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The Development of Dynamic Travel Time Prediction Models for South Jersey Real-Time Motorist Information System

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16. Abstract

This study develops a dynamic travel time prediction model for the South Jersey Motorist Real-time Information System. While developing and evaluating the model, the integration of traffic flow theory, measurement and application of collected data and traffic simulation are considered. Reliable prediction results can be generated with limited historical real-time traffic data. In this study, a number of acoustic sensors are installed at potential congested places to monitor traffic congestions. A developed simulation model is calibrated with the data collected from the sensors and this is 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 simulation model, the Kalman filtering based algorithm is developed and applied to forecast travel times for specific origin-destination pairs over different time periods. Prediction accuracy has been evaluated by the simulation model. Results show that the developed travel time predictive model demonstrates satisfactory performance.

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INTRODUCTION

Background

The Walt Whitman and Ben Franklin Bridges connect the Camden County in the south region of New Jersey and the city of Philadelphia in Pennsylvania, (see Figure 1). The traffic from the southern New Jersey mainly uses Routes 55, 42, 76 and 676, and reaches Philadelphia through the two bridges, while congestion points scattered over the roadway network and at toll plazas during different time periods.

From historical observation it is known that the toll plazas on both bridges were congested before the operation of E-Z Pass. In addition, the northbound direction of Route 42 to the Walt Whitman Bridge where it intersects the southbound of Route 168 are congested in the morning peak. The traffic congestion will be worse in future due to the growing population in southern New Jersey. Other congested points in the morning peak of the study network are mainly caused by the traffic merging from Routes 295 and 55 to Route 42 before entering the Ben Franklin Bridge.

An effective and real-time traffic advisory system is desired to alert motorists of potential congestion and advise them to use less congested routes. For example, the motorists will take the Ben Franklin Bridge to Philadelphia if real-time traffic information is known. If the total travel time through the Ben Franklin Bridge to Philadelphia exceeds a certain time threshold, which leads that using the Walt Whitman Bridge is a cost-effective (in terms of time) way. Predicted travel time information can be transmitted to drivers whom have telecommunication equipment (e.g., aviation system, cell phone, or pagers) or through variable message signs (VMS) to assist their route choice decision. The focus of this study is to develop a dynamic model to estimate and predict path travel times for the South Jersey Real-time Motorist Information System project.

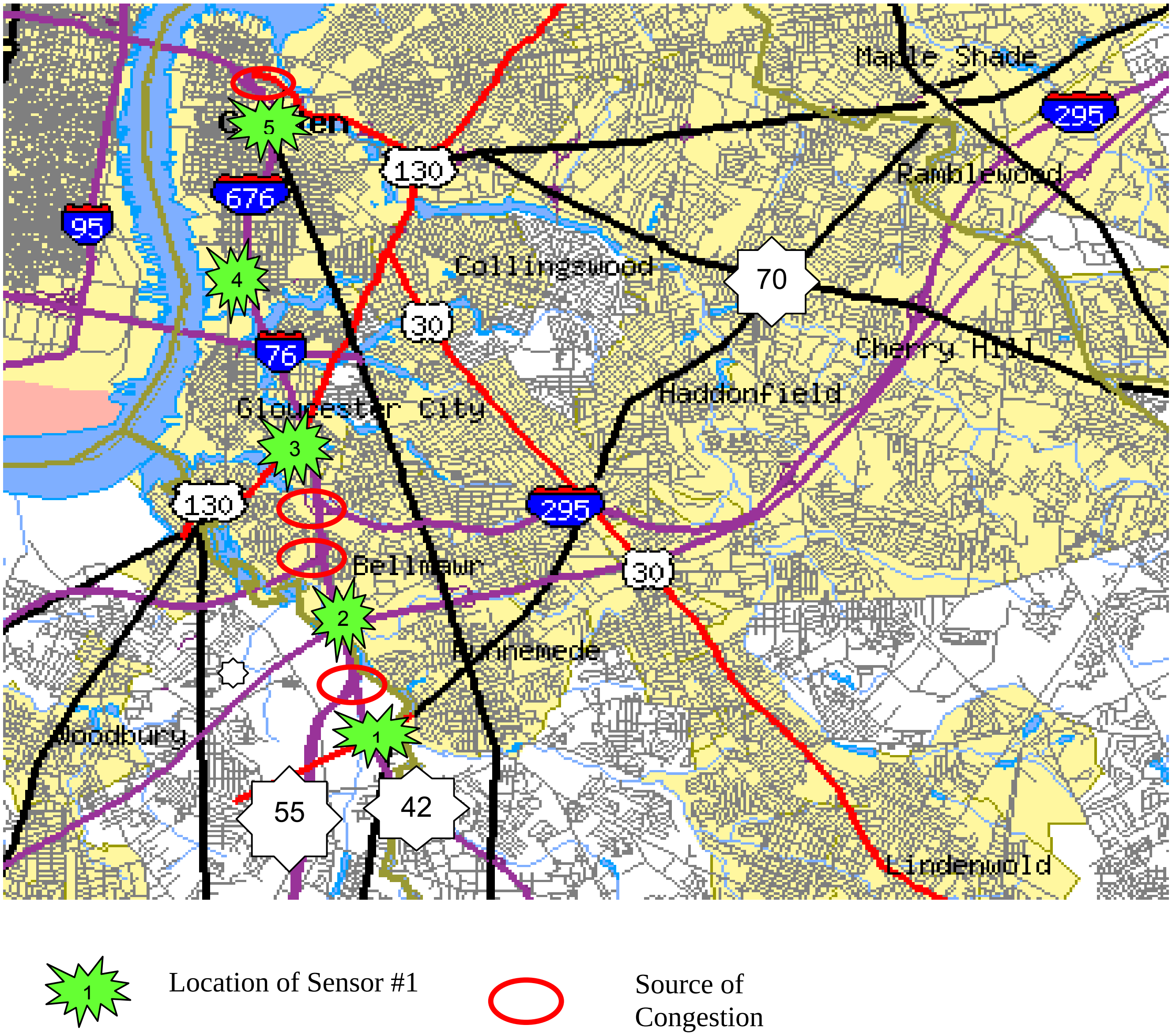


Figure 1. Regional Network Configuration

Objectives and Scope

Traffic congestion, continuing to be one of the major problems in various transportation systems, may be alleviated by providing timely and accurate traffic information to motorists. Thus, they can avoid congested routes by using other alternative routes or changing their departure times. In the advent of Intelligent Transportation Systems (ITS), the Advanced Travel Information Systems (ATIS) have been deployed for this purpose in many places in the United States. Three important issues need to be evaluated for successful deployment of these systems and will be discussed in the study:

- An integrated surveillance and communication system to monitor traffic conditions
- A sound dynamic estimation/prediction system to accurately forecast travel time as well as congestion over space and time; and
- The effectiveness and reliability of the estimation/prediction system.

The objectives of this project include:

- Development of real-time traveler information generation algorithms.
- Dissemination of traveler information
- Development of model for estimating travel time and delays.

To provide accurate traffic information (e.g., travel times and delays), the research team at New Jersey Institute of Technology (NJIT) proposes a model that can dynamically predict travel times as well as delay based on real-time and historical information collected from different data resources. The following tasks are conducted for developing, testing, and evaluating the proposed system.

Task 1: Identify and deploy sensors for collecting real-time traffic information.
In order to provide accurate traveler information to motorists, the fundamental requirement is to deploy a reliable traffic surveillance/communication system. To achieve this objective, there are two steps to proceed. The first step is to determine the

sensor locations to collect real time traffic data (e.g. traffic volumes, occupancies, and travel speeds) effectively. Since the number of sensors may be very limited the data collected from the selected sites must reflect the real world traffic conditions. In order to collect reliable data, the second step is to develop a computer program to retrieve and process real-time traffic data collected by the sensors. Thus, mistakes can be minimized.

Task 2: Development of travel time estimation algorithms.
After retrieving the real-time traffic data collected from sensors, an estimation model should be used to approximate travel times that reflect real-time traffic conditions. Thus, a data procession program must be developed to convert the data into travel times that can be used for predict travel times with the Kalman filter algorithm.

Task 3: Development of travel time and delay prediction model.
With historical and real-time traffic data, the proposed model is developed to predict the short-term future travel times that can be disseminated to the motorists. The historical data used by the model may be collected from the previous time step, previous day, or previous week, depending on the level of congestion on the network.

System Configuration

This section provides an overview of the proposed predictive system and the relationship between the estimation and prediction models. Both of them will be developed in this study. Figure 2 shows the proposed predictive system and data flows among different modules.

Assume that vehicle speeds can be detected directly from the sensors. The travel times on the corresponding links and OD paths could be estimated in real-time. The travel times will be updated at the end of each time interval (say five minutes). The estimated travel times will then be applied as the input of the prediction model. In addition to the real-time travel time information, historical travel times of the study network will be considered to approximate the future travel times for specific links or paths. With the predicted travel time disseminated to motorists, a better route choice decision can be expected.

