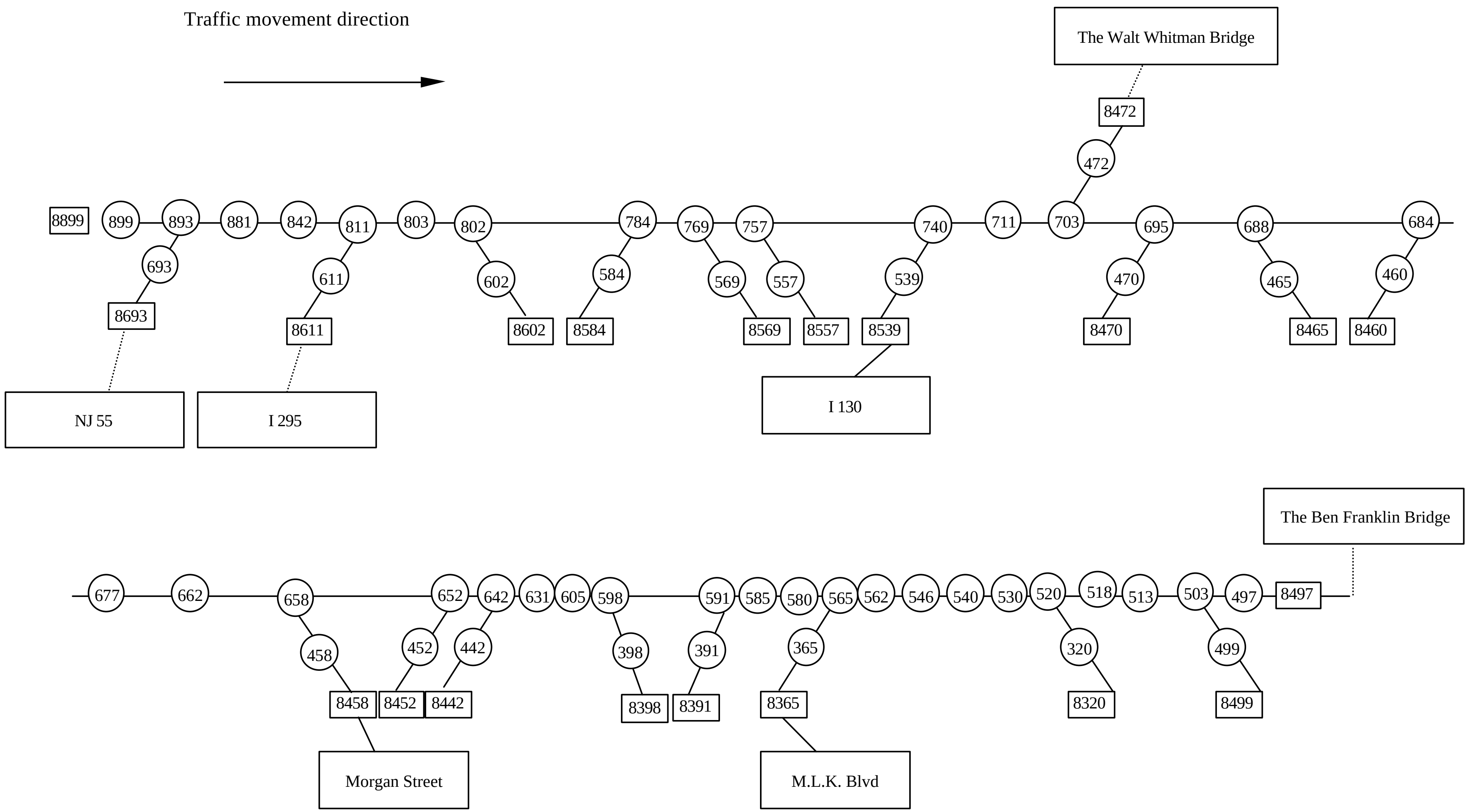

FIGURE 1 Link-node diagram.

