

Development of a Prototype Vehicle-Infrastructure Integration System for Real-Time Traffic Management

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16. Abstract While the vehicle-infrastructure integration (VII) concept has been in existence for a decade, its operational model and implementation strategy remain unclear. What is clear is that the VII if designed to meet its full expectations, must be able to support such applications as incident management, congestion mitigation, air pollution management, driving assistance, and disaster evacuation. However, fully realizing this vision involves meeting challenges beyond just establishing communication links among VII components. New operational algorithms and higher-layer network protocols must be developed in view of the heterogeneous devices, contexts, and wireless technologies that are involved, and the specific missions that must be achieved. Given the expected large scale of the VII system and ever increasing metropolitan areas, the traditional centralized operational concepts have become too costly to implement, maintain, and protect from threats. This research will develop a prototype hierarchical VII system with distributed decision making and reliable distributed networking that adequately accommodates future sophisticated VII applications.			
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EXECUTIVE SUMMARY

Freeway congestion is a major problem in many urban areas. It has been estimated that freeway incidents (events that impede the flow of traffic: accidents, disabled vehicles, etc.) account for one-half to three-fourths of the total congestion on metropolitan freeways in the United States.

Incident detection is the first and most important stage of incident management. The earlier an incident is detected, the sooner the incident is cleared, and the less delay other drivers experience. Highway traffic surveillance systems are widely used for incident management, real-time traffic management, traveler information, and hazard evacuation. Of these surveillance methods, some of the most widely used are closed circuit television (CCTV) systems, driver reports processing, highway crew patrols, and automatic incident detection (AID) systems.

However, CCTV systems and sensor networks for AID require extensive infrastructure support, such as wide bandwidth communication and intensive computation resources. Although many studies argue that driver-based incident detection systems (e.g. enhanced 911 services) can provide quick and accurate detection with less capital, maintenance, and operational costs, these systems do not perform well in areas with low cell phone usage or bad signals. There is also a risk of the phone call processing system becoming jammed during a severe incident. The labor intensive nature of highway crew patrols also tends to limit their wide spread deployment. Consequently, existing highway traffic surveillance is limited to major highways and urban areas.

In order to support the expansion of traffic surveillance systems and improve the performance of existing traffic-sensor-based systems, Morgan State University and Clemson University developed a prototype for a new traffic condition assessment and prediction system. This proposed framework — a vehicle-infrastructure integration (VII) system — assesses and predicts traffic conditions via wireless communication between roadside sensors and VII-equipped vehicles that have on-board processors, communication interfaces, and global positioning systems (GPS). Data gathered from vehicles are utilized to predict travel time, detect incidents, and determine the location of incidents and the likely number of lanes blocked.

Equipping vehicles and roadside infrastructures with wireless communication interfaces makes it possible to provide the traffic surveillance system with changing data on speed, acceleration/deceleration, position, and maneuvers. The expected substantial improvement in the quality and availability of this information would in turn increase the safety and mobility of large-scale highway systems.

The proposed framework does not require all cars to be equipped with the device: The incident detection rate was almost 100 percent when only 25 percent of vehicles on the road were VII-equipped. The proposed system is hierarchical and ad-hoc enabled, meaning the data can be exchanged between vehicles through vehicle-to-vehicle or vehicle-to-infrastructure relay. The roadside sensors collect the data and send it to the local traffic center. Local traffic centers then send the necessary information to the regional center. This hierarchical organization prevents massive amounts of information aggregating to single point.

In the proposed VII-artificial intelligence framework, two artificial intelligence (AI) paradigms — artificial neural networks (ANN) and support vector regression (SVR) — are used to determine existing traffic conditions. Future travel time is based on current travel time and the VII-enabled vehicles' flow and density. To evaluate the proposed framework, computer models of both the VII-ANN and VII-SVR methods were developed and evaluated in a microscopic traffic simulation environment that was based on a highway network in Greenville, S.C. In terms of traffic condition assessments and prediction accuracy, the VII-AI framework was superior to a baseline instantaneous travel-time prediction algorithm. The VII-SVR model also slightly outperformed the VII-ANN model. Moreover, the VII-AI framework performed reasonably well during non-recurrent congestion scenarios that have traditionally challenged traffic sensor-based prediction methods for highway travel time.

INTRODUCTION

The operation of numerous key components of intelligent transportation systems (ITS) — incident management, real-time traffic management, traveler information, and hazard evacuation — rely heavily on the support of an effective and efficient highway traffic surveillance system. Among the different traffic surveillance methods, CCTV systems, driver reports processing, highway crew patrols, and AID systems are the most widely used (Parkany and Xie, 2005). However, CCTV systems and sensor networks for AID require extensive infrastructure support.

Although many studies argue that driver-based incident detection systems (e.g. enhanced 911 services) can provide quick and accurate detection with less capital, maintenance, and operational costs, these systems do not perform well in areas with low cell phone usage or bad signal (Xie and Parkany, 2002; Mussa and Upchurch, 2000 and 1999; Walters et al., 1999; Skabardonis, 1998; and Mussa, 1997). There is also always the risk of the phone call processing system becoming jammed during a severe incident. The labor intensive nature of highway crew patrols tends to limit their wide spread deployment. Consequently, highway traffic surveillance is currently limited to major highways and urban areas.

The VII concept provides an opportunity to improve the effectiveness and efficiency of existing traffic surveillance systems. As envisioned in VII systems, vehicles and roadside infrastructures equipped with wireless communication interfaces provide the traffic surveillance system with current data on speed, acceleration/deceleration, position, and maneuvers. The expected improvement in the quality and availability of information enhances the safety and mobility of large-scale highway systems (National VII Coalition, 2007). While previous research has focused primarily on the potential of using VII for highway and intersection collision avoidance, limited research has been done regarding the feasibility of using VII for real-time highway traffic surveillance.

On the other hand, several researchers have shown that vehicle-generated data can provide reliable estimates of traffic conditions, including identifying incidents and congestion (Sermons and Koppelman, 1996; Qi et al, 2002; and Cheu et al., 2002). In order to take full advantage of the wealth of data likely to be provided by VII, intelligent algorithms are needed for processing the microscopic data generated.

Objectives

The objectives of this research are to develop a VII prototype that can be utilized for real-time travel time prediction. This study evaluated the use of two AI paradigms — ANN and SVR — for a VII-based, real-time freeway traffic condition assessment and travel-time prediction framework.

Support vector machine (SVM), a relatively new computational intelligence paradigm, will be used for real-time traffic condition assessment. Researchers have reported that SVM requires less computational resources, and has greater prediction potential and learning ability compared to other paradigms (Lin, 2004, Sun et al., 2002; Wu et al., 2004; Vanajakshi and Rilett, 2004; and Cheu et al., 2003). Following the development of the proposed VII-SVM framework for

traffic condition assessment, this study evaluated the incident detection functionality and performance of the framework in a microscopic traffic simulation environment. The use of simulation provides an alternative and more affordable evaluation method when compared to the more costly and complex field experiment approach.

LITERATURE REVIEW

Dynamic Traffic Assignment

Traffic assignment is the designation of origin-destination flows to transportation routes based on factors that affect route choice. Traffic assignment can be classified in many ways, but two of the main classifications are static and dynamic. Static assignment models assume that link flows and link trip times remain constant over the planning horizon. In dynamic traffic assignment models, the demand is allowed to be time-varying so that the number of vehicles passing through a link and the corresponding link travel times are time-dependent. Other classifications of traffic assignment models are analytical/simulation-based, system optimal/user equilibrium, stochastic/deterministic, path-based/link-based, and flow-based/vehicle-based. CONTRAM, DynaMIT, and DYNASMART are the most common mesoscopic vehicle-based dynamic traffic assignment software that can be used to implement our test network.