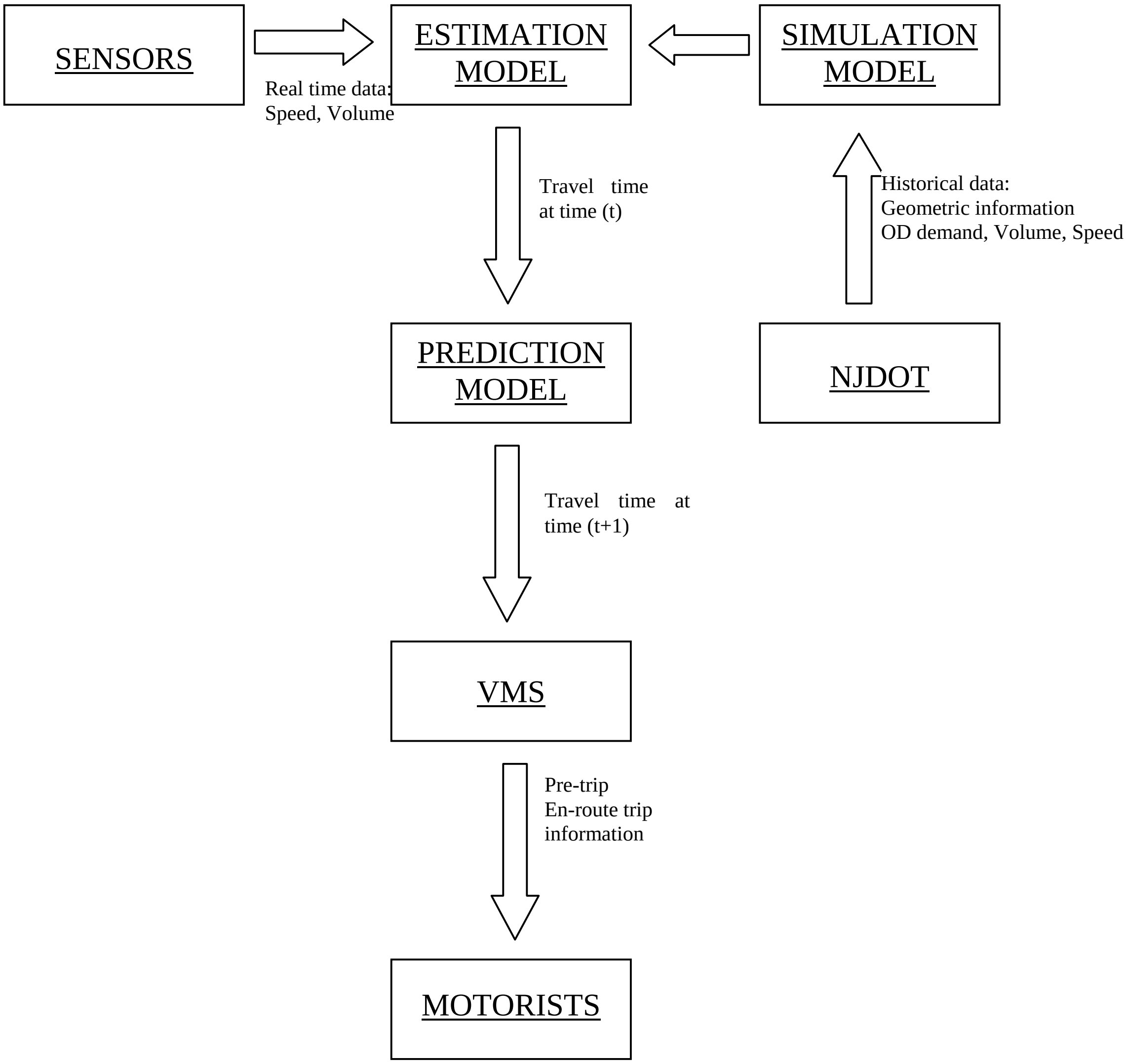


Figure 2. Configuration of the Travel Time Predictive System

LITERATURE REVIEW

Intelligent Transportation Systems (ITS), a set of advanced components, that combine electronic, computer and communication technologies with the applications of the transportation theory, which can collect, restore, process and transmit various traffic information for assisting traffic management.

Advanced Traffic Information Systems (ATIS), as one of core components in ITS, rely on modern technology (e.g., wireless communication), to disseminate reliable real-time information to motorists in order to predict future traffic condition, historical and real-time information are collected and applied for this purpose. Historical information describes the state of the transportation system during previous time periods. Real-time information contains the most up-to-date traffic conditions. Two types of information, long term and short-term predictive information, can be generated for different purpose. The long-term predictive information is mainly used for transportation planning that requires future traffic demand and supply conditions, while the short-term predictive information often encompasses a horizon of a few minutes to a couple hours, and is therefore more suitable for traffic management and information systems. Most of traffic management systems rely on historical and real-time traffic data as a basis for determining appropriate traffic control plans. The performance of these systems, however, is constrained because of weak predictive capabilities. The most useful information for route choices is reliably predicted travel times/delays information. Motorists making decisions in the absence of predictive information are implicitly projecting future conditions based on historical and current information that they experienced. Therefore, short-term predictions of what traffic conditions are likely to be in a few minutes (e.g., five minutes into the future) are needed for traffic management and travelers information systems.

In the Advanced Transportation Management and Information Systems (ATMIS), In-vehicle Route Guidance Systems (RGS) have gained significant popularity worldwide. In previous studies, the basic model for searching the optimal path assumed that the link travel times are constant (e.g., deterministic and time-independent). In a shortest path problem, that can be solved using efficient labeling algorithms.(38, 39) The labeling algorithm has been enhanced to solve the shortest path problem with time-dependent link travel times under the first-in-first-out (FIFO) condition.(40) With the 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 the consideration of predicted traffic information rather than purely current condition.

Travel time estimation and prediction has been an important research topic for decades. In previous studies, probe vehicles(4) or geographic information system (GIS) technology(31) were applied to estimate the travel time. Some prediction models were developed using historical traffic data(33) while others rely on the real-time traffic information.(25) The 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 historical information, for which the emphasis was placed on the relationship between travel time and flow or occupancy.(8) Although the relationship has been explored widely, restrictions still exist to apply that in estimating and predicting travel times. The fitted distribution should be appropriately defined corresponding to different ratios of variance to mean (V/M) to make the predicted results consistent with real traffic conditions.(13)

Data Collection

The most fundamental information for analyzing and evaluating a transportation system is traffic measurement. In this study, the estimation and prediction of travel times are conducted based on the link travel speed and the length of the link.

Recently, two methods that were discussed and widely used for measuring the travel time: (1) roadside equipment, and (2) probe vehicles. The first method uses fixed equipment on the roadside to monitor vehicles passing through the point, at which the vehicle speed, volume and occupancy can be detected. New computer and electronic devices provide more convenient and reliable ways to collect data, such as Automatic Vehicle Identification systems (AVI), Automatic Vehicle Location systems (AVL), cellular phone tracking, and video image processing systems.(28,34) The method using probe vehicles to collect travel times is wildly accepted because it is simple and direct, while the error generated from deduction process in the roadside equipment can be eliminated. However, different amounts of probe vehicles will be required to generate unbiased estimation(4) under different degrees of traffic congestion. Errors may exist when the vehicle tracking system is not well developed.

More advanced technologies developed recently could be applied for data collection, Quiroga and Bullock(23) has demonstrated the feasibility of using Global Positioning Systems (GPS) and Geographic Information Systems (GIS) for automating the data collection, processing, and reporting travel times with probe vehicles. This technology provides consistency, automation, finer levels of resolution, and better accuracy in measuring travel times and speeds than traditional techniques. However, each method has its own advantage and disadvantage according to the research scope and requirement. For example, analyzing aerial photographs or performing numerous moving-vehicle runs was tedious and time-consuming. Although GPS could track wide-area vehicle operation, it cannot provide some traffic characteristic such as flow, roadway occupancy, and spot speed.

Estimation Models

Three fundamental traffic variables used to describe the temporal and spatial traffic characteristics include flow, density and speed. The flow is defined by a number of vehicles passing a point during a specified time period. The density is the number of vehicles occupying a unit distance that often is substituted by roadway occupancy in measurement. The occupancy is the ratios of the detector-activated time to the total observation time. There are two different speed definitions: spot speed and space mean speed. The spot speed is measured at a point, while the space mean speed is measured over a distance. Importantly, the space-mean speed can reflect the speed variations over the distance. Thus, the flow can be estimated as the product of density and space mean speed.

Though there are many technologies used to detect the traffic flows, the high cost makes the coverage of a large-scale network unrealistic. Therefore, it is important to develop an accurate estimation method with limited real-time information. Many studies were conducted to estimate link travel times on freeways, which are basically classified into two categories:

1. Use information collected from one detector to determine the spot speeds and then approximate the link travel time.(11)
2. Use information collected from two detectors, one at each end of the link, to retrieve the link travel times directly.(15,18)

The first method uses the flow and occupancy measured by the single-loop detector to calculate the speed at that point using the equation:

$$S = \frac{F}{O * g} \tag{1}$$

S: speed (mile/hour)

F: flow (vehicle/hour)

O: occupancy (mile/vehicle)

1/g: the average effective car length, or the sum of the car length and the width of the loop detector. The factor of g converts occupancy to density.

Hall and Persaud(11) and Pushkar(22) investigated this relationship and discovered that the accuracy of equation (1) is dependent on location and weather.
Later, Dailey(8) attempted to improve the Equation (1) by taking into account the stochastic nature of various measurements. Thus, speeds were considered as a stationary Gaussian process and the Kalman filter algorithm was applied for estimating speed.

The second method estimates travel times with the use of measurements at two single-loop detectors, one at either end of the link. Luk(15) developed a method to estimate the travel time on a link based on the detected flow. Nam and Drew(18) estimated the link travel times by measuring the cumulative flow passing through two loop detectors at both ends of a link. They found that the travel time is the area between the two accumulative flow curves detected at the detector locations. Later, Dailey(8) used cross-correlation of the flows detected by the upstream and downstream detectors to estimate travel time. Despite its methodological appeal, this statistical method was reported to not work well under congested traffic conditions due to the disappearance of the correlation. Those stochastic models based on the theory that the vehicles follow a common probability distribution of travel times to a downtown point, and use an approximate relationship between flow, occupancy, and speed. The assumptions for those estimations require knowing the number of vehicles currently between the two detectors, which is not available in two detector cases. Hence the cumulative flow can drift over time, the travel time estimates may drift as well.

Nam and Drew(17) applied a new dynamic traffic flow model successfully for normal and congested flow conditions. It was developed based on the characteristics of the stochastic vehicle counting process and the principle of conservation of vehicles. This model estimates spatial variables, such as travel times, as a function of time directly from flow measurements.

Evolving electronic and communication technologies improved the capacity of traffic surveillance. Advanced sensors using acoustic technology could get the travel speed variable directly from the moving vehicles, rather than using the inductive methodology to deduce the link travel times with measured flow. Thus, the measurement error can be reduced and provide more accuracy and efficiency in the estimation. In this project, acoustic sensors are utilized in L-3 IREMBASS system to classify personnel and vehicles, which can detect accurate and reliable spot speed at the designated locations.

Prediction Models

A sound travel time predictive model can accurately forecast freeway travel time in real-time. Most studies have been focused on the predicting travel times. Previous methods can be broadly categorized into the Box-Jenkins time series model,(1,35) the non-parametric regression method,(42) the weighted moving-average method, and the adaptive filtering technique.(19) To each type of model, the functional form decided the flow pattern. The choice of the probabilistic distribution and time structure characterizes the model errors. The ratio of variance to mean (V/M) of the observed flow is an effective indicator in selecting the probabilistic distribution for model errors; Lan and Miaou(13) did the study considering prediction limits by V/M ratio to explore the statistical nature of traffic flows.

