Developments and Applications of a Simulation-Based Online Travel Time Prediction System for Ocean City, Maryland

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ABSTRACT

The paper presents the framework and field application of a simulation-based on-line system for travel time prediction. The proposed system features its design to contend with most critical issues associated with real-time operations, which includes: estimation of missing volumes, detection of incidents, data filtering, and computation of traffic volumes over the projected time intervals so as to activate the simulation function. The proposed system was deployed over two routes of 30 miles between Salisbury and Ocean City, based on a total of 10 detectors. The preliminary application results clearly indicate that, with a proper integration the proposed system offers a cost-effective tool for real-time travel time predictions.

INTRODUCTION

This study presents a <u>Simulation-Based On-line Travel Time Prediction</u> (SBOTTP) system for traffic heading to Ocean City, which is a famous tour destination in Maryland Eastern Shore. Its population in the summer peak season can reach 150,000-300,000 people, compared with 7,000 to 25,000 people during the off-peak season. This large travelers population can lead to serious congestion on the major eastbound entry roads, especially in weekends and holidays. Hence, travelers can certainly benefit from a reliable travel time prediction system.

However, development of such a system is inevitably subjected to the roadway network and the budget constraints. The target network (see Figure 1) from Salisbury to Ocean City includes two major roads of 30 miles, where US-50 is a two-lane arterial with intersections controlled by signals or stop/yield signs on minor streets, but MD-90 is mainly a one-lane expressway with one signalized intersection located near Ocean City. The entire network is covered with only 10 detectors due to the budget constraints in the current phase. Thus, a reliable travel time profile cannot be obtained from existing detector-based travel time estimation models, which generally require densely-distributed detectors.



Figure 1. Illustration of the study network

The lack of extensively-distributed traffic sensors has made most travel time prediction approaches in the literature unsuitable for the Ocean City applications, because their usages of either time-series models or artificial neural network models [1-5] rely heavily on the availability and reliability of the historical travel time data. To deal with such constraints, this study proposes a simulation-based online travel time prediction system. Instead of performing travel time estimation as the prerequisite of prediction, this system employs the microscopic simulation software, CORSIM, to measure travel time directly. Various factors that might affect travel time, such as geometric conditions, speed limit, signal control, etc., can be taken care of with the simulation itself.

Note that to effectively perform on-line simulation with sparsely-distributed detectors, one needs to contend with the following critical issues:

- Filtering out erroneous or missing detector data
- Detecting the occurrence of incidents
- Predicting detector data in the projected time horizon.
- Estimating the entry volumes and turning fractions at all major interchanges/intersections
- Activating the procedure to update prediction results at the proper time interval
- Calibrating the simulation software for the Ocean City network

In the proposed SBOTTP system, various individual modules to tackle with each aforementioned critical issue have integrated together to make the system function seamlessly. The framework of the whole system is illustrated in Section 2, which emphasizes the logical relations and data flows among different modules. Section 3 details the mechanism of each individual module. A numerical study is followed to show the system's applicability in travel time prediction, using actual detector data and survey data collected from the Ocean City network. The last section summarizes the research work.

SYSTEM FRAMEWORK

Figure 2 illustrates the framework of the proposed <u>Simulation-Based Online Travel Time</u> <u>Prediction (SBOTTP)</u> system.



Figure 2. System framework

The entire SBOTTP system consists of three parts. The first part includes three supplemental modules for collecting, storing and providing required data for major functional modules, where:

- Surveillance System is responsible to obtain volume, speed and occupancy data from roadside detectors, and output these raw data into the detector monitor.
- Integrated Database is designed to store not only those filtered detector data, but also volume data both from roadside surveys and from turning-volume estimation module.
- Simulation Calibration module is used to calibrate key simulation parameters, such as driver populations and vehicle composition from field data.