DynaMIT is designed to operate in real-time, accept real-time surveillance data, and estimate time-dependent origin-destination flows. DynaMIT is also organized around two major simulation functions: state estimation and prediction-based guidance generation. State estimation provides the estimates of the current states in the form of network state by giving link or segment-based flows, queues, speed, densities, and origin-destination flows. This relay of information is carried out through successive iterations between demand and supply simulators.

Traffic sensors provide estimates of the current state of the network, and the estimate can vary depending on the type of surveillance system employed. In an ideal system with a two-way communication between the traffic control center and vehicles, perfect information about vehicles' locations — and possibly their origins and destinations — can be obtained. Since most existing surveillance systems are limited to vehicle detectors located at critical points in the network, the information provided by these traffic sensors must be used to infer traffic flows, densities, and queue lengths at all locations in the network. However, the VII system developed in this study found more precise information through the use of roadside agents, vehicles, and control centers.

Online Travel Time Prediction

Depending on the prediction period horizon, the real-time travel time prediction can be categorized as pre-travel or en-route (Chung et al., 2004). Pre-travel prediction usually has a prediction horizon of 30-60 minutes. On the other hand, en-route prediction, the focus of this study, has a time horizon of 0-5 minutes. Existing short-term online travel time prediction methods include the simulation-based techniques DYNAMIT and DYNASMART (Ben-Akiva et al., 2002; Fei et al., 2005); statistical analysis of historical and real-time data (Rice and Van Zwet, 2001); linear model (Zhang and Rice, 2003); pattern matching (Bajwa et al., 2003); and AI-based techniques.

Simulation-based travel time prediction methods are generally regarded as accurate and robust. However, the requirements of dynamic origin-destination estimation make them resource intensive and complicated to implement and operate. Statistical methods are relatively simple

and easy to implement, even though they don't work well for congested conditions due to their insufficient consideration of the highly stochastic and complex nature of the traffic network.

Previous studies have reported promising results from the applications of AI in travel time prediction. Among the different AI paradigms used for travel time prediction, feed-forward neural networks appear to be the most popular (e.g. Dia, 2001; Huisken and Van Berkum, 2003; Innamaa, 2001; Park and Rilett, 1998; Park and Rilett, 1999). For example, one study used a state-space neural network model to explicitly consider the prediction of travel time in each section to derive the future travel time of the entire network (Van Lint, 2006).

While the AI methods for travel time prediction are fairly accurate and computationally efficient, their developments are usually labor intensive and tailored for specific application (Van Lint 2006). The conventional ANN method suffers from the highly nonlinear and non-monotonic function for the real-time travel time prediction problem. This specific application challenges the slow convergence and local optimization issues of the popular feed-forward neural network (Park et al., 1999).

Pre-classification and pre-mapping of the input data have been proposed to remedy the problem in several studies. More recently, support vector regression (SVR), a relatively new AI paradigm, was suggested for short-term travel time prediction (Wu et al., 2004). Though the inputs included the travel time (which would not be available for a real-time application), the work demonstrated that SVR is a promising tool for travel time prediction. Other researchers have reported that SVR requires less computational resources and has greater prediction potential and learning ability than other paradigms.

Support Vector Regression

SVR is a member of the SVM paradigm family, which is based on statistical learning theory and the principal of structural risk minimization (Sewell, 2005; Vapnik, 1995). SVM algorithms include a suite of supervised machine learning algorithms that are applicable to classification. They use kernel functions to map the input data into a high-dimension feature space where linear classification becomes feasible. Since the kernel mapping is implicit — meaning that it depends only on the inner or dot product of the input data vectors — it is possible to map the data into high dimensions and still keep the computational cost low.

The SVM model depends on a subset of the training samples known as support vectors. Support vectors are used to determine the hyper-plane for classification or regression. Examples of other SVM applications to transportation problems include their use for traffic speed and traffic flow predictions, and incident detection in the context of ITS applications (Cheu et al., 2003; Ding et al., 2002; Sun et al., 2002; Vanajakshi et al., 2004; Wu et al., 2004).

Vehicle Infrastructure Integration

Since 2003, the Federal Highway Administration has sponsored a variety of efforts that have led to the development of the national VII architecture and its functional requirements (FHWA, 2005). Currently, the U.S. Department of Transportation is conducting a research

program — the Mobility Applications for Vehicle Infrastructure Integration Initiative — in which the potential for transmitting information between infrastructure and vehicles to enhance safety and mobility is being studied. Several states, including California and Michigan, are testing various methods for implementing these types of programs (ITS America, 2007).

VII California established the efficacy of using VII for online traffic condition assessment (UC Berkeley, 2006). In that demonstration, individual vehicles were used as probe vehicles to send their location, speed, direction, and time stamp to a centralized processing center for traffic surveillance and traveler information dissemination. Two studies — Crabtree and Stamatiadis (2007), and Tanikella et al. (2007) — illustrated that travel time data generated from VII can reliably estimate traffic conditions and identify incidents. Many other studies investigated the potential of VII for road and weather condition assessment (Petty et al., 2007; Tanka and Piotrowicz, 2007). However, none of these studies appears to have used VII for online travel time prediction.

This study proposes the use of direct traffic measurements available from individual VII-enabled vehicles and ANN or SVR for real-time highway travel time prediction.

METHODOLOGY

The proposed VII-ANN and VII-SVR frameworks were developed and evaluated in a microscopic simulation environment. The highway network in Spartanburg, S.C., was used for highway traffic condition assessment, and online travel time prediction was based on the network in Greenville, S.C.

Basic Assumptions and Proposed Framework

Roadside units with microprocessor and wireless interfaces were assumed to be located at every interchange along the highways in the selected test networks. Traffic data collected by the roadside units from VII-enabled vehicles was aggregated at a master controller where ANN or SVR algorithms would be running to relate the current traffic condition to the travel time of vehicles departing the start point during the next time step. Each VII-enabled vehicle could communicate with the roadside units on approach or through the relay of other vehicles.

The VII system was designed to use time stamp and vehicle location information from the individual VII-enabled vehicle to identify macroscopic traffic measurements. After a preliminary study, current travel time, flow, and density were selected as the three input variables that best predict travel time. The current travel time was determined from the average travel time for the VII-enabled vehicles that completed their trip during the last time step. The flow was calculated as the total number of VII-enabled vehicles entering the segment during the previous time step, and the density was calculated as the total number of VII-enabled vehicles remaining within the segment divided by the segment length.

Building Test Network

Paramics, the microscopic traffic simulation model, was used to create a realistic traffic environment to develop and evaluate the VII-ANN and VII-SVR framework for travel time prediction (Quadstone, 2008). Paramics is a time-step, behavior-based model and can incorporate detailed network and traffic control information to provide a realistic representation of traffic conditions.

A unique feature of the Paramics model that made it quite appropriate for this study is its application programming interface (API). API is an add-on module that allows users to modify many features of the underlying Paramics models and program any additional functionality. In this study, the API was used to collect current traffic measurements and apply the ANN and SVR models for estimating future travel time.

With the simulation model developed, the next step was to build the SVM model that would be used by the VII-enabled vehicles for traffic condition assessment. The development and calibration of the SVM algorithm required a set of training cases with the designed input parameters (namely speed and lane-changing), and the correct vehicle decisions on the classification of the traveling experience.

Traffic Condition Assessment

The idea of using the microscopic traffic data from an individual vehicle to detect incidents was based on the assumption that the kinetics of vehicles passing an incident site or stopped in a queue would be affected when an incident occurs. These kinetics — speed changes, increased lane-changing maneuvers, and significant acceleration and deceleration — could then be recorded by VII-enabled vehicles. The VII-enabled vehicles' speed profiles and lane-changing behavior over a selected sending interval s_t , were used to identify the patterns that indicate the occurrence of incidents. The percentage of VII-enabled vehicles in the total traffic population is the penetration rate. In the Paramics model, the VII-enabled vehicles were assigned as a special vehicle type, with varying percentages relative to the entire traffic population depending on the penetration rate of the VII-enabled vehicles. An API program was then developed for each VII-enabled vehicle to log an array of historical speed values and lane-change indicators for each time slice s_t .