TABLE 2 Traffic Counts Look-Up Results

Station Number	Route Number	Milepost	Station Location	AADT
7-4-103	676	0.70	BETWEEN I-76 & MORGAN BLVD	69,252
7-9-355	676	2.50	JUST NORTH OF ATLANTIC AVE	61,047
7-4-104	676	2.95	AT HADDON AVE OVERPASS	58,065
7-5-001	76	0.50	JUST SOUTH OF MARKET ST.	112,310
7-1-24	76	1.60	AT NICOLSON ROAD OVERPASS	136,310
7-2-11	76	2.40	WALT WHITMAN BRIDGE, TOLL	99,330
7-4-303	42	12.20	BETWEEN RT 544 & NJ 55	97,184

Finally, by comparing the simulated speeds with the detected speed data, the average errors are 1.4%, 0.9%, 11.2%, 16.7%, and 9.1% on Sensors 1 through 5, respectively. This implies that the calibrated simulation model can replicate traffic operations reasonably well for the studied corridor. To test the performance and accuracy of the proposed prediction model, the link travel times generated by CORSIM are treated as actual travel times for comparison with that provided from the prediction model.

Three scenarios classified by three different types of historic data are proposed for analyzing the accuracy of the predicted travel times. The first scenario uses the previous time-interval data to predict the next time-interval travel times. The second scenario takes the travel time recorded in the same period on the same day a week before the input, while the third uses the 5-weekday average travel time collected from the same link a week ago. The outputs are predicted travel times from the start point of the network to the Ben Franklin Bridge. The