The next level in Figure 2 is the core of the system, which includes the following major functional modules:

- Detector Monitor is designed to filter unreliable detector data from the surveillance system, and to impute missing data if only a short period of data is not available or acceptable.
- Incident Monitor is expected to determine if the available on-line data indicates any incidents.
- Detector Volume Prediction module will be activated to predict detector volumes in the projected time intervals if the newly collected detector data are significantly inconsistent with simulation results from previous simulation runs, or if the operation has reached the pre-scheduled update interval.
- Turning Volume Estimation module is used to generate the key simulation input (entry/exiting volumes at interchanges or intersections) based on both actual and predicted detector data.
- Online Simulator can then be executed to provide predicted travel times, based on all input volumes and associated information.

The last part of the system includes three types of output information, where Maintenance Message will be sent out whenever the detector monitor has identified persistent errors in the raw detector data. VMS Message will be activated if the incident monitor has detected an incident. The Information Website is mainly to display predicted travel times for potential users, and to provide the travel time and detector profile for system operators.

Note that the proposed system framework features its module-based structure. For instance, to provide required data for system operations, all supporting modules and functional modules are integrated seamlessly with each other through the carefully-designed data exchange process. On the other hand, each individual module is relatively independent with respect to its input and output needs, which offers the flexibility for further system expansion or algorithm update.

Key logic of some principal system modules

This section will detail the structure of some key system modules, which include: Detector Monitor, Incident Monitor, Detector Volume Prediction module, Turning Volume Estimation Module, Online Simulator, and Simulation Calibration Module.

Detector Monitor

The main purpose for having Detector Monitor module is to filter raw detector data from the surveillance system, and to eliminate invalid or unreliable data.

There are two types of methodologies available in the literature for identifying faulty data. The first type focuses on data in each individual detection interval without considering the potential correlations among sequential intervals. Payne et al. [6] presented several ways to detect various types of detector malfunctions, mainly based on preset thresholds for minimum and maximum flows, densities, and speeds. Jacobsen and Nihan [7] defined an acceptable region in the flow-density plane, and declared data to be good only if they fell inside. The second type of approaches simultaneously evaluates detector data from consecutive detection intervals with the assumption that data quality is consistent over these intervals. Chen et al. [8] proposed a Daily Statistics Algorithm to compare the statistics of potentially invalid data with a preset critical value.

For real-time operations of the proposed system, this study has adopted a method along the same line as that by Payne. This proposed Detector Monitor module will identify unqualified data over each detection interval through the following three steps:

- Filtering data with preset minimal and maximal flow rates, speeds and occupancies.
- Checking the interrelations between these three parameters based on well-known traffic flow properties.
- Setting the speed to the calibrated free-flow speed if all three parameters equal zero. This is for the scenario where no vehicle appears in the detection interval.

An index is assigned to each detector, which can remember the number of consecutive invalid or missing observations up to the current detection interval. If this index is greater than a predetermined tolerance value, the system will send out a warning message to the maintenance team and concurrently activate its Detector Volume Prediction module. Otherwise, the imputation function of the Detector Monitor will be employed to estimate the lost or erroneous data for further examination.

Data imputation subject has been extensively studied in the literature. Based on the data utilized, the imputation techniques fall into two general categories, namely, temporal relation-based and spatial relation-based [9, 10]. The former approaches employ measurement Ψ (q, v, or o) of the same detector *i* from surrounding intervals or from the same interval *t* of previous days *d*. A straightforward method to compute the estimated measurement $\hat{\Psi}_i(t)$ is to use a historical average. Other related techniques include moving average, weighted moving average, or time series models. The spatial relation-based techniques utilize data from neighboring detectors, D(i), at the same location or nearby locations, taking advantage of the potential lane-to-lane and location-to-location correlations in the imputation. Other than the direct use of mean or median or identified lane distribution patterns, Bickel et al. [11] proposed the following multi-point imputation approach based on linear regression:

$$\hat{\Psi}_{i}(t) = \operatorname{average}(\hat{\Psi}_{ij}(t), j \in D(i)), \text{ where } \hat{\Psi}_{ij}(t) = \hat{a}_{ij} + \hat{b}_{ij}\Psi_{j}(t)$$
(1)

Here $\hat{\Psi}_{ij}(t)$ is the estimated measurement of detector *i*, based on one of its neighboring detector *j*, while \hat{a}_{ij} and \hat{b}_{ij} are regression parameters estimated using historical data.