The Spartanburg, S.C., network contains three freeway corridors — I-85, I-26, and I-85 Business — which meet to form a triangle (Figure 1a). This section was chosen for evaluating the proposed VII-SVM incident detection system because of the high accident volumes on I-85 from Exits 68-70. The freeway segment has three lanes in each direction, and incidents were simulated by the blocking of one, two, and three lanes. The simulated incidents' impacts on vehicle kinetics were then recorded.

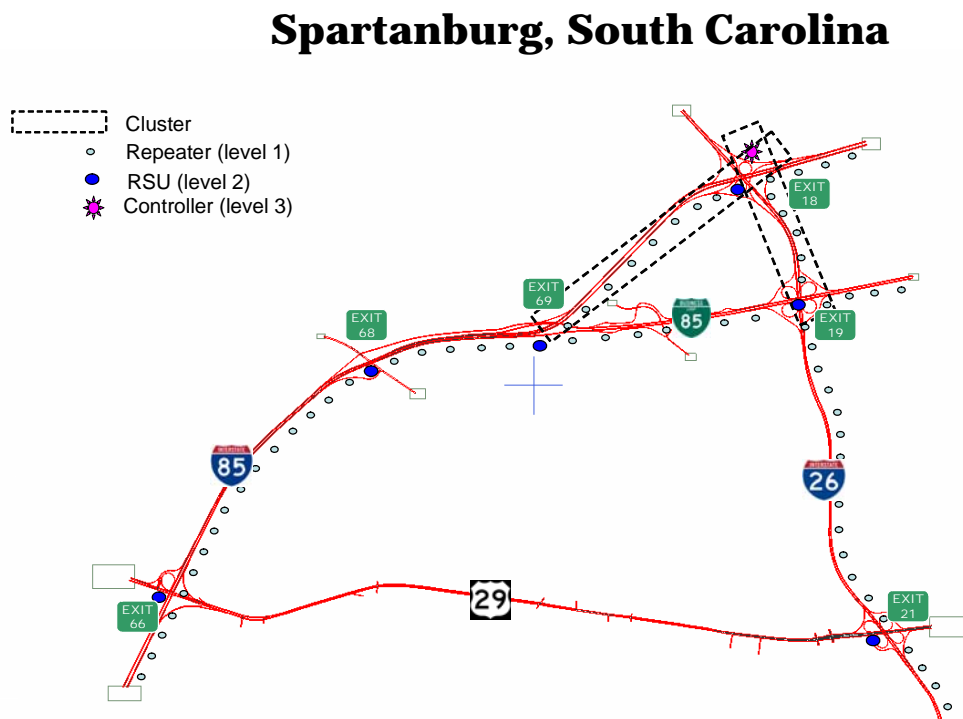


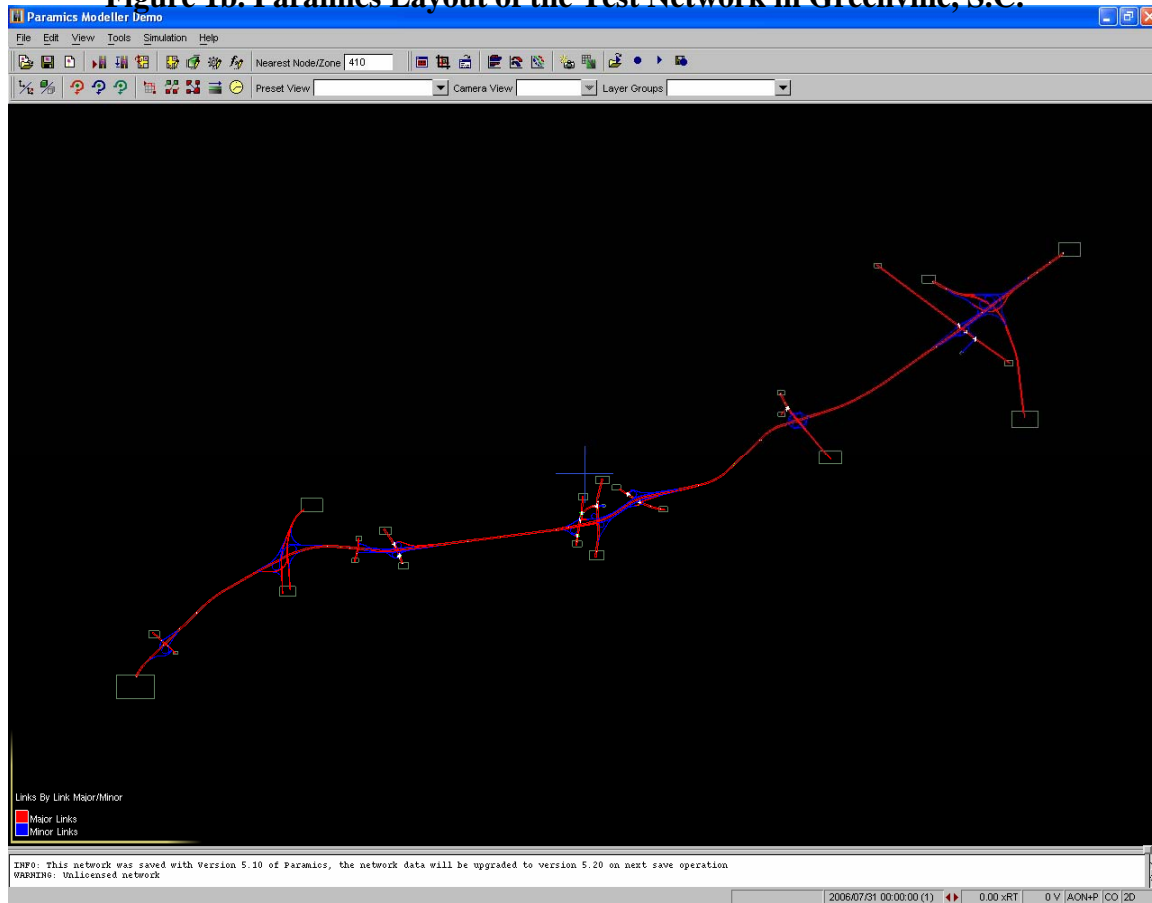
Figure 1a. Functional Elements Set Up of a Case Design for the VII-SVM Framework Implemented in Spartanburg, S.C.

Network building in Paramics for the Spartanburg and Greenville networks were done in the same way. First, geometric, traffic control, and traffic volume data were collected. The networks were then calibrated according to methodology used by other researchers (Gardes et al., 2002; Hourdakis et al., 2003). The simulated volume output was compared to the field traffic counts data, and simulator animations were judged against the site observation. The calibration process also compared site-collected queue lengths and travel times to those produced by the simulation model. After many iterations and adjustments to the road network and driver behavior parameters, the simulation models were considered to accurately reflect the observed travel times within one percent. In the both networks, no significant difference was observed between the observed and simulated queue lengths at bottleneck segments.

Traffic Condition Prediction

The I-85 corridor in Greenville, S.C., consists of approximately 11 miles of freeway and six interchanges (Figure 1b). This section of I-85 is part of the corridor that connects Atlanta, Ga., to Charlotte, N.C. It also services the traffic to and from the Greenville metropolitan area, which has a population of 601,986 according to the 2006 census estimate. Both long-distance (about 30 percent of the total traffic volume) and local traffic (the remaining 70 percent) have a significant impact on the freeway network. While this freeway section is further supported by I-385, there are no major arterials parallel to I-85 that can accommodate traffic diversion during congestion.