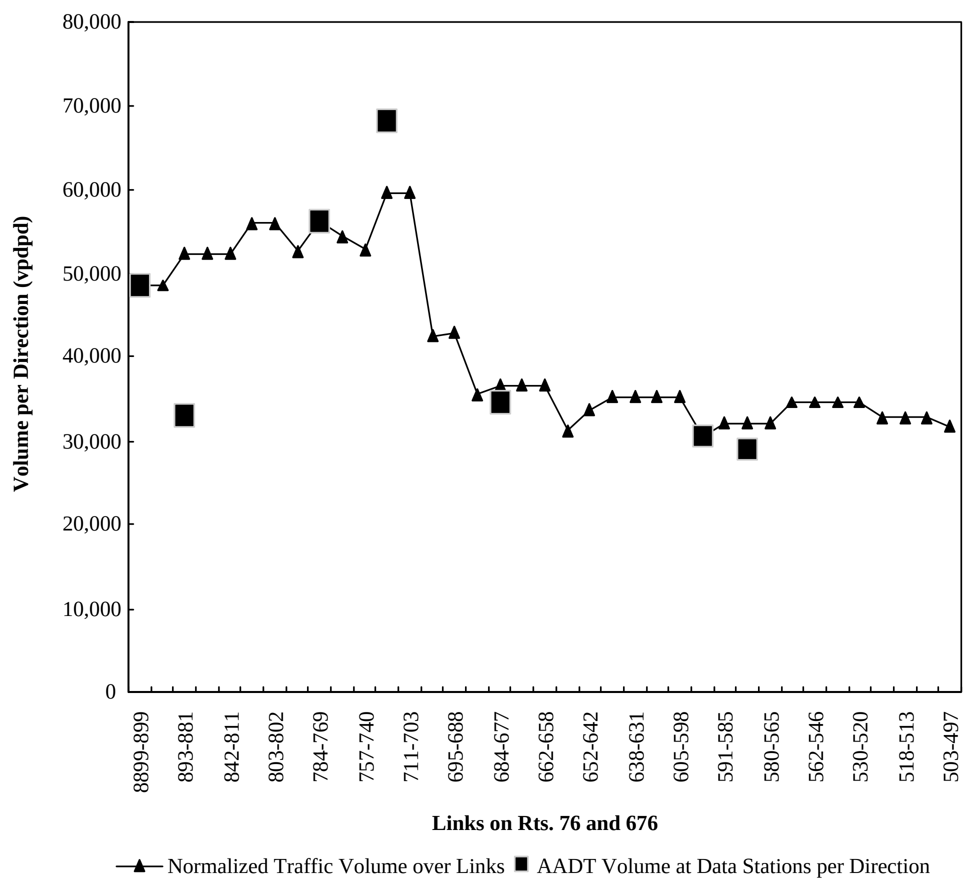

FIGURE 2 Deduced AADT volumes per direction.

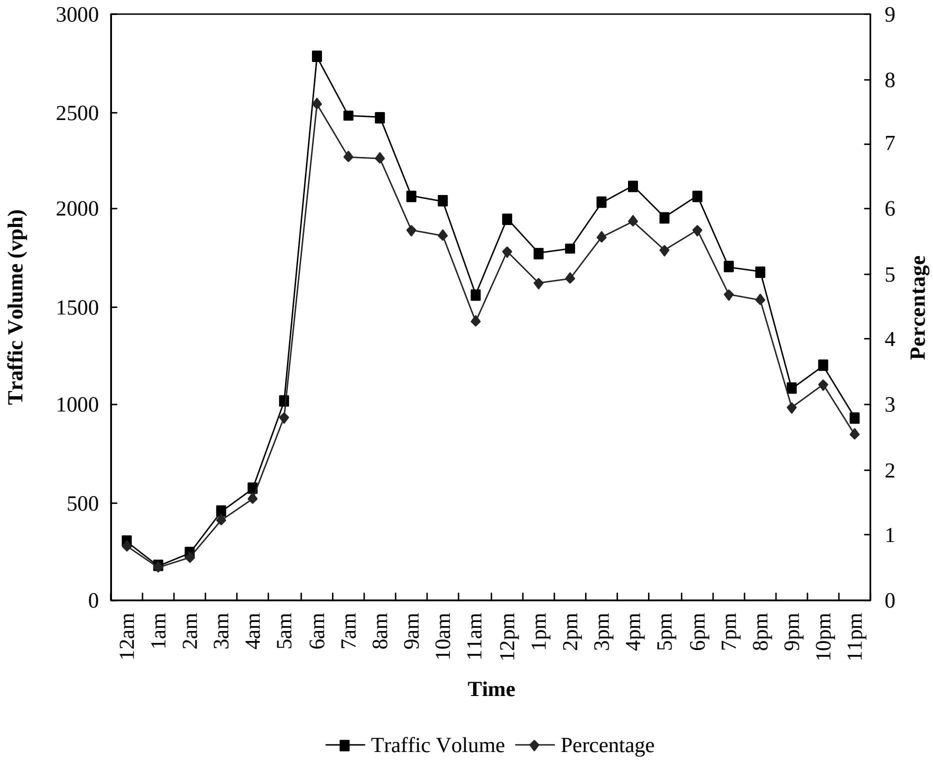

FIGURE 3 Traffic distributions over time at Sensor 1.

TABLE 3 Default and Calibrated Parameters

Variable Description	Default Value	Calibrated Value	Unit
New car-following sensitivity factor for driver type 1	125	120	Hundredths of Seconds
New car-following sensitivity factor for driver type 2	115	110	
New car-following sensitivity factor for driver type 3	105	100	
New car-following sensitivity factor for driver type 4	95	90	
New car-following sensitivity factor for driver type 5	85	80	
New car-following sensitivity factor for driver type 6	75	70	
New car-following sensitivity factor for driver type 7	65	60	
New car-following sensitivity factor for driver type 8	55	50	
New car-following sensitivity factor for driver type 9	45	40	
New car-following sensitivity factor for driver type 10	35	30	
New value for Pitt car following constant	10	5	Feet
Time to complete a lane-change maneuver	20	10	Tenths of Seconds
% of drivers desiring to yield right-of-way to lane-changing vehicles attempting to merge	20	30	Percentage
Multiplier for desire to make a discretionary lane change	5	8	Tenths of Units

best data for least prediction error are identified and applied into the proposed predictive model. It was found that the first scenario provided the best results for the study site during peak periods.