The most common predictors use constant parameters determine off line with historical data. For example, there is a prediction model, called Urban Transportation Control System (UTCS), whose parameters are determined off-line using a representative data set collected from the location in question. The UTCS-2 predictor employs both historical and current-day measurements. With current-day traffic measurements, the UTCS-2 predictor will reduce the predicted deviations from the average historical data. In contrast, the UTCS-3 predictor, employing only current-day measurements, uses the interpolation between the most recent smoothed and un-smoothed measurements as the predicted values. Further, under normal traffic conditions, the algorithms employing historical information as reference provide better prediction than those use only current-day measurements. (36)

These models, mostly Autoregressive Integrated Moving Average model (ARIMA)-typed Box-Jenkins time series models, assume that travel time prediction is a point process and use purely statistical techniques to identify the stochastic nature in the observed data. Currently available statistic models, such as ARIMA and regression model, cannot capture the dynamics of traffic conditions and employ historical traffic pattern to predict the current-day trend. Therefore, the accuracy of these algorithms depends on the similarity between the trend of the historical data used for the determination of the parameters and that of the actual measurements. Application of fuzzy logic and neural networks was applied to incorporate flexible reasoning and capture non-linear relationship between link specific detector data and travel times.(20) Although the algorithms that applied current-day measurements were more responsive to traffic variations, time-lag prediction errors were inherent with those algorithms. The Kalman filter algorithm was first applied by Okutani and Stephanedes(19) to predict traffic volumes in an urban network. Unlike off-line algorithms that only use historical data for prediction, the Kalman filter 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.

Artificial Neural Networks (ANN) can be applied when the functional form that relates traffic measurements to predicted value is not available. 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 Kalman filter algorithm, prediction with ANNs may be less accurate then Kalman filter when the future traffic patterns did not exist in the training samples. In a study conducted by Taylor and Meldrum(41) discussed two disadvantages of ANN. It was found that ANN needs to consume a long time period in training for achieving better accuracy as well as searching the best structure to fit the studied problem.

Simulation Models

Simulation is one of the most important tools to emulate traffic information when there are not enough traffic measurements available to be applied for estimation and prediction.

Theoretically, the traffic data can be collected by all kinds of equipment, however it is impossible to equip a large scale network due to the high installation and maintenance costs. It is effective to derive reliable traffic information with a calibrated simulation model,(26) which was built to simulate the traffic operation on the basis of the known traffic counts and geometric information.

In terms of design, simulation models can be macroscopic, which represent traffic in aggregate bunches or platoons, and microscopic, which process each vehicle individually. Microscopic models, though requiring more computing time and resources to run, can represent vehicles more realistically than the macroscopic models. Microscopic models theoretically are more responsive to different traffic strategies and can also produce more accurate Measures of Effectiveness (MOE's) and provide enough flexibility to test various combinations of supply and demand. The macroscopic traffic simulation models just use shock waves and continuum theory to model dynamic traffic situations, therefore no individual vehicle could be tracked down for analysis.

The validation of the simulation model should be conducted after the calibration of the simulation model.(37) Simulated traffic data are compared with monitored data from the real world. The discrepancy between the real traffic data and simulation results could be minimized by fine-tuning the corresponding parameters, the simulation model can then replicate the real world traffic condition.

Literature Review Summary

The basic algorithm and deduction process for estimation and prediction application is selected based on the literature review study and available information for the studied project. A new approach for prediction travel time along a corridor is proposed considering both the real-time data and historical data. The time varying data (e.g. travel time) are derived from speed data collected by the sensors. In this study, a number of sensors will be installed at potential congested places to monitor traffic operations. Since the real-world data may be unavailable, a simulation model is proposed to emulate traffic operations for the study site, while the time varying traffic information can be obtained. With the travel times is collected from real world or simulation model, the Kalman filter model will be applied to forecast the travel times. As discussed in the literature review, the Kalman filter algorithm can provide accurate and reliable predicted results, however, both historical and real-time travel time information must be available.

METHODOLOGY

Sensor Locations

There are five sensors available to be installed in the network to collect real time traffic data that will be applying for the estimation and prediction model. The decision of sensor locations is dependent on the potential locations of congestion points. In the study network, the links equipped with sensors are on Routes 76, 676, and 42, and the link length is shown in Table 1. The aerographic map of the study site is shown in Figure 3. The proposed five-sensor locations could provide traffic volume and speed data. In order to monitor congestion along the Route 42, the sensors are allocated with certain priority, which could make the detected data consistent for calibration of the simulation model. The detailed sensor location is described and shown in Table 2 and Figure 4:

- Sensor #1 measures the traffic on Route 42 northbound at the start point of the studied network. The sensor located 50 feet before the ramp from Route 55 merging into Route 42, where it is also a congestion place in the network.
- Sensor #2 measures the traffic flow on northbound Route 76, where the traffic flows are fed up from the northbound Route 295 and diverge again from northbound Route 76 at the end point of the section.
- Sensor #3 measures the traffic condition before the toll Plaza of the Walt Whitman Bridge. All traffic from northbound Route 76 and westbound Route 130 merge together at this section.
- Sensor #4 measures the traffic on the northbound Route 676 between two bridges.
- Sensor #5 measures the traffic on 676 northbound as it merges into Ben Franklin Bridge, where Route 30 westbound and the Linden Avenue merge at the adjacent area. (Linden Ave is the last Westbound exit off of Route 30.) Drivers may take Linden Ave to avoid heavy congestion and take 7th Avenue to avoid the backup on Route 676 northbound. Traffic under the worst case conditions backs up to the Martin

Luther King Blvd exit into downtown Camden and farther to the South. Worst-case conditions are on Sunday evening and Monday morning during summer as shore traffic returns to the metropolitan area. The sensor may be located 0.5 mile from the dead end to gauge congestion. Drivers to Philadelphia can opt for the Walt Whitman Bridge if the backup on Northbound Route 676 is severe.

By considering the majority of commuter motorists, demands on two OD pairs are studied by the research team. The first OD pair is from the starting point on Route 42 and ending at the Walt Whitman Bridge. The second OD pair still departs from the starting point of the Route 42 and the destination point is Ben Franklin Bridge. Those are the alternatives for motorists coming from southern Jersey to Pennsylvania. A simulation model will estimate travel time, while travel time data of the second OD pair are used for demonstrating the development of a prediction model in the case study.

Table 1. Link Lengths on Routes 42, 76, and 676

Distance	Link 1	Link 2	Link 3	Link 4	Link 5
Feet	4668	7850	7898	8765	11550
Miles	0.88	1.49	1.50	1.67	2.19

Table 2. Sensor Locations

Sensor #	Position	Nearby Node #
1	50 feet upstream of conjunction between Route 55 to Route 42	893
2	15 feet upstream of Route 295 touching down on 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 those sensors are located on northbound of routes.

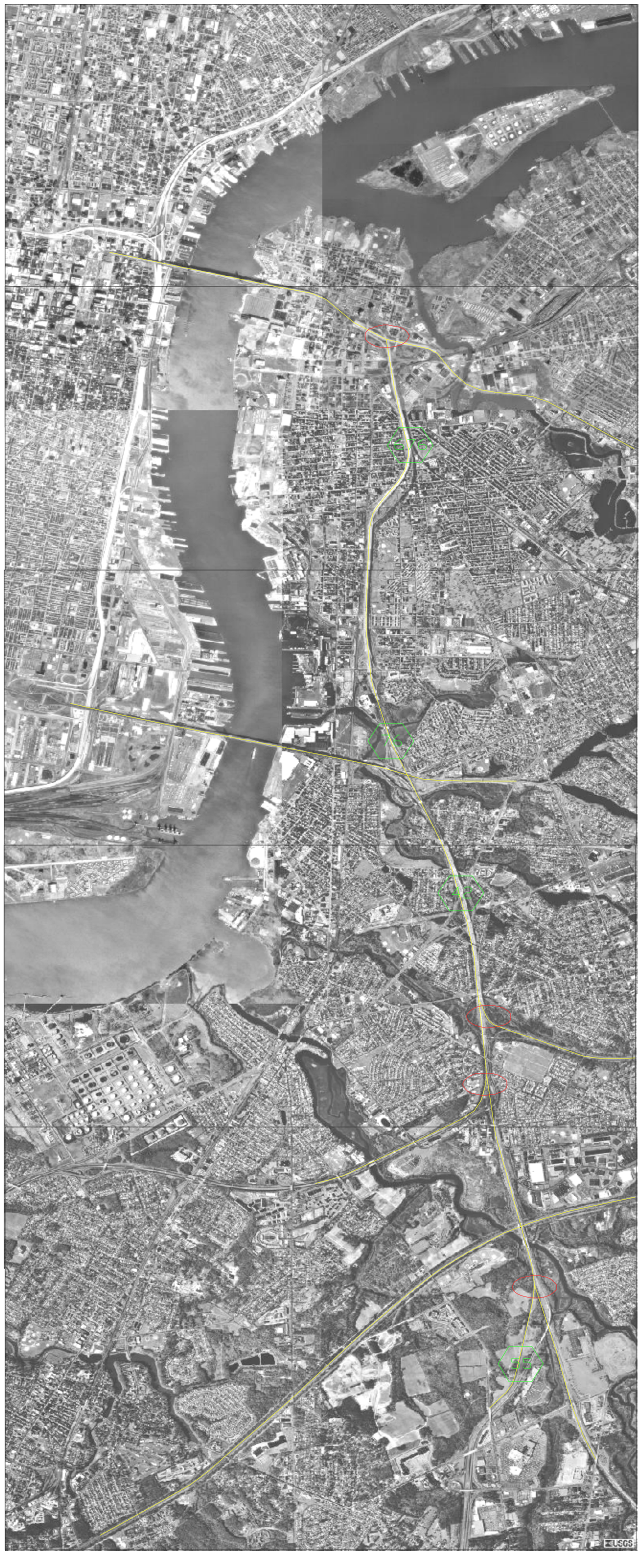


Figure 3. Aerographic Map of the Study Site

Figure 4. Sensor Locations

Data Collection

The data needed for developing a simulation model include geometric and traffic data. Various agencies have been contacted to get that information, which is summarized below.

The necessary geometric data is available from construction plans, straight line diagrams, and geographical information system data. The geometric data can be found from the construction plans, which record the detailed information about the study network, such as the length of each segment, the number of lanes, the radius of the curvature, the grades and super-elevation, etc. Most geometric data were collected from the construction plans of the study site, provided by NJDOT. Another source to get the geometric data is the straight-line diagram, which is available at http://www.state.nj.us/transportation/framed/stright.htm. Although the radius of the curvature are unavailable, the names of the streets, the connecting ramps, the Mile Post (MP), the number of the lanes, and traffic station ID, can be found.