Figure 1b. Paramics Layout of the Test Network in Greenville, S.C.



The prototype travel-time prediction system considered in this study predicts travel time along the northbound segment of I-85 from Exits 40-51. The free flow travel time for that segment is around 10 minutes. During congestion, it could take more than 20 minutes to traverse the segment. The traffic scenario that this study focused on was the weekday p.m. peak period. Simulations started at 4:00 p.m. and were allowed 20 minutes of warm up time. After traffic was fully loaded onto the network (i.e. at 4:20 p.m.), the travel-time prediction system started working and continued until 9:40 p.m. Peak traffic flow generally occurred between 4:30-6:30 p.m.

With the simulation model developed, the next step was to generate the training and testing cases for the VII-ANN and VII-SVR travel time prediction model. The development and calibration of these two AI algorithms required a set of training cases with the three input variables (current travel time, VII-enabled vehicles flow, and density), and the target output (the simulation-generated travel time for vehicles departing the start point during the next time step).

As with the traffic condition assessment, the VII-enabled vehicles were assigned a special vehicle type, with varying percentages relative to the entire traffic population dependent on the penetration rate of the VII-enabled vehicles considered. An API program was then developed to log a series of cases or vectors (x_i, y_i) , where y_i is the target travel time and x_i is the input vector that has the three aforementioned member variables. This study used a time step of 2 minutes.

Table 1 shows an example of the training cases for the ANN and SVR algorithm. To create the training and testing cases set, a simulation model with various penetration rates generated the traffic data. The data for the I-85 study segment included four weeks of weekday afternoon peak periods with recurrent congestion. The traffic demand profile for each weekday was varied to represent the day-to-day travel time pattern and test the robustness of the VII-AI framework.

Table 1. Sample Data Log in Controller for Travel Time Prediction

	Measured Travel Time (second)	VII-enabled Vehicle Density (vehicle / segment length)	VII-enabled Vehicle Volume (vehicle / time step)
Inputs	599.21	175	54
Target Travel Time		718.75	

Figure 2 illustrates the variation in the travel time patterns of ten weekdays with five different traffic demand inputs. Those travel time data created a realistic and challenging test environment. However, the same traffic demand inputs could result in a different travel time pattern due to the random nature of the microscopic traffic simulation model.

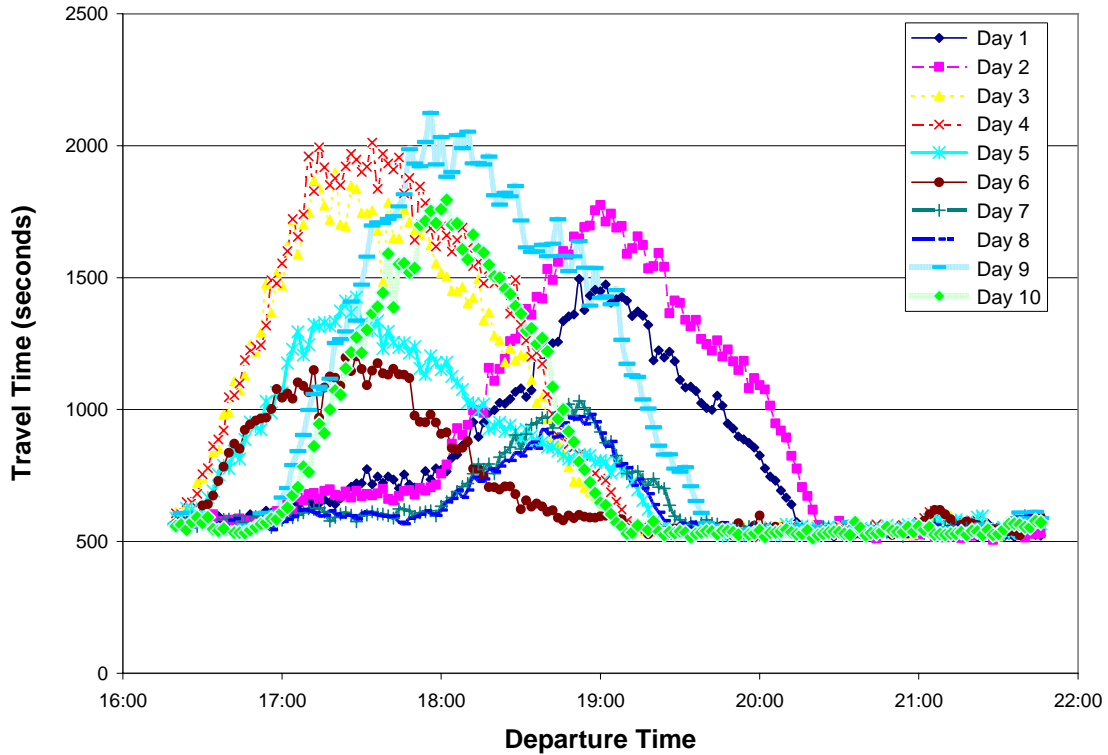


Figure 2. Travel Time Pattern with Different Demand Inputs

Developing the ANN Model

Because the target travel time is roughly monotonic with the input variables (previous travel time, density and flow) and the dimension of the input vector is only three, the conventional and widely-used multilayer feed-forward (MLF) neural network with back propagation learning was used for developing the VII-ANN model for online travel time prediction. The MLF neural network consists of one input layer, two hidden layers, and one output layer. Sigmoid functions were used as the transfer functions for the hidden layers, and a linear function was used for the output layer. The NeuroSolutions[®] (NeuroDimension 2008) software was used to find the 10 neurons in the first hidden layer and five neurons in the second. The training ended when the number of training epochs exceeded 10,000 or the cross validation error started to increase. A learning rate equal to 0.01 was used.

Developing the SVR Model

ε -SVR was adopted to find the prediction function that optimized the minimum distances between the regression hyper-plane for any sample of the training data. This can be achieved by solving Equation 1 (Hsu et al., 2007; Chang and Lin, 2005):

$$\begin{aligned} \min_{w,b,\xi,\xi^*} \quad & \frac{1}{2} w^T w + C \sum_{i=1}^l \xi_i + C \sum_{i=1}^l \xi_i^* \\ \text{subject to} \quad & w^T \phi(x_i) + b - y_i \geq \varepsilon - \xi_i \\ & -w^T \phi(x_i) - b + y_i \leq \varepsilon - \xi_i^* \\ & i = 1, \dots, l \text{ and } \xi_i, \xi_i^* \geq 0 \end{aligned} \quad (1)$$

where:

- $(x_i, y_i), i = 1, \dots, l$ is the data training set;
- $x_i \in R^3$ represents the input vector with three real numbers;
- $y_i \in R$ is the target output;
- $w, b, \xi / \xi^*$ are the coefficient, constant, and error term for the SVR prediction function;
- ε is a parameter in ε -SVR representing the marginal error of regression; and
- ϕ is the transformation function, which mapped the training vectors x_i into a higher dimensional space and enabled the SVR to find a hyper-plane for linear regression with the maximal margin in this higher dimensional space. The support vectors are those (x_i, y_i) whose error terms ξ / ξ^* are not 0.