Since the current system for Ocean City utilizes RTMS detectors, all lanes at each detector location are covered with only one detector, and thus have the similar data quality. This fact, along with a large spacing between detectors, renders the temporal relation-based approach as the most appropriate option. Thus, the prototype of the Detector Monitor module employs a multi-point temporal relation, based on the following imputation approach:

$$\hat{\Psi}_{i}(t) = a_{1}\hat{\Psi}_{i}^{1}(t) + a_{2}\hat{\Psi}_{i}^{2}(t)$$
(2)

$$\hat{\Psi}_{i}^{1}(t) = \operatorname{average}(\Psi_{i}(t-1), \Psi_{i}(t-2), \dots, \Psi_{i}(t-T))$$
(3)

$$\hat{\Psi}_{i}^{2}(t) = \operatorname{average}(\Psi_{i}(t,d))$$
(4)

 $\Psi_i^2(t) = average(\Psi_i(t, d))$ (4) Where a_1 and a_2 are operator defined weighting factors, and $\hat{\Psi}_i^1(t)$ is the estimated measurement of detector i at interval t, based on previous intervals on the same day, while $\hat{\Psi}_{i}^{2}(t)$ is estimated measurement of detector *i* at interval *t*, based on the same interval from previous weekdays/weekends d.

Incident Monitor

Since the proposed simulation-based online travel time prediction system is for incidentfree traffic conditions, the filtered detector data from Detector Monitor will enter the Incident Monitor module to identify the occurrence and clearance of a detected incident.

Automatic incident detection (AID) has been extensively studied for both freeway and arterial streets in the literature. Examples of freeway AID approaches are pattern recognition algorithms, statistical approach based algorithms, neural network algorithms and etc., which have been reviewed in detail by Chang et al. [12]. More recent research work includes wavelet algorithms and GA algorithms [13, 14]. For incident detection on arterials, the ADVANCE project (1991-1996) has performed a series of research mainly along the same line as freeway incident detection [15]. Luk, et al. [16] tried to differentiate arterial incident from freeways incidents and emphasized the importance of upstream detectors in detecting arterial incidents.

Due to the real-time operation requirements as well as the limited data availability in the current phase of this study, the prototype of the Incident Monitor applies the most commonly used pattern recognition algorithm, the California-type Algorithms. The basic concept is to compare the preset thresholds with some measured parameters, and trigger an alarm when parameters exceed the thresholds.

Detector Volume Prediction

Since the proposed system aims to provide a predicted travel time profile for travelers intending to depart in the later time intervals, the embedded simulation engine needs not only the up-to-current detector volumes, but also estimated volume data in the projected time intervals.

To build the future volume vector in the projected time intervals for each detector, this study employs two types of statistical algorithms in the Detector Volume Prediction module. The first algorithm is for the locations where real-time detector information is available. In this case, in addition to historical volume data from previous days, volumes from previous intervals **vol'** = [v(t), v(t-1), ...] on the current day c are also used for prediction. A nearest neighbor statistical analysis is applied here, where each volume vector $\mathbf{vol} = [v(t+1), v(t+2), ...]$ for day d is defined as a point in a multi-dimensional space, with its coordinates as the vector (\mathbf{vol}_d) of the same day. Two indices are employed to define the distance between each historical day and the current day c. The first is the direct distance between two points in the defined space, or the root mean squared error between the cells of coordinate vectors, **vol**'_d, and, **vol**'_c.

dist₁ =
$$|\mathbf{vol'}_{d} - \mathbf{vol'}_{c}| = \sqrt{ave_{t,t-1,...}} [v_{d}(k) - v_{c}(k)]^{2}$$
 (5)

The second index is the Theil's U-statistic, which explicitly takes into account the fact that these two coordinate vectors are both auto-correlated time series [17]. Treating the coordinate of the historical record as the predicted series and the coordinate of the current record as the actual series, the Theil's U-statistic is defined as

$$dist_{2} = \sqrt{\sup_{k=t,t-1,\dots} \left[\frac{v_{d}(k) - v_{c}(k)}{v_{c}(k-1)}\right]^{2} / \sup_{k=t,t-1,\dots} \left[\frac{v_{c}(k) - v_{c}(k)}{v_{c}(k-1)}\right]^{2}}$$
(6)

If a historical day has a similar volume pattern as the current day, which means their coordinates will also be similar, the two distance indices will be closer to zero. After the nearest neighbor(s) is found, the predicted volume vector can simply use the arithmetic mean of the volume vectors (vol_d) from the nearest neighbors.