Another source has been searched to get geometric and traffic information is from database of Geographic Information Systems (GIS). The GIS database at NJIT contains geometric information of the study area, by which the accurate layout and related geometric information can fill the gap that can't be found from construction plans and the straight diagram. In addition to that, the aerographic maps taken by the satellite are available at http://terraserver.homeadvisor.msn.com. It reflects the real image of the study network in scale, and therefore provides the layout for identifying the OD pairs of the study area.

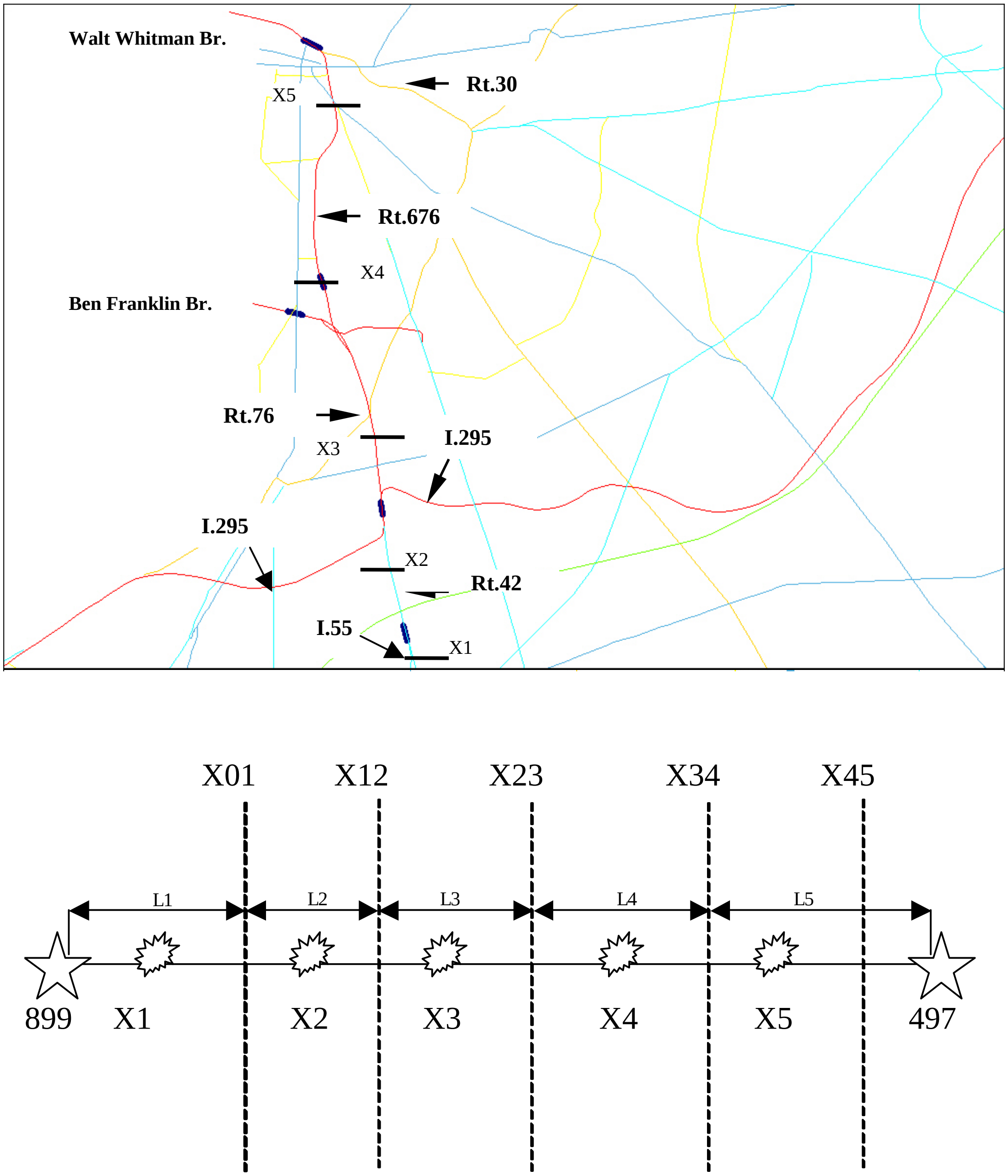
Regarding the traffic data, the traffic volume and speeds can be obtained from the sensors exclusively equipped for this project and traffic counts collected by data stations by the Bureau of Transportation Data Development (BTDD). BTDD is responsible for the collection, verification and dissemination of basic data used for transportation related activities.

In addition to BTDD data, traffic data are collected by data stations distributed in the network. However, only AADT data were recorded. It is necessary to get the traffic distribution over time for the development of simulation models. Regarding speed data, only speed limit information can be found in the straight-line diagram. The free-flow speed in the simulation model is assumed 5-10 mph over the speed limit.

Travel Time Estimation Models

Travel times in highway transportation networks are highly variable and dependent on the traffic conditions and occurrence of random incidents that happen along the freeway and before the toll plaza. In the study network, the estimation of the travel time is focused on those potential congested area with the real time traffic data from the acoustic sensors that can provide the spot speeds of each passing vehicle. Travelers are anticipated to choose appropriate route that reduces their travel times and thus, the network efficiency can be improved.

Both historical and current travel times are collected before applying the estimation model. To construct the historical profile, the travel time data in every previous time period should be identified. A digital map chosen for this study has been originally prepared from GIS at NJIT. The GIS file has been converted into the map with MapInfo. The prepared map highlights the sections along the corridor, as shown in Figure 5. The studied network is divided into different sections by middle points of those five sensors, their travel speed is assumed to be the spot speed detected by the acoustic sensors installed in each sections then the travel time could be derived by the detected spot speeds and the corresponding section lengths, the travel time on those links are calculated iteratively over the study time period, the result is shown in the Table 3.



X1 Location of sensor 1
X12 the middle point between sensors 1 and 2
L2 the length of link 2

Figure 5. Sensor Locations and Network Segmentation

Table 3. Estimation of Travel Time with Real Acoustic Sensor Data (10/26/01)

Time	**Average Speed (miles/hour)**					**Travel Time (seconds)**					
	Sensor 5	Sensor 4	Sensor 3	Sensor 2	Sensor 1	Link 5	Link 4	Link 3	Link 2	Link 1:	Path
6:00AM	60	63	60	47	41	131	95	90	114	78	507
6:05AM	55	60	58	51	45	143	100	93	105	71	511
6:10AM	64	66	53	46	47	123	91	102	116	68	499
6:15AM	58	68	60	50	45	136	88	90	107	71	491
6:20AM	57	68	60	50	39	138	88	90	107	82	504
6:25AM	61	65	60	58	48	129	92	90	92	66	469
6:30AM	55	62	56	56	34	143	96	96	96	94	525
6:35AM	56	72	57	59	21	141	83	94	91	152	560
6:40AM	54	66	57	47	21	146	91	94	114	152	596
6:45AM	58	60	57	47	45	136	100	94	114	71	514
6:50AM	56	60	54	65	40	141	100	100	82	80	502
6:55AM	59	71	58	47	48	133	84	93	114	66	491
7:00AM	55	59	62	51	32	143	101	87	105	99	536
7:05AM	62	68	59	51	36	127	88	91	105	88	500
7:10AM	63	68	56	45	35	125	88	96	119	91	519
7:15AM	65	62	58	47	37	121	96	93	114	86	510
7:20AM	60	64	58	47	30	131	93	93	114	106	537
7:25AM	64	73	59	59	34	123	82	91	91	94	480
7:30AM	65	68	56	51	34	121	88	96	105	94	504
7:35AM	63	62	58	47	20	125	96	93	114	159	587
7:40AM	65	62	56	47	8	121	96	96	114	398	825
7:45AM	59	62	58	61	7	133	96	93	88	455	865
7:50AM	58	63	58	55	13	136	95	93	97	245	666
7:55AM	57	75	62	54	18	138	80	87	99	177	581

Travel Time Prediction Models

Travel time can be affected by various factors, such as volume, geometric conditions, speed limits, incidents, vehicle composition, etc. In real world applications, it is quite difficult to model the relationship among all these factors, especially when traffic volume is near capacity (this could happen during the peak period). Therefore, instead of using speed or volume data collected by conventional loop detectors and convert them into travel time information, we directly estimate the travel times for dynamically predicting travel time.

Various techniques have been used to predict travel time, as mentioned earlier. The Kalman filtering method is chosen in the study because it enables the prediction of the state variable (e.g., travel time) to be continually updated as new observation (of travel time) becomes available. This approach has been used in the forecasting of traffic volume and real-time demand diversion, as well as the estimation of trip-distribution and traffic density. In this study, this technique is used to perform travel time prediction based on real-time information provided from sensors. Specifically, the average travel time of probe vehicles at each time period is used as the real-time observation to predict the travel time in the next (or future) time period.

The step procedure of applying the Kalman filter algorithm is discussed below.
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

$$x(t) = \phi(t-1)x(t-1) + w(t-1) \qquad (2)$$

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

$$z(t) = x(t) + v(t) \qquad (3)$$

In our application, z (t) is obtained from averaging the travel times reported by probe vehicles at time interval, t. Historical data (e.g., travel time data from the same time period of a previous day with similar traffic situation) are used to obtain the transition parameter Φ(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 same between these two 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. Note that the notations (+) and (-) represents the prior and posterior values of variables (e.g. P(t) and x(t)), respectively. The filtering procedure is shown as follows:

Step 0: Initialization

Set t=0 and let $E[x(0)] = \hat{x}(0)$ and $E\left[(x(0) - \hat{x}(0))^2\right] = P(0)$ (4)

Step 1: Extrapolation

State estimate extrapolation: $\hat{x}(t)_- = \phi(t-1)\hat{x}(t-1)_+$ (5)

Error covariance extrapolation: $P(t)_- = \phi(t-1)P(t-1)_+\phi(t-1) + Q(t-1)$ (6)

Step 2: Kalman Gain Calculation

$$K(t) = P(t)_-\left[P(t)_- + R(t)\right]^{-1} \tag{7}$$

Step 3: Update

State estimate update: $\hat{x}(t)_+ = \hat{x}(t)_- + K(t)\left[z(t) - \hat{x}(t)_-\right]$ (8)

Error covariance update: $P(t)_+ = \left[I - K(t)\right]P(t)_-$ (9)

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

CASE STUDY

Introduction

In order to test the performance of the developed model, both simulation data and real-world data are collected and applied in this section. Both geometric conditions and traffic related data are required for developing a simulation model with CORSIM that can replicate traffic operations of the study network. The link-node diagram of the studied network is shown in Figure 6. The collected geometric data of the network has been discussed in Data Collection section, as shown in Table 4. The distribution of traffic volumes AADT over the study network was collected from the traffic counts from data stations and summarized in Table 5 and Table 6. Since the traffic data collected by all stations are AADT, the hourly data has been normalized with assumed peak hour factor for simulation use. The normalized traffic data and the AADT distributed over space are shown in Figures 7 and 8, respectively. The traffic distribution over time, for example at sensor 1, is illustrated and shown in Figure 8 that was used to deduce traffic volumes over all links.