After the training process identified the support vectors and all the mapping function coefficients and constants, the prediction function for a new input can be expressed as:

$$y = w^T \phi(x) + b \quad (2)$$

Furthermore, the kernel function $K(x_i, x_j) = \phi(x_i)^T \phi(x_j)$ determines the form of the transformation function ϕ . In this study, radial basis functions were used as the kernel functions for their good performance in many scenarios (Vanschoenwinkel et al., 2006).

$$\begin{aligned} K(x_i, x_j) &= \exp(-\gamma \|x_i - x_j\|^2), \\ \gamma &> 0 \end{aligned} \quad \text{Here, } \gamma \text{ is the kernel parameter.} \quad (3)$$

Scaling is important for the success of AI paradigms such as ANN and SVR (Hsu et al., 2007; Sarle, 1997). Before training, all the data were linearly scaled to a range of [0, 1] using a common range file that was saved and re-used later during the prediction phase. Moreover, the authors randomly divided the data into five groups to maximize the utility of the training data while searching for the SVR optimal parameters set. Each time, four groups of data were used to train a SVR model with a possible combination of parameters, while the trained model was tested on the remaining group to estimate the prediction accuracy in terms of mean squared error. This process was repeated five times with the same parameter combination for different training and testing groups in order to obtain an average value for the cross-validation prediction

accuracy rate. The SVR algorithm for the travel time prediction was implemented using Paramics API.

Evaluation of the VII-ANN and VII-SVR Model

Different penetration rates were tested to evaluate the effectiveness of the proposed travel-time prediction framework. The measures of performance for the VII-AI framework included a frequency plot that gave the percentage of prediction cases corresponding to different levels of the relative error between the predicted and the simulated travel time. In addition, four other measures were used to assess the prediction accuracy:

- 1) root mean of squared error proportional (RMSEP);
- 2) mean relative error (MRE);
- 3) mean absolute relative error (MARE); and
- 4) standard deviation of relative error (SRE).

These four measures are defined in Equations 4-7, where t_i is the target value of the travel time; y_i is the predicted value; $e_i = y_i - t_i$ is the prediction error i ; $re_i = e_i / t_i$ is the relative error; and N is the number of experiments.

$$\text{RMSEP in percentage: } \frac{100}{\bar{t}} \sqrt{\frac{1}{N} \sum_{i=1}^N (e_i)^2} \quad \text{with } \bar{t} = \frac{1}{N} \sum_{i=1}^N t_i. \quad (4)$$

$$\text{MRE in percentage: } \frac{100}{N} \sum_{i=1}^N re_i \quad (5)$$

$$\text{MARE in percentage: } \frac{100}{N} \sum_{i=1}^N |re_i| \quad (6)$$

$$\text{SRE in percentage: } 100 \sqrt{\frac{1}{N-1} \sum_{i=1}^N (re_i - MRE/100)^2} \quad (7)$$

In order to provide a baseline algorithm for comparison with the developed intelligent algorithms, the instantaneous algorithm was coded and compared with the proposed VII-ANN and VII-SVR models on the same network and under the same traffic conditions (Van Lint, 2006; Wu et al., 2004). The instantaneous travel time prediction model assumes that the travel time does not change for a short period. As a result, it only uses the available travel time collected within the immediate previous time step to predict the travel of vehicles that will start within the immediate following time step. Since the VII system is able to collect the travel time directly, the averaged travel time of the VII-enabled vehicles arriving at the end point during each time interval will be considered as the predicted travel time of the vehicles departing the start point during the next time interval for the instantaneous algorithm.

RESULTS AND ANALYSIS

Identification of the optimal parameters is an important step in the development of an SVR algorithm. However, the parameters of the SVR algorithm must be adjusted for optimal performance before the algorithm can be evaluated.

Parameter Adjustments for the SVR Algorithm

Figure 3 shows the results of the grid search for the three optimal parameters: cost coefficient C ; kernel function γ ; and loss function ε . The cost coefficient varied between 2^0 - 2^{10} ; the kernel function parameter between 2^{-2} - 2^8 ; and the loss function parameter between 2^0 - 2^{10} .

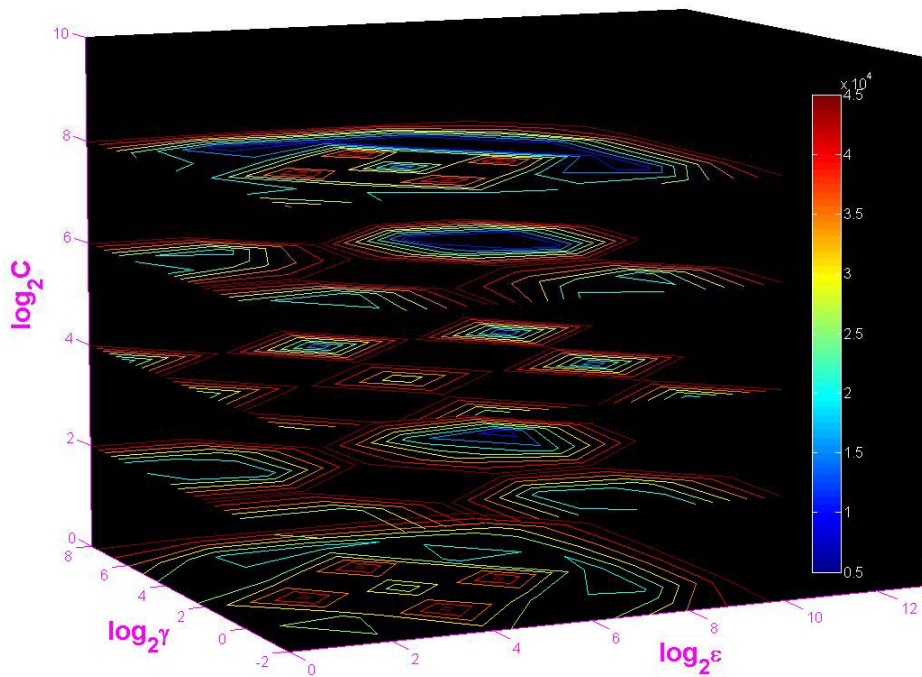


Figure 3. Prediction Accuracy (in terms of MSE) Contour of Parameters Combination for Developed SVR Algorithm

Each contour line on this contour map represents a specific combination of C , γ , and ε that produce the same prediction accuracy in terms of mean square error (MSE). The highest prediction accuracy was found with the combination $C = 2^8$, $\gamma = 2^4$, and $\varepsilon = 2^4$, resulting in a MSE of 2411 for cross-validation.

Incident Detection Performance

When under identical traffic conditions, the VII-SVM model outperforms the California #7 algorithm in terms of detection and false alarm rates (Figure 4). The developed SVM achieved a 100 percent detection rate with very low false alarm rates, while the California algorithm approached a 100 percent detection rate at the cost of a substantial increase in false alarms.