The second algorithm in Detector Volume Prediction module is for the locations where volumes cannot be updated because of detector malfunction. In this case, the only usable source for prediction is historical volume data from previous days. A similar nearest neighbor concept is applied here, but the lack of volumes from previous time intervals has motivated the following decision tree in Figure 3 instead of using the exact distance computation in selecting the historical records. Using this decision tree, the algorithm will check all historical records for these three criteria – season, weekdays and events. If a historical day falls in the same category as the current day based on each criterion, it will be viewed as a nearest neighbor with its data used for the detector volume prediction on the current day.



Figure 3. The decision tree to select historical records for detector volume prediction

Note that this decision tree is designed specifically for this study in Ocean City, Maryland as the city is a famous summer resort and the season is thus differentiated according to general peak/off-peak season of summer travelers.

Turning Volume Estimation

In most network systems, the detectors are usually deployed on the mainline segments, not ramps or intersections. However, most simulation software packages require entry volumes and turning fractions in all entry nodes and conjunctions, such as interchanges and intersections. To accommodate such information needs, this module is designed to estimate both ramp volumes and turning fractions, based on the detected mainline volumes and historical turning fractions.

Figure 4 shows the example freeway segment where the detectors are installed on the mainline segments (i.e., D_0 , D_3 and D_6). The objective of this module is to estimate reliable on-ramp volumes (i.e., q_2 and q_5) and off-ramp volumes (i.e., y_1 and y_4). To ensure the on-line application and to capture dynamic nature of the entire system, this study has tackled this problem with the following steps:



Step-1. Network Decomposition

The freeway segment is first divided into several sub-segments to formulate the relationship between detected volumes and unknown turning fractions. All sub-segments can be classified into three types:

- Type 1: Sub-segment with a detector upstream and an off-ramp downstream as L₁ and L₄ in Figure 4.
- Type 2: Sub-segment between an on-ramp and an off-ramp as L₂ and L₅ in Figure 4.
- Type 3: Sub-segment with an on-ramp upstream and a detector downstream as L₃ and L₆ in Figure 4.

Figure 5 shows a more general expression of these three types of sub-segments. The next step is to formulate the temporal and spatial interrelationships between detector data and unknown parameters, based on the properties of these three types of sub-segments and the travel time information.



Figure 5. Three Types of Segments

Step-2. Model Formulations

The proposed formulations are based on the following assumptions to accommodate the on-line needs:

- The historical data are sufficient for setting the upper and lower bounds of the turning proportions.
- The travel times between two successive time intervals do not change dramatically.
- The travel times for vehicles to traverse on each sub-segment do not exceed M time intervals.

Based on these assumptions, the relationships between detected data and unknown turning volumes for these three types of sub-segments can be formulated as follows:

• Type 1 – As shown in Figure 4(a), the detected volume, D_i , contributes to the mainline volume, U_{i+1} , and off-ramp volume, y_{i+1} . By taking into account travel times from the upstream node to the downstream node, one can formulate the following equation:

$$U_{i+1}(k) + y_{i+1}(k) = \sum_{m=0}^{M} \alpha_i^m(k) \cdot D_i(k-m)$$
(7)

 Type 2 – As shown in Figure 4(b), this sub-segment has no detected volume involved since all detectors are deployed on mainline segments. The formulation for this subsegment is applied to transit the mainline volume from detector i to detector i+1 shown as follow:

$$U_{i+2}(k) - q_{i+2}(k) = \sum_{m=0}^{M} \alpha_{i+1}^{m}(k) \cdot U_{i+1}(k-m)$$
(8)

Type 3 – As shown in Figure 4(c), the mainline volume, U_{i+2}, and on-ramp volume, q_{i+2}, contributes to the detected volume, D_{i+3}.