In this case study, 4-hour traffic operation (6:00 am-10:00 am) on the study network is simulated based on time varying travel volumes. Another two different input datasets were prepared (e.g., mean travel times with 5-minute data and 30-second data in every 5 minutes) for estimating the travel times. This analysis is conducted based on acoustic sensors applied in this network. In order to test the performance and accuracy of the proposed prediction model, the link travel times during the peak period of 6:00 am to 8:00 am was generated by CORSIM, which were treated as actual travel times for evaluating the developed prediction model. Three scenarios with three different types of historic data are proposed for analyzing the accuracy of predicted travel times with the Kalman Filter algorithm. 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 time period on the same day a week before as the input, while the third one uses the 5-weekday average travel time collected from the same link a week ago. The outputs are predicted travel times. The best data in terms of the least prediction error is identified and applied into the proposed predictive model. We found that the first scenario provided best results for the studied case.

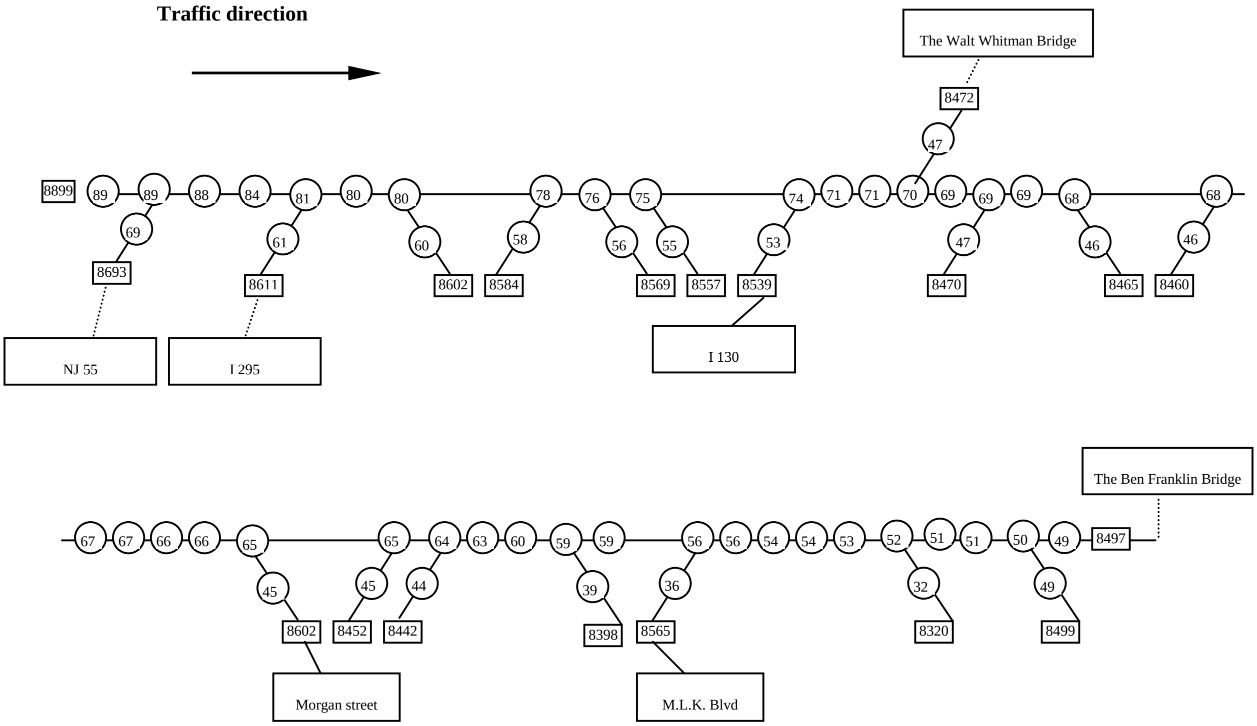


Figure 6. Link – Node Diagram

Table 4. Geometric Characteristics of the Study Site

				AUXILIARY LANE						
				ONE		TWO				
LINK NAME	TYPE	LNGTH (FT)	NO.THRU LANES	TYPE	LNGTH (FT)	TYPE	LNGTH (FT)	THRU DEST NODE	CURV RADIUS (FT)	GRADE
(8899,899)	F	0	3	-		-	-	893	-	0
(899,893)	F	600	3	-		-	-	881	-	1
(893,881)	F	1200	3	A	300	-	-	842	-	0
(881,842)	F	3900	3	-		-	-	811	-	0
(842,811)	F	3100	3	-		-	-	803	-	0
(811,803)	F	800	3	W	800	-	-	802	-	0
(803,802)	F	500	4	D	400	-	-	784	-	0
(802,784)	F	1750	4	-		-	-	769	-	2
(784,769)	F	1500	5	W	1500	A	500	757	-	1
(769,757)	F	1200	5	D	700	D	400	740	-	-2
(757,740)	F	1700	5	-		-		711	-	0
(740,711)	F	3000	5	A	900	A	500	703	-	0
(711,703)	F	780	4	D	300	-	-	695	3396	0
(703,695)	F	850	3	-		-	-	688		-2
(695,688)	F	650	3	W	650	-	-	684	3459	0
(688,684)	F	400	3	-		-	-	677	6067	0
(684,677)	F	750	3	A	450	-	-	662	3428	0
(677,662)	F	1500	4	-		-	-	658	6067	0
(662,658)	F	400	4	D	350	-	-	652	3993	0
(658,652)	F	570	4	-		-	-	642	4000	0
(652,642)	F	960	4	A	400	-	-	631	-	0
(642,631)	F	1170	3	A	500	-	-	605	-	0
(631,605)	F	2600	3	-		-	-	598	-	0
(605,598)	F	550	3	D	400	-	-	591	-	0
(598,591)	F	700	3	-		-	-	585	700	0
(591,585)	F	600	3	A	300	-	-	580	1900	0
(585,580)	F	500	3	-		-	-	565	4000	0
(580,565)	F	1500	3			-	-	562	1920	0
(565,562)	F	300	3	A	250	-	-	546	1920	0
(562,546)	F	1600	3	-		-	-	540	-	0
(546,540)	F	600	3	-		-	-	530	4800	0
(540,530)	F	1000	3	-		-	-	520	-	0
(530,520)	F	1000	3	D	800	-	-	518	949	0
(520,518)	F	200	3	-		-	-	513	949	0
(518,513)	F	775	3	-		-	-	503	-	0
(513,503)	F	607	3	D	400	-	-	497	2200	0
(503,497)	F	918	3	-	-	-	-	8497	-	0
(497,8497)	F	0	3	-	-	-	-	-	-	0

F: Freeway R: Ramp A: Acceleration lane D: Deceleration lane W: Full auxiliary lane

Table 4 Geometric Characteristics of the Study Site (continued)

				AUXILIARY LANE						
				ONE		TWO				
LINK NAME	TYPE	LNGTH (FT)	NO.THRU LANES	TYPE	LNGTH (FT)	TYPE	LNGTH (FT)	THRU DEST NODE	CURV RADIUS (FT)	GRADE
(497,8497)	R	2289	1	A	-	-	-	471	2956	0
(703,472)	R	750	1	A	-	-	-	8471	-	0
(472,471)	R		1	A	300	-	-	695	-	0
(8470,470)	R	600	1	A	-	-	-	688	700	0
(470,695)	R	200	1	A	-	-	-	8465	350	0
(688,465)	R		1	A	800	-	-	684	-	0
(8460,460)	R	180	1	A	400	-	-	677	700	0
(460,684)	R		1	A	-	-	-	652	-	0
(8452,452)	R	230	1	A	1500	A	500	642	2822	0
(452,652)	R		1	A	700	D	400	642	-	0
(8442,442)	R	400	1	A	-	-		631	1578	0
(442,642)	R	300	1	A	900	A	500	8398	500	0
(598,398)	R	200	1	A	300	-	-	8458	-	0
(658,458)	R		1	A	-	-	-	591	450	0
(8391,391)	R	300	1	A	650	-	-	585	1000	0
(391,591)	R	300	1	A	-	-	-	8602	-	0
(802,602)	R		1	D	450	-	-	784	2200	0
(8584,584)	R	400	1	D	-	-	-	769	1100	0
(584,784)	R	300	1	A	350	-	-	8569	1000	0
(769,569)	R	300	1	D	-	-	-	8557	-	0
(757,557)	R		1	D	400	-	-	740	1100	0
(8539,539)	R	460	1	D	500	-	-	711	-	0
(539,740)	R		1	A	-	-	-	565	5000	0
(8365,365)	R	300	1	A	400	-	-	562	750	0
(365,565)	R	400	1	A	-	-	-	8320	-	0
(520,320)	R		1	A	300	-	-	893	1400	0
(8693,693)	R	600	1	A	-	-	-	881	-	0
(693,893)	R		1	A	-	-	-	811	1300	0
(8611,611)	R	600	1	A	250	-	-	803	350	0
(611,811)	R	400	1	A	-	-	-	8499	5000	0

F: Freeway R: Ramp A: Acceleration lane D: Deceleration lane W: Full auxiliary lane

Table 5. Traffic Counts Lookup Results

Station Number	Route Number	Milepost	Station Location	Year	Q
7-4-103	676	0.70	BETWEEN I-76 & MORGAN BLVD	1999	69,252
7-9-355	676	2.50	JUST NORTH OF ATLANTIC AVE	2000	61,047
7-4-104	676	2.95	AT HADDON AVE OVERPASS	2000	58,065
7s5d001	76	0.50	JUST SOUTH OF MARKET ST	2000	112,310
7-1-24	76	1.60	AT NICOLSON ROAD OVERPASS	2000	136,310
7-2-11	76	2.40	WALT WHITMAN BR, TOLL	2000	99,330
7-4-303	42	12.20	BETWEEN RT 544 & NJ 55	1999	97,184