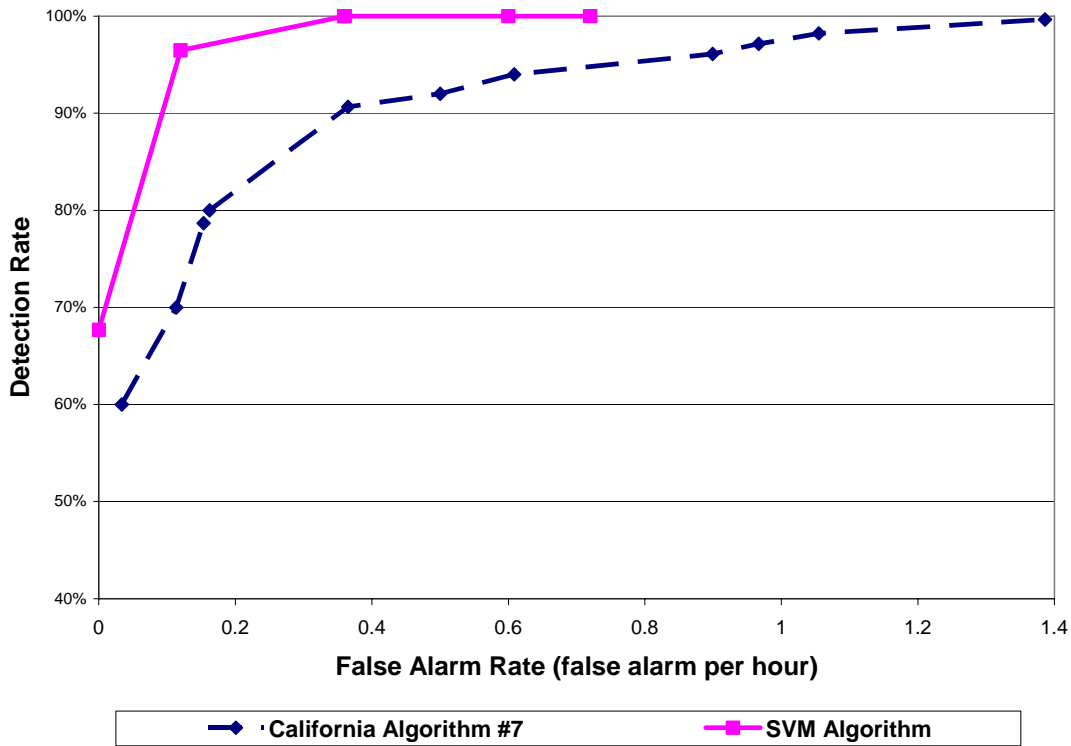


Figure 4. Comparison of California and VII-SVM Algorithm for Detection Rate and False Alarm Rate

Figure 5, which assumes a 20 percent penetration rate for VII-enabled vehicles, compares the detection time of the California and SVM algorithms under various traffic volumes. The detection times of both the California and SVM algorithms decrease as link volume increases, but the effects diminish when the link volume is over 2400 vehicles per hour. The detection times of the SVM algorithm appear to be less than that of the California algorithm under all traffic conditions.

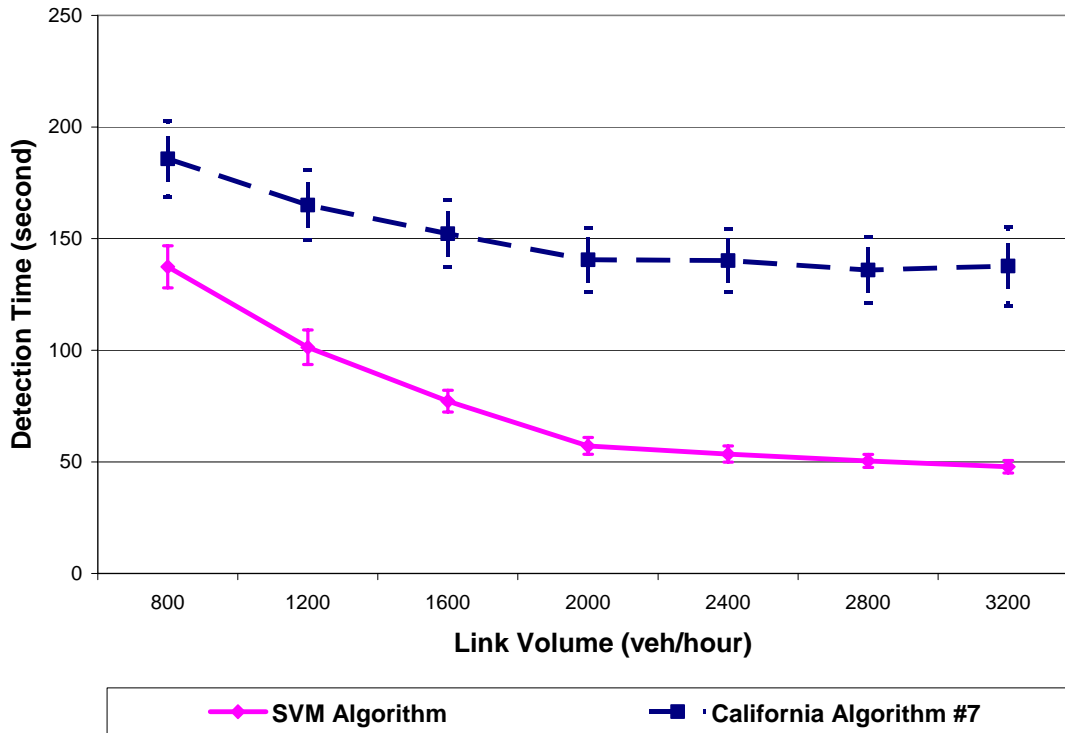


Figure 5. Comparison of California Algorithm and VII-SVM Algorithms for Detection Time

As detailed in Table 2, the detection and false alarm rates for the SVM algorithm are encouraging. Even with a penetration rate as low as 5 percent, the SVM incident detection algorithm can achieve a detection rate of 75-100 percent depending on the number of lanes blocked by incidents. When the penetration rate is above 15 percent, the VII-SVM incident detection system identifies almost all incidents. The false alarm rate slightly increased as the penetration rate increased, but remained within the acceptable range. However, the false alarm rate is expected to increase as the network size increases.

Table 2. Detection Rate and False Alarm Rate of the VII Model

		Penetration Rate					
		5%	10%	15%	20%	25%	30%
Detection Rate	incidents blocking one lane	75%	89%	99%	100%	100%	100%
	incidents blocking two lanes	98%	99%	100%	100%	100%	100%
	incidents blocking three lanes	100%	100%	100%	100%	100%	100%
False Alarm Rate (false alarms per hour)		0.00	0.00	0.00	0.00	0.00	0.10

As seen in Table 3, when 20 percent of vehicles are VII-enabled, the SVM algorithm’s detection rate maintains 100 percent for any vehicular traffic volume except 800 vehicles per hour. However, the false alarm rate increased considerably as the link volume grew to over 2400 vehicles per hour. This increase was due to the fact that the incident identification mechanism in the roadside units was designed for moderate to low traffic volumes.

Table 3. Detection Rate and False Alarm Rate of the VII Model with 20% VII-Enabled Vehicles for Different Traffic Volumes

		Link Volume (veh/hr)						
		800	1200	1600	2000	2400	2800	3200
Detection Rate	incidents blocking one lane	93%	100%	100%	100%	100%	100%	100%
	incidents blocking two lanes	100%	100%	100%	100%	100%	100%	100%
	incidents blocking three lanes	100%	100%	100%	100%	100%	100%	100%
False Alarm Rate (false alarms per hour)		0.00	0.00	0.00	0.00	0.10	0.50	0.85

The plotted points in Figure 6 present the range of expected detection times with 95 percent certainty. Incidents that blocked a greater number of lanes were detected faster as they affected more traveling vehicles. Detection time decreased as the penetration rate increased, but the extra benefits diminished when the penetration rate approached 25 percent. The detection time of the proposed VII-SVM system is comparable or superior to most existing AID algorithms at penetration rates as low as 15 percent.