$$D_{i+3}(k) = \sum_{m=0}^{M} \alpha_{i+2}^{m}(k) \cdot U_{i+2}(k-m)$$
(9)

In Equations (7)-(9), $\alpha_i^m(k)$ is the parameter that denotes the percentage of the upstream volumes that traverses *m* time intervals to join the downstream volumes at time interval k. This parameter also satisfies the following natural constraints:

$$\sum_{m=0}^{M} \alpha_{i}^{m} (k-m) = 1$$
(10)

$$0 \le \alpha_i^m(k) \le 1 \tag{11}$$

<u>Step-3. Solution Algorithm</u>

The formulations presented in Step-2 may not have the exactly solution due to insufficient observations. Hence, the recursive estimation approach is employed, as it can estimate the unavailable traffic volumes recursively, based on the time-varying traffic volume information on mainline segments. This study applied Kalman filtering algorithm to perform the estimation.

Online Simulator

The online simulator module functions to project the network traffic conditions given the actual network control strategies and the estimated traffic demand patterns.

The online simulator in the current system is developed with CORSIM, a microscopic CORridor SIMulation program combining two of the most widely used traffic simulation models, NETSIM for surface streets and FRESIM for freeways. For online operations, the system has customized the program to reduce its computing time. Currently, the simulator needs only about 2 minutes to simulate the traffic conditions on the entire network over a 2-hour period, which is sufficiently fast to update traffic conditions in a timely manner.

To display the target travel time information on the website, the system has embedded a specially written program based on Visual Basic Runtime Extension. The program functions to aggregate vehicle travel time data based on different routes and different departure times from simulation output files.

Simulation Calibration

As one of the supporting system, the Simulation Calibration module functions to provide the most possible values for parameters embedded in the simulator, so as to reflect the actual traffic composition and driving behaviors in the target area. The importance of simulation calibration has been widely recognized in the literature, and procedures/methodologies for specific simulation software packages, such as CORSIM, PARAMICS and MITSIM, have emerged in recent years. Some calibration methods, such as those by Park [18, 19] and Merritt [20], have emphasized the following three key steps: the identification of calibration parameters; the definition of measures of effectiveness; and the selection of parameter value. For the first issue, Jayakrishnan [21] claimed that the selection of calibration parameters should base on sensitivity analysis. Along this line, Merritt and Zhang, et al. [22, 23] have identified various key parameters needed for calibration for CORSIM simulator. With respect to MOE, a wide range of parameters can be found in the literature, including both the aggregated indices such as Root Mean Squared Error or Mean Percentage Error, and the disaggregated indices based on various statistical tests [24]. As to the determination of parameter value, two commonly employed techniques are the iterative try-and-error approach, and the gradient-free-optimization algorithms such as Genetic Algorithm, Simplex based Algorithm and etc. [25, 26].

Based on the literature review, the Simulation Calibration module of the proposed system works offline and follows the following procedures:

- Identify calibration parameters that may affect vehicle travel times in the CORSIM simulation network. These parameters may be related to traffic compositions, such as driver population distribution and vehicle composition, or related to driving behavior such as start-up lost time, queue discharge headway or accepted gaps, etc.
- Perform sensitivity analysis, based on simulation experiments so as to identify the most important parameter in travel time computation.
- Define the measures of effectiveness to calibrate these parameters. Since the proposed system is focused on travel time information, an aggregated index based on simulated travel time and actual travel time will be used in this study.
- Design and perform field surveys to collect necessary data for simulation calibration.
- Select the parameters that could be directly measured from the survey results, such as the vehicle composition.
- Determine other parameters that could not be measured directly, based on iterative try-and-error procedures in simulation environment.
- Validation of the calibration results.

System Application – Ocean City, Maryland

This section presents the application of the proposed travel time prediction system for trips to the well-known holiday resort, Ocean City in Maryland. Field Survey was first performed during the memorial weekend, May 28 - May 30, 2005. To provide essential data for system evaluation, the survey includes turning volumes at critical intersections and interchanges, and travel time measurements over the entire study area.