Q (vehicles): AADT traffic volume (vehicles) at both directions

Table 6. Normalized Peak Hour (6 am-10 am) Volumes

Link Name	AADT	Q1	Q2	Q3
(784,769)	112310	8985	7862	6739
(740,703)	136310	10905	9542	8179
(703,497)	99330	7946	6953	5960
(684,658)	69252	5540	4848	4155
(598,591)	61047	4884	4273	3663
(591,565)	58065	4645	4065	3484
899 entry	97184	7775	6803	5831
(513, Franklin Br.)	100360	8029	7025	6022

Q1: 8% volume of total AADT in peak hour on one direction (vph)
Q2: 7% volume of total AADT in Peak hour one direction (vph)
Q3: 6% volume of total AADT in Peak hour one direction (vph)

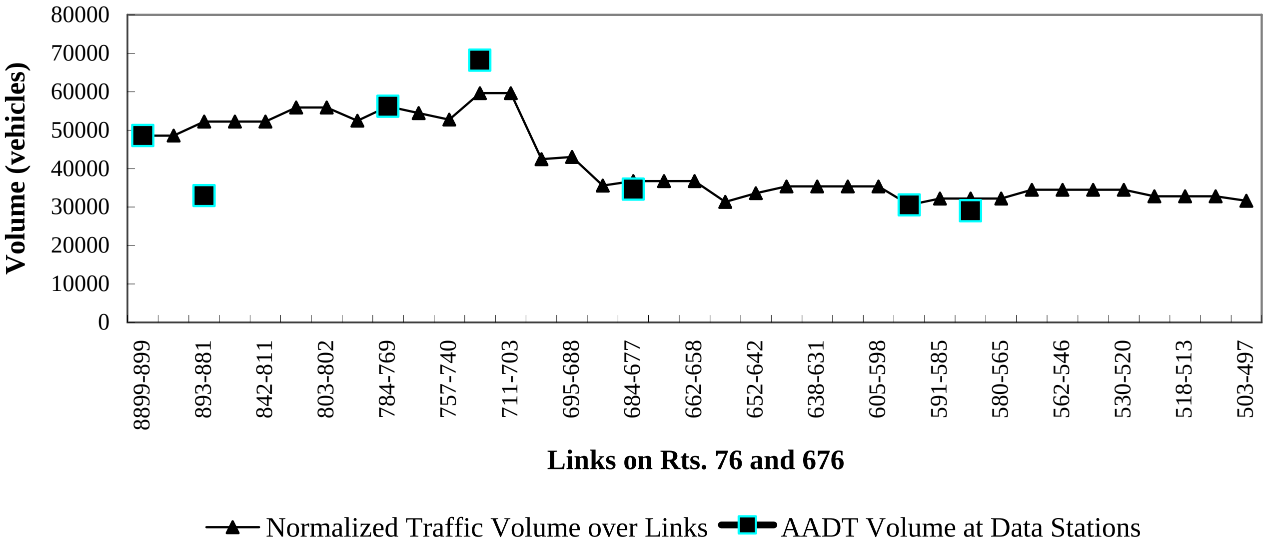


Figure 7. Deduced AADT Volumes

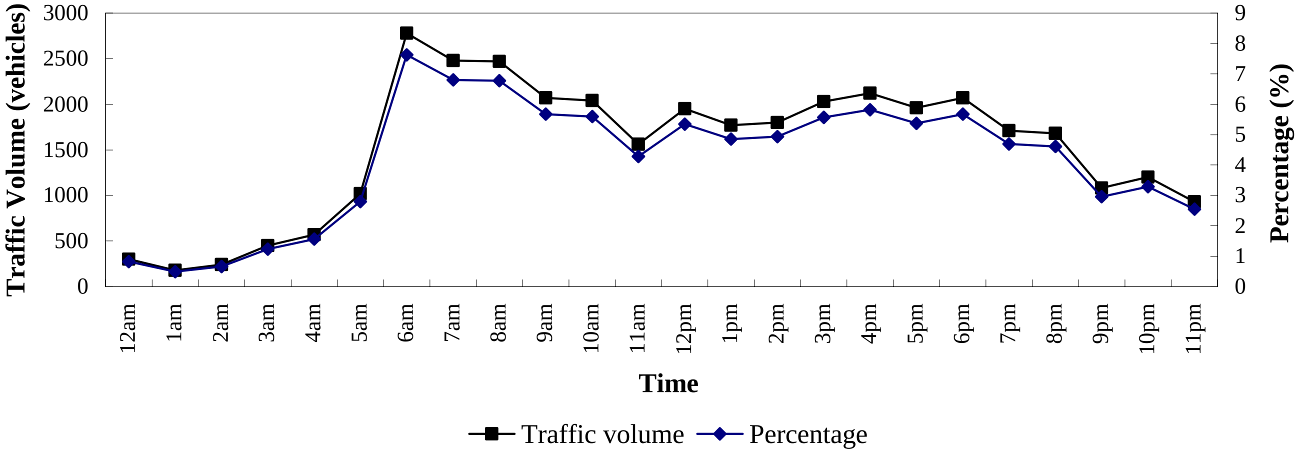


Figure 8. Traffic Distribution over Time at Sensor 1

Results of Analysis

The 5-minute measurement from the field data is based on 30-second estimate in every 5 minutes, which is compared to 5-minute traffic measures (e.g. speed/travel time) generated by CORSIM. This experiment is designed based on the calibration of acoustic sensors that report 30-second data in every 5-minute interval. With the pre-specified parameters, the Kalman filter algorithm updates the state variable (travel-time) iteratively shown in Table 7. In this case, the real-time information and the previous time interval information are used to predict the travel time in the next time interval. The final result with the use of 5-minute traffic information is shown in Figure 9.

The travel time information is detected and updated every 5 minutes, but 30-seconds' traffic information brings significant deviation in estimated travel times with 5-minute data. The analysis of the 5-minute and 30-second average travel times is conducted and shown in Figure 10. The coefficient of variation is generated in Figure 11 based on the data collected from 6:00 am to 6:30 am at sensor 1. The prediction results and their errors are shown in Figures 12 and 13, respectively.

Finally, the real traffic data detected from the 5 acoustic sensors are also applied in the prediction model from the start point (node 899) to the Ben Franklin Bridge (node 497) during the time period of 6:00am - 8:00am. The prediction results are shown in Figure 14.

Table 7. Predicted Travel Times with the Kalman Filter Algorithm

(0) Time	(1) True	(2) Historical	(3) $\hat{Xt}(+)$	(4) Error	(5) Φ• (t)	(6) Rt	(7) Qt	(8) Kt	(9) $\hat{Xt}(-)$	(10) Pt (-).	(11) Pt (+).	(12) Measured
6:00-6:05	470.9	470.9	470.9		1	50	1				0	470.9
6:05-6:10	469.1	469.1	470.86	0.38	1.00	50	1	0.02	470.90	1.00	0.98	469.1
6:10-6:15	468.8	468.8	469.06	0.05	1.00	50	1	0.04	469.07	1.97	1.90	468.8
6:15-6:20	464.8	464.8	468.57	0.85	0.99	50	1	0.05	468.79	2.90	2.74	464.8
6:20-6:25	472.3	472.3	465.09	1.65	1.02	50	1	0.07	464.56	3.69	3.44	472.3
6:25-6:30	469.0	469.0	472.33	0.76	0.99	50	1	0.08	472.62	4.55	4.17	469.0
6:30-6:35	469.8	469.8	469.10	0.17	1.00	50	1	0.09	469.02	5.11	4.64	469.8
6:35-6:40	470.3	470.3	469.93	0.10	1.00	50	1	0.10	469.88	5.65	5.08	470.3
6:40-6:45	469.9	469.9	470.38	0.11	1.00	50	1	0.11	470.44	6.09	5.43	469.9
6:45-6:50	468.0	468.0	469.74	0.42	1.00	50	1	0.11	469.96	6.42	5.69	468.0
6:50-6:55	464.4	464.4	467.41	0.73	0.99	50	1	0.12	467.81	6.64	5.86	464.4
6:55-7:00	469.8	469.8	464.56	1.27	1.01	50	1	0.12	463.85	6.77	5.97	469.8
7:00-7:05	464.6	464.6	469.29	1.14	0.99	50	1	0.12	469.95	7.11	6.22	464.6
7:05-7:10	465.2	465.2	464.25	0.23	1.00	50	1	0.12	464.12	7.08	6.21	465.2
7:10-7:15	461.0	461.0	464.33	0.82	0.99	50	1	0.13	464.81	7.22	6.31	461.0
7:15-7:20	459.9	459.9	460.13	0.06	1.00	50	1	0.13	460.17	7.20	6.29	459.9
7:20-7:25	462.1	462.1	459.41	0.66	1.00	50	1	0.13	459.02	7.26	6.34	462.1
7:25-7:30	458.6	458.6	461.20	0.64	0.99	50	1	0.13	461.57	7.40	6.45	458.6
7:30-7:35	464.4	464.4	458.62	1.42	1.01	50	1	0.13	457.78	7.35	6.41	464.4
7:35-7:40	465.7	465.7	464.51	0.29	1.00	50	1	0.13	464.33	7.57	6.57	465.7
7:40-7:45	461.9	461.9	465.33	0.85	0.99	50	1	0.13	465.85	7.61	6.61	461.9
7:45-7:50	459.9	459.9	461.34	0.35	1.00	50	1	0.13	461.55	7.50	6.52	459.9
7:50-7:55	461.1	461.1	459.60	0.37	1.00	50	1	0.13	459.38	7.47	6.50	461.1
7:55-7:00	461.0	461.0	460.78	0.07	1.00	50	1	0.13	460.74	7.53	6.54	461.0
8:00-8:05	461.0	461.0	460.77	0.05	1.00	50	1	0.13	460.74	7.54	6.55	461.0
8:05-8:10	460.8	460.8	460.71	0.02	1.00	50	1	0.13	460.70	7.55	6.56	460.8
8:10-8:15	461.1	461.1	460.62	0.13	1.00	50	1	0.13	460.55	7.56	6.56	461.1
8:15-8:20	460.1	460.1	460.84	0.19	1.00	50	1	0.13	460.96	7.57	6.58	460.1
8:20-8:25	460.9	460.9	459.93	0.23	1.00	50	1	0.13	459.79	7.55	6.56	460.9
8:25-8:30	465.4	465.4	461.33	1.00	1.01	50	1	0.13	460.71	7.58	6.58	465.4
8:30-8:35	466.1	466.1	465.89	0.06	1.00	50	1	0.13	465.85	7.71	6.68	466.1
8:35-8:40	460.9	460.9	465.87	1.23	0.99	50	1	0.13	466.63	7.70	6.67	460.9
8:40-8:45	464.1	464.1	461.13	0.74	1.01	50	1	0.13	460.68	7.53	6.54	464.1
8:45-8:50	467.3	467.3	464.71	0.64	1.01	50	1	0.13	464.32	7.63	6.62	467.3
8:50-8:55	463.2	463.2	467.28	1.00	0.99	50	1	0.13	467.90	7.71	6.68	463.2
8:55-7:00	459.2	459.2	462.70	0.87	0.99	50	1	0.13	463.22	7.57	6.57	459.2
9:00-9:05	459.8	459.8	458.83	0.24	1.00	50	1	0.13	458.68	7.46	6.49	459.8
9:05-9:10	457.6	457.6	459.17	0.39	1.00	50	1	0.13	459.40	7.51	6.53	457.6
9:10-9:15	457.8	457.8	457.08	0.18	1.00	50	1	0.13	456.97	7.46	6.49	457.8
9:15-9:20	459.0	459.0	457.51	0.38	1.00	50	1	0.13	457.29	7.50	6.52	459.0
9:20-9:25	458.0	458.0	458.62	0.16	1.00	50	1	0.13	458.72	7.56	6.56	458.0
9:25-9:30	457.3	457.3	457.53	0.06	1.00	50	1	0.13	457.57	7.53	6.55	457.3