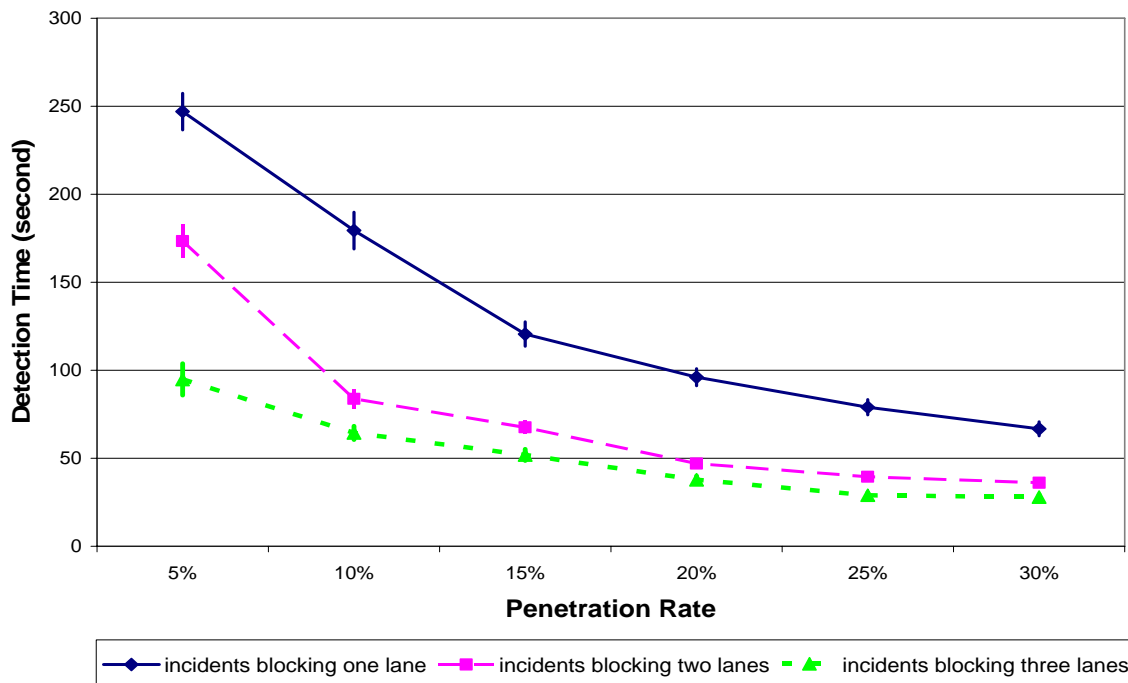


Figure 6. Incident Detection Time of the VII-SVM Model with Various Penetration Rates of VII-Enabled Vehicles

Figure 7 shows the detection time of the SVM incident detection algorithm for different traffic volumes when 20 percent of the vehicles on the study segment are VII-enabled. Since the peak hourly traffic volume on the study segment was around 1600 vehicles per hour, this value was varied within a range of -50 to +200 percent in order to investigate the impact of volume changes on detection time. An increase in traffic volume had a positive impact on the detection time due to the corresponding increase in the number of VII-enabled vehicles. However, there appear to be volume threshold values beyond which the detection times do not differ significantly for incidents blocking one, two, and three lanes.

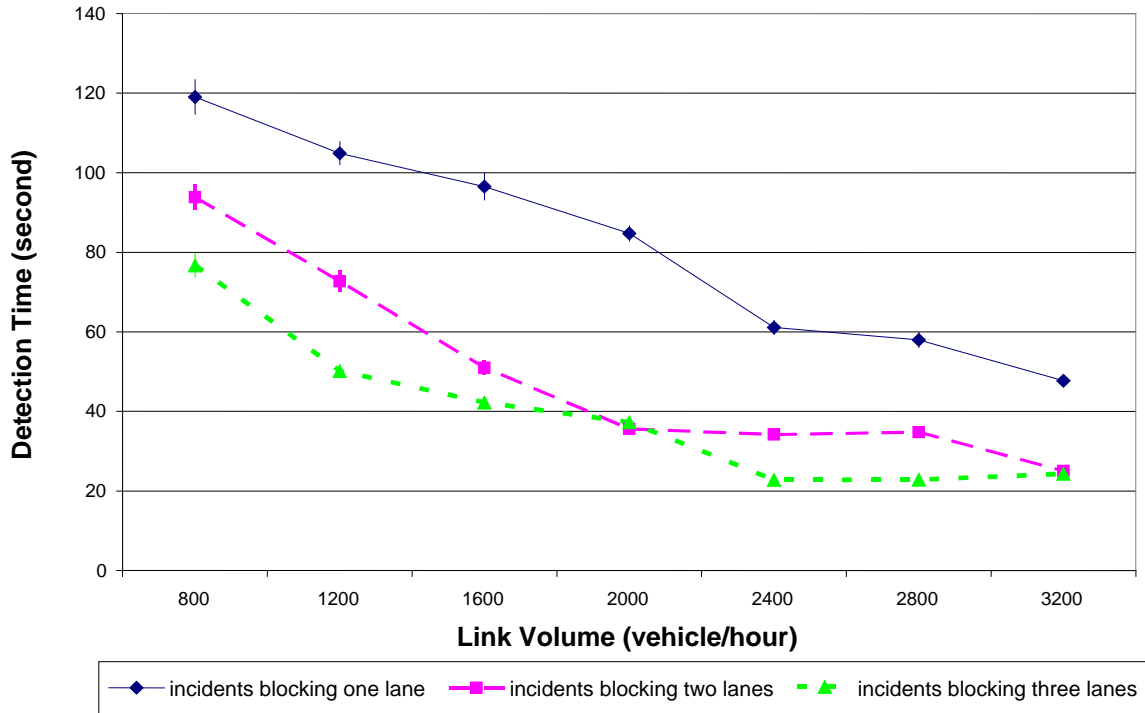


Figure 7. Incident Detection Time of the VII-SVM Model with 20% VII-Enabled Vehicles for Different Traffic Volumes

Most predicted incident locations were within 1000 feet of the actual incident sites. More incident locations were predicted as being downstream of the actual location because many vehicles were not able to detect an incident prior to passing the incident scene. The VII-SVM model predicted the incident location based on the locations where VII-enabled vehicles reported an abnormality. To achieve a low false alarm rate, many vehicles only detected an abnormality after traveling certain distance away from the incident site.

As shown in Figure 8, the RSMEPs of prediction on incident location were generally between 7-10.5 percent even when penetration rates and the number of lanes blocked varied. Figure 9 illustrates the RMSEPs of prediction on incident locations for the VII-SVM model when the penetration rate is 20 percent. As expected, there was no significant difference in the prediction accuracy when traffic volumes were changed. Here, the RMSEP ranged from 5.4-10.2 percent.

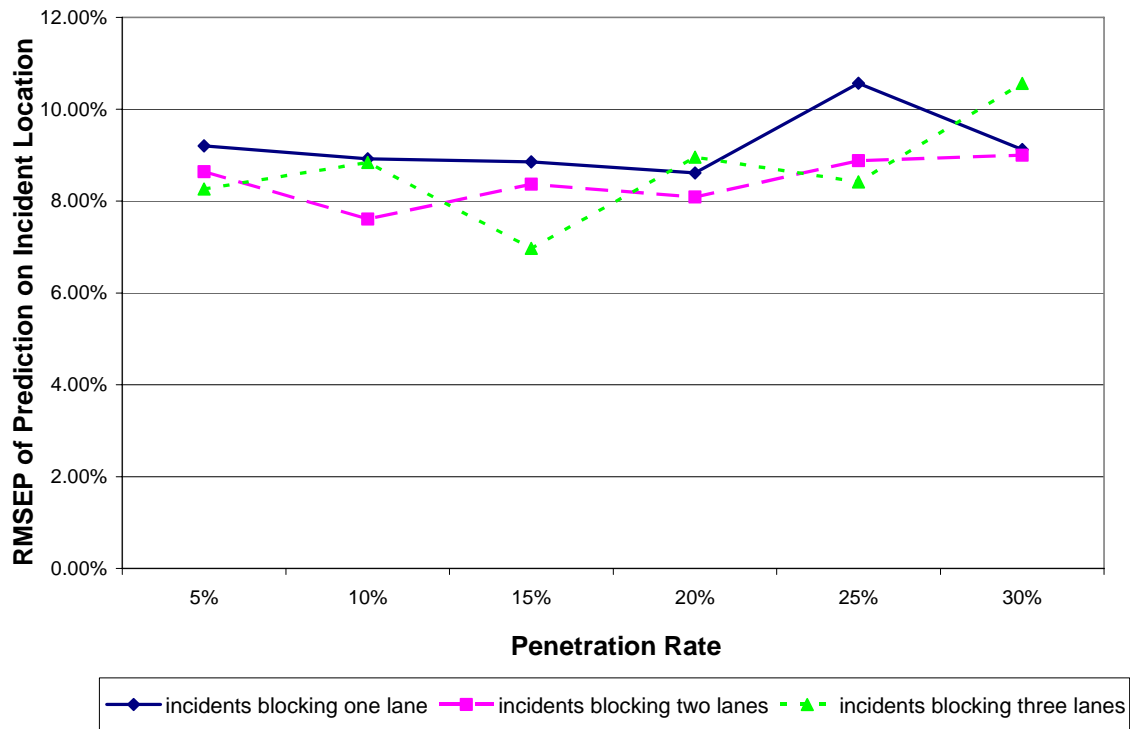


Figure 8. RMSEP of Prediction on Incident Locations of the VII-SVM Model with Various Penetration Rates of VII-Enabled Vehicles