Data Generation for Simulator Input

Prior to executing the simulator to produce predicted travel times, the system needs to perform the following tasks with its supporting modules:

Online-Data Filtering

This data filtering procedures are applied to reorganize the raw data from detectors, including fixing missing data and data smoothing. Figure 6 shows an example of the raw volume

data, measured by lane at an interval of one minute, directly received from the Detector 01 on May 29, 2005. The proposed data-filtering procedures are first used to remove outlier data and interpolate missing points, and then to smooth the remaining data to an interval of 5 minutes. Figure 7 illustrates the refined volume data in the unit of vehicle per hour. These sets of data are further used for predicting future detector volumes and estimating turning volumes.



Figure 6. Raw Data from Detector 01 – Volume



Figure 7. Refined Data for Detector 01 – Volume

Figure 8 shows the raw speed data with one-minute interval from Detector 06 on May 29, 2005. After exercising the data filtering procedure, the refined speed data at an interval of 5 minutes are illustrated in Figure 9.



Figure 8. Raw Data from Detector 6 – Speed



Figure 9. Refined Data for Detector 6 – Speed

This set of refined volume data is used as the basis for evaluating the performance of the proposed volume prediction and estimation modules. Both refined volume and speed data are also used to compare with the simulator output.

Detector Volume Prediction

The Detector Volume Prediction module serves to predict the detector volumes in the projected time horizon, and to provide the input for Turning Volume Estimation module. Figure 10 illustrates the predicted volumes and actually detected volumes on May 30, 2005 from 15:00 to 18:00. Figure 10 presents the predicted volume information on these 10 detector locations for 16:00-17:00 and 17:00 to 18:00, based on the current traffic condition at 15:00-16:00 on May 30, 2005 and available historical data over previous days.



Figure 10a. Predicted Volumes v.s. Detected Volumes



Figure 10b. Predicted Volumes v.s. Detected Volumes

Turning Volume Estimation

Based on the predicted detector volumes, the entry and exiting volumes can then be estimated with the Turning-Volume Estimation Module. With all essential input, the system can, thus, simulate the future traffic condition to generate the predicted travel time for the projected time intervals. Figure 11 shows the estimation results of the turning volumes compared with the survey data collected from May 28 to 30, 2005.



Figure 11a. Estimated Turning Volumes v.s. Observed Turning Volumes



Figure 11b. Estimated Turning Volumes v.s. Observed Turning Volumes





As shown in Figures 10 and 11, these two essential system modules can yield dependable volume information to serve as input for the simulator. Furthermore, to ensure the simulator is well calibrated, the output from simulator will be compared with the detected and observed data.

Simulator Output

To facilitate the use of the proposed system, this study has simulated the network of interest, and created an interface to monitor the simulator performance and the detector status. Figure 12 shows the proposed interface. As shown in Figure 12, this interface has three main functions:

- Execution Function including the "start" and "stop" buttons for the system
- Monitor Function including the simulator status and detector status.
- Display Function including the map-based output for the predicted travel time information and historical travel time data.



Figure 12. Snapshot of System Interface

To ensure the simulator is well calibrated, the system operator can always monitor the comparison results between the predicted and actually detected volumes (or speeds) as shown in Figures 13-15.









Figure 15. Speeds from Simulator v.s. from Detector 08

Note that travelers from Salisbury to Ocean city can take either one of the following two routes:

- Route 1 from US-50 and MD-90, and
- Route 2 only through US-50.

Figure 16 illustrates the predicted travel times and the actual travel times obtained from the field survey. Notably, all predicted travel times for both routes lie in a reasonable range for the target trip purpose. As shown in Figure 16, the predicted travel times for Route 1 are more reliable than those predicted for Route 2. It is probably due to the fact that Route 2 contains more signalized intersections, while Route 1 only has few intersections at the very beginning of the route.



Figure 16a. Travel Times from the Simulator v.s. from Surveys – Route 1



Figure 16b. Travel Times from the Simulator v.s. from Surveys – Route 2

Website for the Ocean City SBOTTP system

To facilitate the application of potential users, this study has set up a website for the Ocean City SBOTTP system. The website offers the following functions:

- The current status and data from each of these 10 detector (See Figure 17)
- The historical data from each of these 10 detectors
- The real-time predicted travel times (See Figure 18)

- The historical travel time profile computed from the system
- The current and historical profile of vehicle presence in Ocean City (See Figure 19). This population information is computed from the entry/exit volumes of Detector 5 and Detector 7, which will be used as the base for evacuation planning. Note that the vehicles through Route 1, which is not the major entry/exit route for tourists, are not counted due to the short of detectors in the current system.