Table 7. Predicted Travel Times with the Kalman Filter Algorithm (Continued)

(0) Time	(1) True	(2) Historical	(3) $\hat{Xt}(+)$	(4) Error	(5) Φ. (t)	(6) Rt	(7) Qt	(8) Kt	(9) $\hat{Xt}(-)$	(10) Pt (-).	(11) Pt (+).	(12) Measured
9:30-9:35	457.4	457.4	456.92	0.12	1.00	50	1	0.13	456.85	7.53	6.54	457.4
9:35-9:40	457.4	457.4	457.09	0.09	1.00	50	1	0.13	457.03	7.55	6.56	457.4
9:40-9:45	454.1	454.1	456.74	0.66	0.99	50	1	0.13	457.13	7.56	6.57	454.1
9:45-9:50	457.3	457.3	453.96	0.85	1.01	50	1	0.13	453.45	7.47	6.50	457.3
9:50-9:55	455.9	455.9	456.98	0.28	1.00	50	1	0.13	457.15	7.59	6.59	455.9
9:55-0:00	460.3	460.3	456.13	1.04	1.01	50	1	0.13	455.50	7.55	6.56	460.3

(0) Time.

(1) True value of the state variable, or travel time, in our case we set it equal to the measured value (seconds).

(2) Historical travel time (seconds), which could provide the state transition matrix F.

(3) Updated state estimated value, or updated predicted travel time $\hat{x}_t(+)$

(4) Prediction error percentage = predicted travel time / real travel time Error *100 %.

(5) State transition matrix $\Phi(t)$.

(6) Covariance matrix of observational (measurement) uncertainty.

(7) Covariance matrix of process noise in the system state dynamics.

(8) Kalman gain matrix K (t).

(9) State estimates (seconds), it is the predicted travel time $\hat{x}_t(-)$

(10) Estimation error covariance P_t (-).

(11) Updated estimation error covariance Pt (+).

(12) Measured travel time (seconds) from real world or simulation model X (t).

Note that the initial value for estimation error covariance P(0)=0 and the initial value for $\Phi(0)=1$.

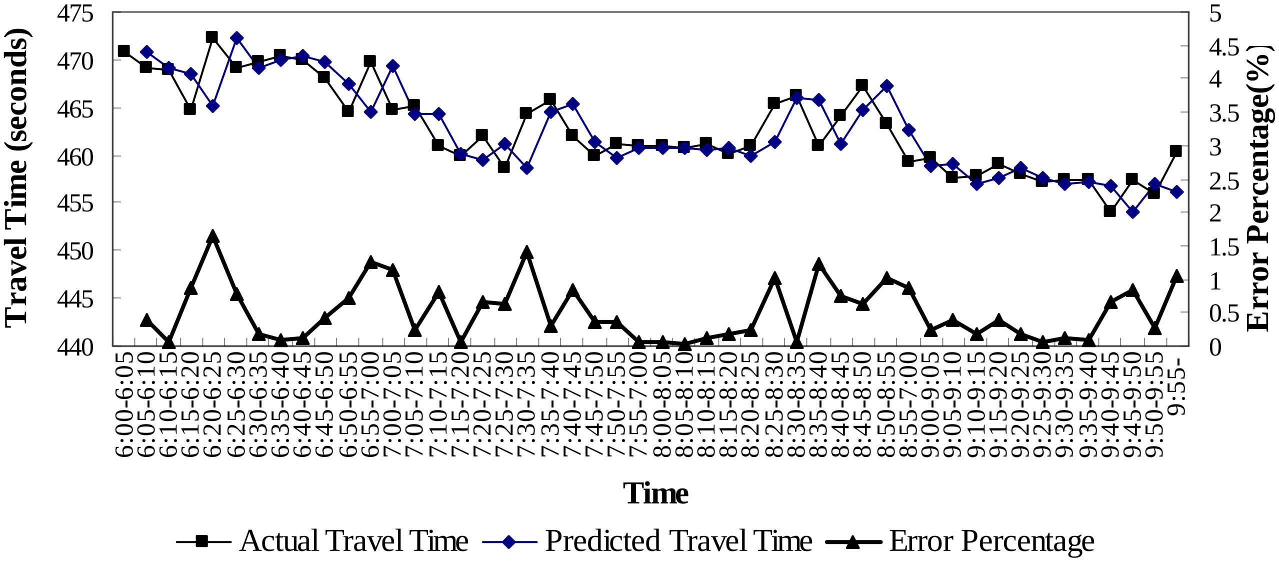


Figure 9 Predicted Travel Time from Start Point (899) to Ben Franklin Bridge (497)
(Length = 40730 feet)