With the prespecified covariance parameters $R(t) = 50$, the Kalman filtering algorithm updates the state variable (travel-time) iteratively. In this case, both the real-time information and the previous time interval information are applied to predict the travel time in the next time interval. The sample process of the Kalman filtering algorithm is illustrated in Table 4, and the final results with the use of 5-min traffic information are shown in Figure 4. (Note that Node 899 is the starting point of the studied corridor, where NJ-55 and NJ-42 intersect. Node 497 is the end point, at the Ben Franklin Bridge.)

The selected prediction error indices for evaluating the accuracy of the developed model, including mean absolute relative error (*MARE*), root relative square error (*RRSE*), and maximum relative error (*MRE*), formulated in Equations 3, 4 and 5, are applied in this analysis:

$$MARE = \frac{1}{N}\sum_{t}\frac{|x(t) - \hat{x}(t)|}{x(t)} \tag{3}$$

TABLE 4 Travel Times Predicted with Kalman Filtering Algorithm

(0)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Time	True	Historic	$\hat{Xt}(+)$	Error	Φ (t)	Rt	Qt	Kt	$\hat{Xt}(-)$	Pt (-)	Pt (+)	Measured
6:00-6:05	557.0	557.0	557.0		1	50	1				0	557.0
6:05-6:10	542.8	542.8	556.7	2.61	0.97	50	1	0.02	557.0	1.00	0.98	542.8
6:10-6:15	537.8	537.8	542.3	0.88	0.99	50	1	0.04	542.5	1.93	1.86	537.8
6:15-6:20	549.2	549.2	538.0	2.17	1.02	50	1	0.05	537.3	2.83	2.67	549.2
6:20-6:25	547.9	547.9	549.3	0.28	1.00	50	1	0.07	549.4	3.79	3.52	547.9
6:25-6:30	544.3	544.3	547.7	0.68	0.99	50	1	0.08	548.0	4.51	4.13	544.3
6:30-6:35	543.0	543.0	544.0	0.21	1.00	50	1	0.09	544.1	5.08	4.61	543.0
6:35-6:40	546.0	546.0	543.0	0.61	1.01	50	1	0.10	542.7	5.59	5.03	546.0
6:40-6:45	530.9	530.9	544.4	2.84	0.97	50	1	0.11	546.0	6.08	5.42	530.9
6:45-6:50	521.6	521.6	528.5	1.48	0.98	50	1	0.11	529.4	6.13	5.46	521.6
6:50-6:55	532.2	532.2	520.7	2.44	1.02	50	1	0.11	519.2	6.27	5.57	532.2
6:55-7:00	543.6	543.6	532.8	2.27	1.02	50	1	0.12	531.3	6.80	5.99	543.6
7:00-7:05	529.9	529.9	542.4	2.70	0.97	50	1	0.13	544.2	7.24	6.33	529.9
7:05-7:10	536.5	536.5	529.6	1.46	1.01	50	1	0.12	528.6	7.01	6.15	536.5
7:10-7:15	516.9	516.9	533.7	3.73	0.96	50	1	0.13	536.2	7.30	6.37	516.9
7:15-7:20	504.6	504.6	513.1	1.92	0.98	50	1	0.12	514.3	6.92	6.08	504.6
7:20-7:25	553.8	553.8	507.2	9.56	1.10	50	1	0.12	500.9	6.79	5.98	553.8
7:25-7:30	542.3	542.3	554.7	2.65	0.98	50	1	0.14	556.7	8.20	7.05	542.3
7:30-7:35	555.3	555.3	544.8	2.19	1.02	50	1	0.13	543.2	7.76	6.71	555.3
7:35-7:40	539.0	539.0	555.2	3.49	0.97	50	1	0.14	557.8	8.04	6.93	539.0
7:40-7:45	550.2	550.2	540.4	2.06	1.02	50	1	0.13	538.9	7.53	6.54	550.2
7:45-7:50	522.1	522.1	547.7	5.66	0.95	50	1	0.14	551.7	7.82	6.76	522.1
7:50-7:55	522.6	522.6	520.1	0.56	1.00	50	1	0.12	519.7	7.09	6.21	522.6
7:55-8:00	531.3	531.3	521.9	2.02	1.02	50	1	0.13	520.6	7.22	6.31	531.3