Figure 17. Web Page to Display Current Detector Status



Figure 18. Web Page to Display Travel Time Prediction Results



Figure 19. Web Page to Display Population Information

Experience and Lessons for Large Scale Applications

The proposed SBOTTP system has been in operation for a period of almost four months (06/05/2005-10/30/2005) on the actual network from Salisbury to Ocean City. Although the system generally functions well, it has encountered several operational problems that should be considered carefully in future large-scale applications.

- The selection of detector locations. The current system only covers the most critical locations of network. These locations include the entry segment of the study network, end segments of the two routes, and segments immediately after an intersection/interchange with large entry/exiting volumes. Some of the traffic information is inevitably missing due to the limited number of available detectors, such as the number of vehicles from/to the minor roads.
- The calibration of detectors. Since the system predicts travel time mainly based on detector data, prediction accuracy will be greatly influenced by detector reliability. Thus, extensive field study is required to calibrate all the detectors before system operation. These detectors have to function properly under both free flow and congested traffic, or under traffic with a large percentage of heavy vehicles.
- The transmission of data from field devices to the system server. This function is currently realized in two steps: the subcontractor first obtains detector data via wireless network and then the system server automatically downloads these data every one minute via the Internet. However, communication failures are sometimes encountered, which can only be identified manually and has to be solved through the subcontractor. This may cause data loss for several hours.
- The effects of update interval. The current system updates travel time prediction for every five minutes, if there is no significant difference between actual and simulated detector data. This interval is selected because it has to capture the traffic conditions in a timely manner while subjected by some operational constraints. For example, the interval has to be long enough to allow the completeness of all prediction algorithms.

CONCLUSIONS

In summary, this study has presented a simulation-based online travel time prediction system for Ocean City, Maryland. The proposed system features its effectiveness in performing travel time prediction under limited available detectors. The core concept of such a system is to fully utilize the embedded capacity of microscopic simulation, and to capture various factors that may affect the travel time over different departure times. To contend with real-time operational requirements, the proposed system has integrated various supporting and functional modules in filtering erroneous detector data, monitoring traffic conditions, and generating necessary input for the online simulator. The key logic embedded in each module has been presented in the paper.

The field application presented in the paper clearly demonstrates the promise of the proposed system under the real-world operational constraints. Using only limited detector data and field survey data from the Ocean City network, the proposed system with all its supporting modules has performed as expected over the summer season in MD. The comparison results between these real-world data and simulation output have shown the potential of the proposed system for use in the target application. The performance of the proposed system is expected to increase with the number of available detectors, and the system's module-based structure is sufficiently flexible to accommodate any new available sensors.

REFERENCES

- 1. Roden, D., "Forecasting travel time." *Transportation Research Record* 1518, Transportation Research Board, Washington, D.C., pp. 7–12, 1996
- 2. D'Angelo, M., Al-Deek, H., and Wang, M., "Travel time prediction for freeway corridors." Presented at the 78th TRB Annual Meeting (CD-ROM), Washington, D.C., 1999
- Rilett, L., and Park, D., "Direct forecasting of freeway corridor travel times using spectral basis neural networks." *Transportation Research Record 1617*, Transportation Research Board, Washington, D.C., pp. 163–170, 1999
- Chien, S., and Chen, M., "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, 2001
- 5. Chien, S., Kuchipudi, C.M., "Dynamic Travel Time Prediction with Real-Time and Historic Data," Journal of Transportation Engineering, Vol. 129, No. 6, pp. 608-616, 2003
- 6. Payne, H.J., Helfenbein, E.D., and Knobel, H.C., "Development and testing of incident detection algorithms," Technical report FHWA-RD-76-20, Federal Highway Administration, 1976
- 7. Jacobson, L., Nihan N., and Bender, J., "Detecting erroneous loop detector data in a freeway traffic management system," *Transportation Research Record* **1287**, pp. 151-166, 1990.
- 8. Chen, C., Kwon, J., Rice, J., Skabardonis, A., and Varaiya, P., "Detecting errors and imputing missing data for single loop surveillance systems," Accepted for publication for 82nd Annual Meeting, Transportation Research Board, Washington, D.C., 2003
- 9. Conklin, J.H. and Smith, B.L. "The Use of Local Lane Distribution Patterns for the Estimation of Missing Data in Transportation Management Systems," Transportation Research Record, 1811, pp. 50-56, 2002