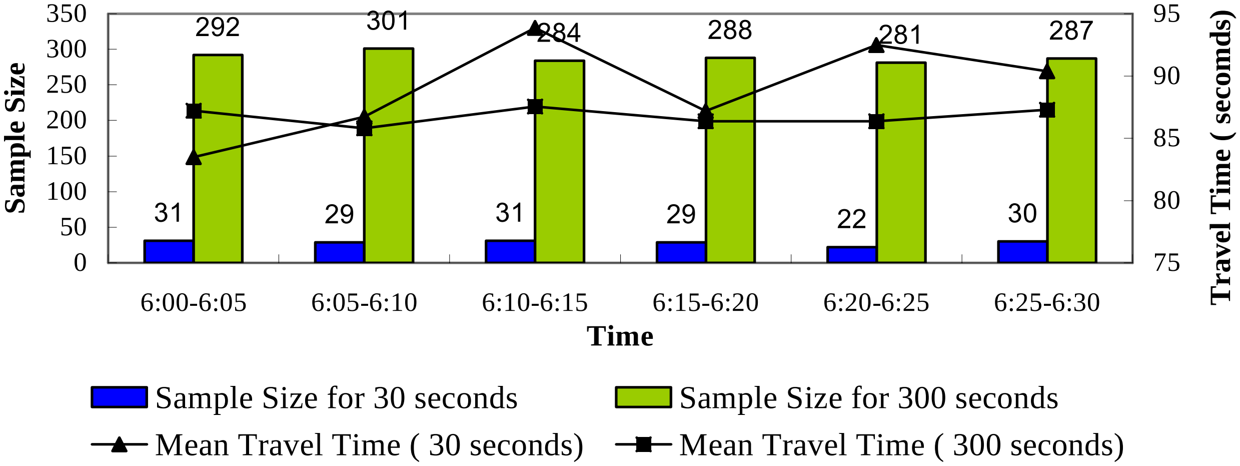


Figure 10 Comparison of Mean Travel Times at Sensor 1

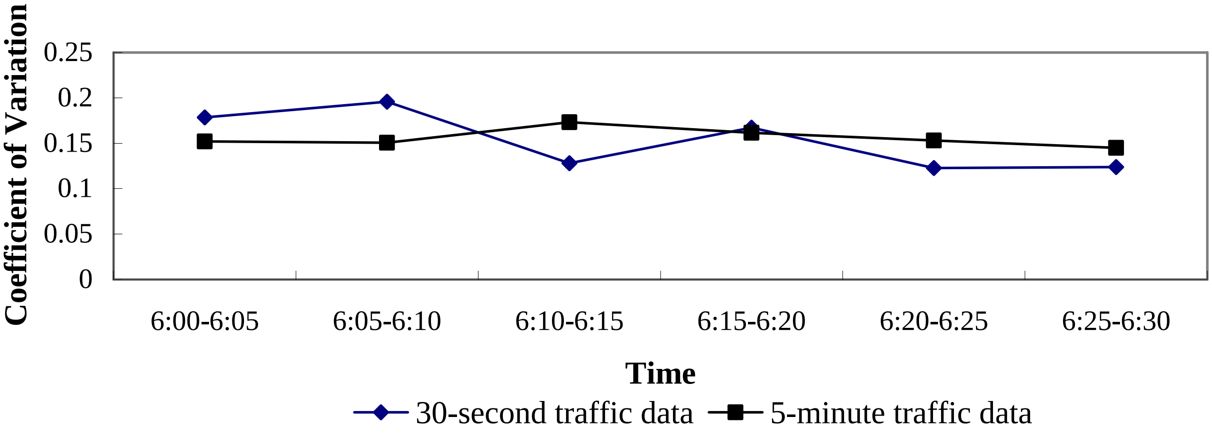
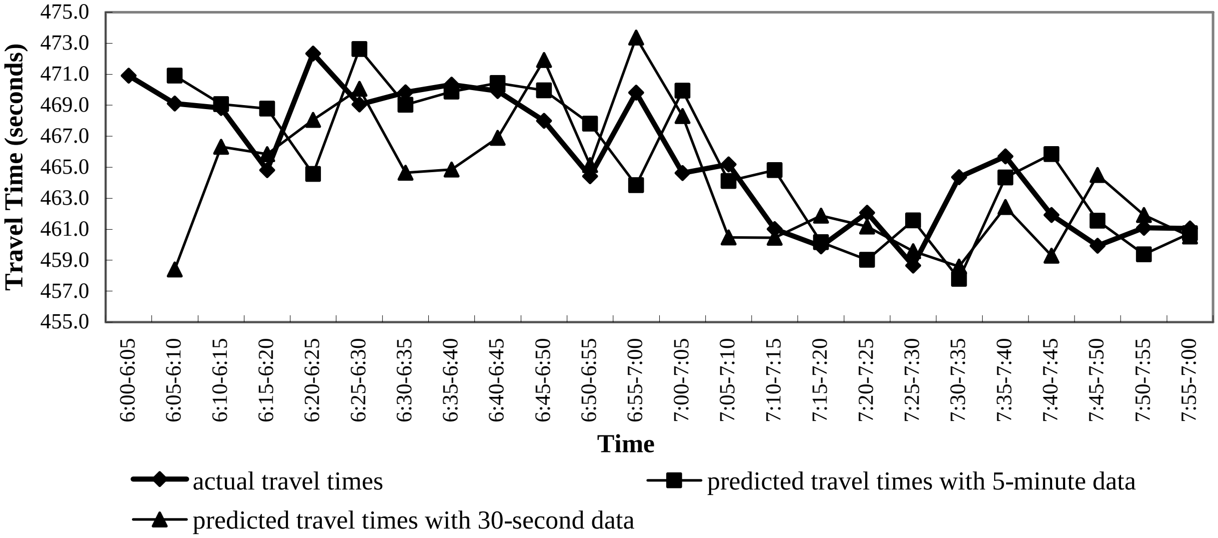
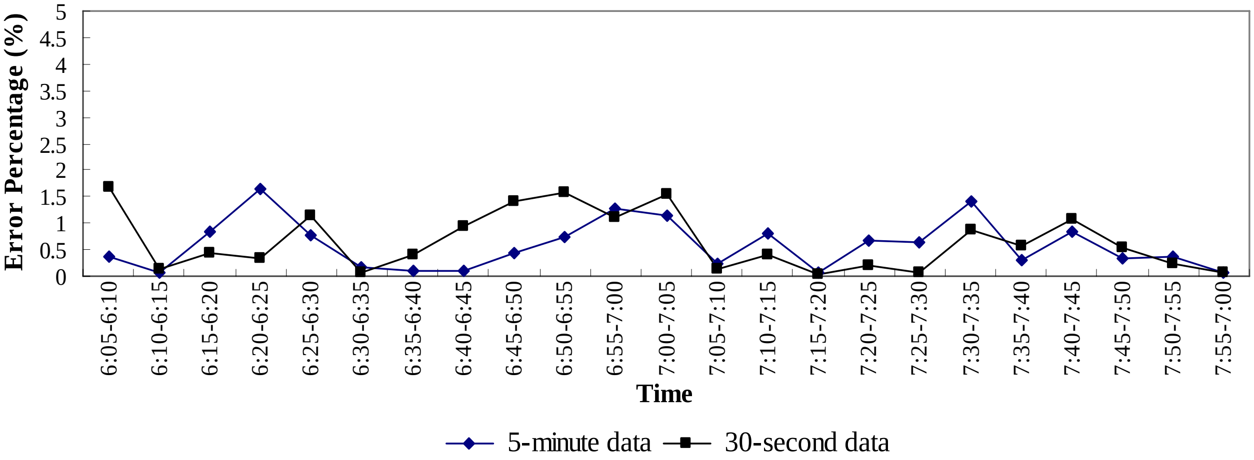


Figure 11 Comparison of Coefficient of Variation



Note: the predicted results are generated with the input obtained from simulation.

Figure 12 Predicted Travel Times with Different Data



Note: the predicted results are generated with the input obtained from simulation.

Figure 13 Prediction Errors

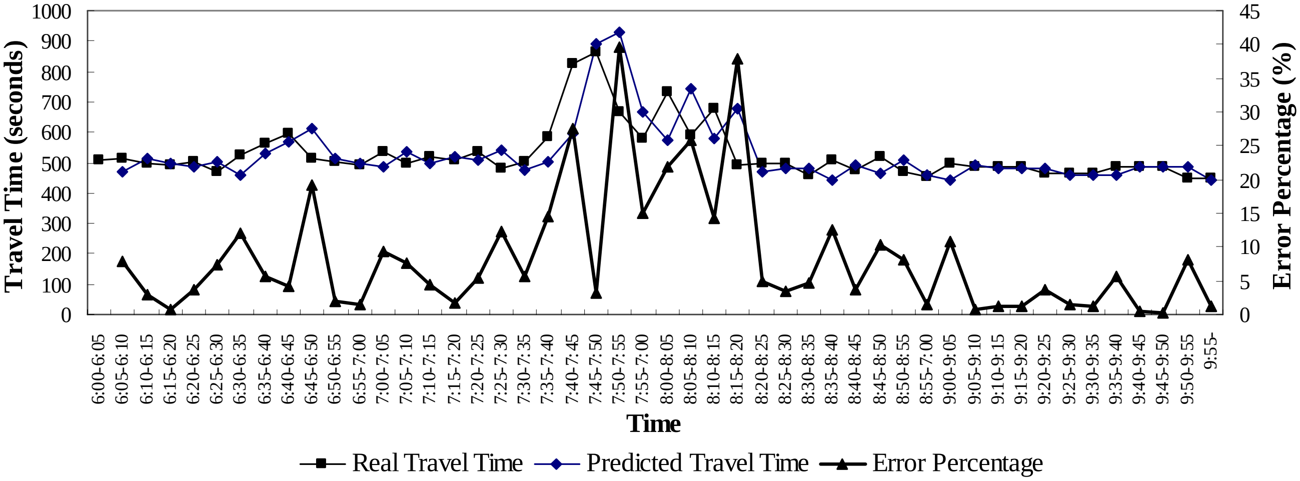


Figure 14 Predicted Travel Time with Real Sensor Data

Model Evaluation with Simulation Data

As discussed before, there is deviation of the data collected from 30-second in every 5-minute interval to that of the 5-minute average travel time. In Figure 11, it is shown that from 6:00 am to 6:30 am, the travel-time variance is 15.3 second^2 for the 30-second data set, while it is only 0.5 second^2 for the 5-minute data. The prediction results and accuracy with both types of data collected from simulation output are shown in Figures 12 and 13, respectively. In general, the prediction accuracy with 5-minute data is superior to that with 30-second data. However, the prediction errors (Figure 13) from both applications are less than 5 percents. This concludes that the 30-second data can be applied for predicting travel time with acceptable error.

Several prediction error indices, such as mean absolute relative error (MARE), root relative square error (RRSE), and maximum relative error (MRE), are used in this analysis and computed with Equations. 9, 10, and 11, respectively.

$$MARE = \frac{1}{N}\sum_t \frac{\left|x(t) - \hat{x}(t)\right|}{x(t)} \tag{10}$$

$$RRSE = \sqrt{\frac{1}{\sum_t x(t)} \sum_t \left[\frac{x(t) - \hat{x}(t)}{x(t)}\right]^2 x(t)} \tag{11}$$

$$MRE = \max \frac{\left|x(t) - \hat{x}(t)\right|}{x(t)} \quad \forall t \tag{12}$$

Note N is the number of samples, $x(t)$ and $\hat{x}(t)$ represent the actual and predicted travel time, respectively. The results of prediction error indices are summarized in Table 8.

Table 8 Comparisons of Predicted Travel Times with Different Data

Data	MARE	RRSE	MRE
5-minute data	0.0058	0.0074	0.0127
30-second data	0.0067	0.0084	0.0228

Note: the travel time of path from node 899 to node 497 comes from simulation model during the time period of 6:00am to 8:00am.

Real-world Data Application

Due to a limit number of sensors used in this study, the potential congested points are identified for locating the sensors because these places greatly contribute the variation of path travel times of the network. The acoustic sensors can record 30-second spot mean speed and volumes in every 5 minutes, which provide time varying traffic information for the use of travel-time estimation and prediction models. Both the mean and the variance of travel times can be recorded for each time period, and that will be the input of the prediction model. The developed simulation model can also be calibrated and validated with the real-world data collected by the acoustic sensors.

The real-time traffic information collected from five acoustic sensors is applied as input of the prediction model, which results are shown in Figure 14. Significant prediction error found during 6:00 am to 10:00 am is mainly caused by the inaccurate or biased travel-time estimates.

CONCLUSIONS

Conclusions

A method for estimating and predicting travel time to generate short-term future travel times for the motorist traveling in the study network is developed, while Kalman filter algorithm is applied for improving prediction accuracy.

For collecting traffic data, five acoustic sensors were installed at potential congested places in the study area to monitor the real-time traffic information. Besides that information, the installed sensors can generate speed estimates as well as provide data for calibrating simulation and prediction models.

The Kalman filter algorithm was applied to predict the travel time with the simulated travel time or real data detected from sensors. The historical data (travel times) for deriving the state variable transition parameter are chosen from the previous time interval. The covariance for measured variables and state variables are set to be constant. The traffic operation during a time period of 6:00am-10:00am is selected for testing predictive model, during which the traffic condition experienced a dramatic change due to the peak hour traffic flow.

The evaluation results show that the developed model could generate satisfactory results with the use of simulated output (e.g. 30-second and five-minute travel times). As shown in Figures 11 and 13, it is worth noting that the prediction error is comparatively high when coefficient of variation value is large, and error decreases when the coefficient of variation decreases. Statistical analysis demonstrates that in order to get a better performance of prediction, it is critical to investigate the relationship between coefficient of variation and prediction error. This should help to improve predictive performance of the developed model, and should be studied thoroughly.

Besides the inaccurate or biased travel-time estimates as the main reason for significant prediction error, since the prediction model is developed with the application of the Kalman filter algorithm, some parameters should be pre-specified according to the traffic characteristics of the study network. If the real traffic condition experienced a dramatic change, the constant covariance set in the Kalman algorithm cannot reflect the traffic-changing tendency under such situation and therefore also can bring bigger prediction error.

Future study

In future, four factors should be researched and addressed for developing more robust prediction algorithms development. First, the relationship between the covariance of measurement and process variability 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 filter algorithm can represent the real world data rather than setting it as a constant. This is necessary to increase the prediction accuracy in the real-world application. Second, the relationship between the coefficient of variation and prediction performance should be further explored. More statistical 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 to optimize the prediction-updating interval, by which the prediction model can catch traffic condition quickly and accurately. Fourth, according to different characteristic of real time traffic condition, how to identify the best historical data set for prediction use, which can guarantee that prediction models produce reliable results under various traffic conditions.

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