NOTE:
(0) Time interval.
(1) True value of the state variable, in this case set equal to the measured travel time (seconds), $(1)_t = (12)_t$.
(2) Historic travel time (seconds), which could provide the state transition matrix F. Since the travel time of previous time interval were taken as the historic data, $(2)_t = (12)_t$.
(3) Updated state estimated value, $(3)_t = (9)_t + (8)_t * [(12)_t - (9)_t]$.
(4) Prediction error percentage, $(4)_t = \text{abs}\,[(9)_t-(1)_t]/(1)_t * 100$ %.
(5) State transition matrix Φ(t), $(5)_t = (2)_t/(2)_{t-1}$.
(6) Covariance matrix of observational (measurement) uncertainty, $(6)_t = 50$.
(7) Covariance matrix of process noise in the system state dynamics, $(7)_t = 1$.
(8) Kalman gain matrix K (t), $(8)_t = (10)_t * [(10)_t+(6)_t]^{-1}$.
(9) State estimates (seconds), $(9)_t = (5)_{t-1} * (3)_{t-1}$.
(10) Estimation error covariance, $(10)_t = (5)_{t-1} * (11)_{t-1} * (5)_{t-1} + (7)_{t-1}$.
(11) Updated estimation error covariance, $(11)_t = [1-(8)_t] * (10)_t$.
(12) Measured travel time (seconds) from simulation model.