- 10. Conklin, J. H., Scherer, W. T., "Data Imputation Strategies for Transportation Management Systems," Research report, UVACTS-13-0-80, 2003
- 11. Bickel, P., Chen, C., Kwon, J., Rice, J., van Zwet, E., and Varaiya P., "Measuring Traffic," 2004
- 12. Chang, G.L., Li, Y.L., Payne, H.J., Ritchie, S.G., "Incident detection issues task A report: automatic freeway incident detection, a state-of-the-art review," Technical report for Federal Highway Administration, 1993
- 13. Teng, H., Qi, Y., "Application of wavelet technique to freeway incident detection," Transportation Research, Part C, Vol.11, pp.289-308, 2003
- 14. Abdulhai, B., Ritchie, S.G., "Development of a universally transferable freeway incident detection framework," The 76th Annual Meeting of the Transportation Research Board, Washington, DC, 1997.
- 15. Papers and reports about the Static and Dynamic Travel Time Estimation and Incident Detection Software of *ADVANCE*: Algorithms and Supporting Research, <u>http://ais.its-program.anl.gov/advance/reports/travel.time.software.html</u>
- 16. Luk, J.Y.K., Chung, E.C.S., Sin, F.Y.C., "Characterization of Incidents on an Urban Arterial Road," Journal of Advanced Transportation, vol. 35, no. 1, 2001
- 17. Theil, H., Applied Economic Forecasting, North Holland, 1966
- 18. Park, B.B., Schneeberger, J.D., "Microscopic Simulation model calibration and validation: a case study of VISSIM for a coordinated actuated signal system," The 82nd Annual Meeting of the Transportation Research Board, Washington, DC, 2003
- 19. Park, B.B., Qi, H., "Development and evaluation of simulation model calibration procedure," The 84th Annual Meeting of the Transportation Research Board, Washington, DC, 2005
- 20. Merritt, E., "Calibration and Validation of CORSIM for Swedish Road Traffic Conditions," The 83rd Annual Meeting of the Transportation Research Board, Washington, DC, 2004.
- Jayakrishnan, R., Oh, J.S., Sahraoui, A.E.K., "Calibration and Path Dynamics Issues in Microscopic Simulation for Advanced Traffic Management and Information Systems," UCI-ITS-WP-00-22, 2001
- 22. Zhang, L., Colyar, J., Halkias, J., Zhang, Y., "Validation and Calibration of CORSIM Traffic Simulation Model at Signalized Intersections," The 83rd Annual Meeting of the Transportation Research Board, Washington, DC, 2004.
- 23. Ben-Akiva M.E., Davel, A., Toledo, T., Koutsopoulos, H.N., Burghout W., Andreasson, I., Johansson, T., Lundin, C., "Calibration and Evaluation of MITSIMLab in Stockholm," The 81st Annual Meeting of the Transportation Research Board, Washington, DC, 2002
- 24. Barcelo, J., Casas, J., "Methodological notes on the calibration and validation of microscopic traffic simulation models," The 83rd Annual Meeting of the Transportation Research Board, Washington, DC, 2004.
- 25. Kim, K.O., Rilett, L.R., "Simplex based calibration of traffic micro-simulation models using ITS data," The 82nd Annual Meeting of the Transportation Research Board, Washington, DC, 2003.
- 26. Kim, K.O., Rilett, L.R., "A genetic algorithm based approach to traffic micro-simulation calibration using ITS data," The 83rd Annual Meeting of the Transportation Research Board, Washington, DC, 2004.
- 27. Town of Ocean City, Maryland, Emergency Operations Plan, December 2002