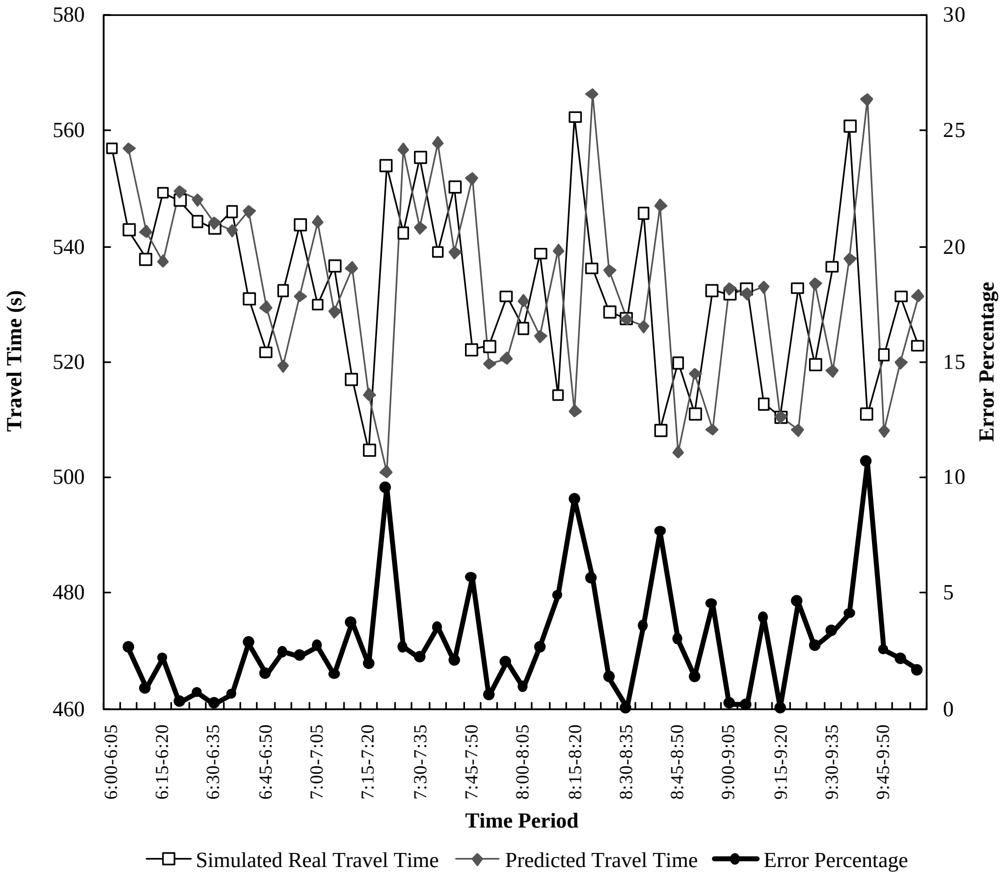

FIGURE 4 Predicted travel time from Node 899 to Node 497 (length = 40,730 ft).

$$RRSE = \sqrt{\frac{1}{\sum_t x(t)} \sum_t \left[\frac{x(t) - \hat{x}(t)}{x(t)}\right]^2 x(t)} \qquad (4)$$

$$MRE = \max_t \frac{|x(t) - \hat{x}(t)|}{x(t)} \qquad (5)$$

Note that N is sample size, while $x(t)$ and $\hat{x}(t)$ represent the actual and predicted travel times, respectively. The values of *MARE, RRSE,* and *MRE* are 2.8%, 3.8%, and 9%, respectively, which implies that the developed model performed reasonably well. The Shapiro–Wilk test was also performed to check the noise distribution. The result shows that a *P*-value equal to 0.612 is greater than 0.5. It implies that the measurement noise follows a normal distribution, which satisfies the condition for applying the Kalman filtering algorithm in this study.

CONCLUSIONS

A method for predicting travel times for motorists traveling in the study site was developed, and the Kalman filtering algorithm was applied. Five acoustic sensors were installed at potential congested places in the studied area to monitor traffic conditions. The collected information, including speed and volume estimates by the sensors, was used to calibrate the developed simulation model to evaluate the developed predictive model. The Kalman filtering algorithm was applied to predict the travel time with the simulated data. The historic data (travel times) for deriving the state variable transition parameter were chosen from the previous time interval. The covariances for measured and state variables were set to be constant. Traffic during the period of 6:00 to 10:00 a.m. was selected for testing the predictive model, and during this period, the traffic conditions experienced a dramatic change because of peak-period traffic flow. The evaluation results show that the developed prediction model could generate satisfactory results. With reliable predicted travel times, better route choice decisions by motorists can be expected.

Four factors should be researched and addressed for developing more robust prediction algorithms. First, the relationship between the covariance for measurement noise and process noise should be investigated from the real-world information, such as traffic volume, travel, speeds, or travel times for each time interval. Thus, a covariance parameter assumed in the Kalman filtering algorithm can vary with the change in the real-world data rather than being set as a constant. This extension may be necessary to increase prediction accuracy in real-world applications. Second, the relationship between the coefficient of variation of the state variables and prediction accuracy should be explored. More statistic analysis should be carried out to provide not only mean value but also the variance of the prediction results. Third, the algorithm should be tested and calibrated for different traffic conditions—for example, optimizing the prediction-updating interval to catch the change in traffic condition quickly and accurately. Fourth, according to the characteristics of traffic distribution, applying the best historic data set as a seed to predict accurate and timely information under various traffic conditions would be another extension of this study.

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Publication of this paper sponsored by Committee on Urban Transportation Data and Information Systems.