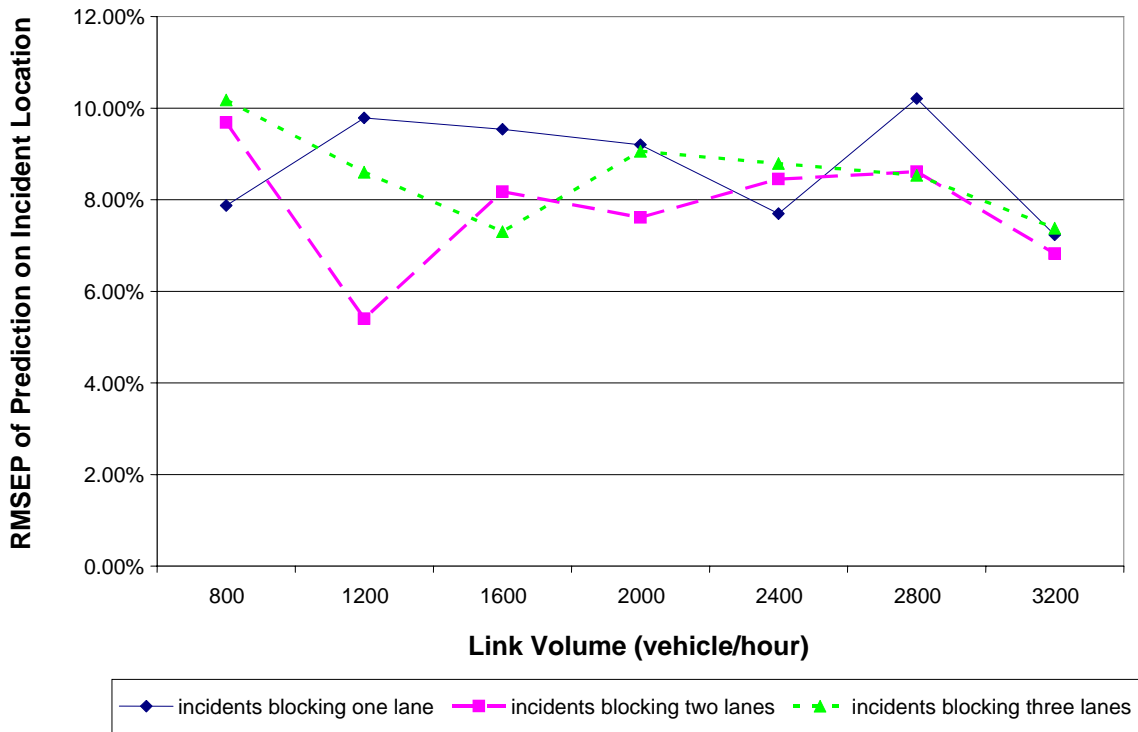


Figure 9. RMSEP of Prediction on Incident Locations of the VII-SVM Model with 20% VII-Enabled Vehicles for Different Traffic Volumes

The proposed VII-SVM model can also predict the number of lanes blocked by incidents. As demonstrated in Figure 10, the prediction accuracy for incidents blocking two or three lanes increased as the percentage of VII-enabled vehicles increased. On the other hand, the prediction accuracy for incidents blocking one lane increased as the penetration rate increased from 5 to 10 percent, but decreased as the penetration further increased. In general, it appears that the model can predict lane blockage for incidents blocking three lanes. However, it was somewhat biased toward overestimating the number of lanes blocked.

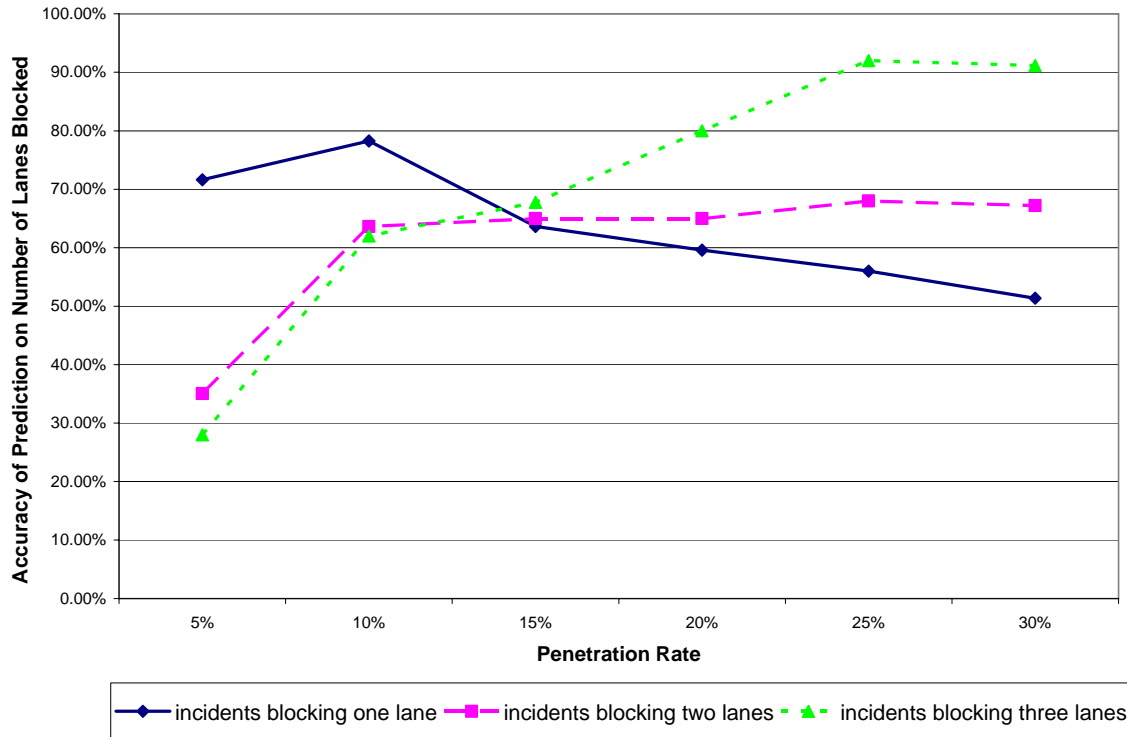


Figure 10. Prediction Accuracy on Number of Lanes Blocked of the VII-SVM Model with Various Penetration Rates of VII-Enabled Vehicles

Figure 11 compares the predictive accuracy of the instantaneous VII-ANN and VII-SVR models. Only 46 percent of cases for the instantaneous algorithm had relative errors in the range of -5 to 10 percent, and these are indicated by the vertical lines in the figure. For the ANN and SVR, these numbers were 71 and 74 percent, respectively. Consequently, the ANN and SVR appear to outperform the instantaneous method, with the SVR slightly outperforming the ANN. This can be seen further in Table 4 where both the VII-ANN and VII-SVR model statistics appear to be superior to the instantaneous algorithm.

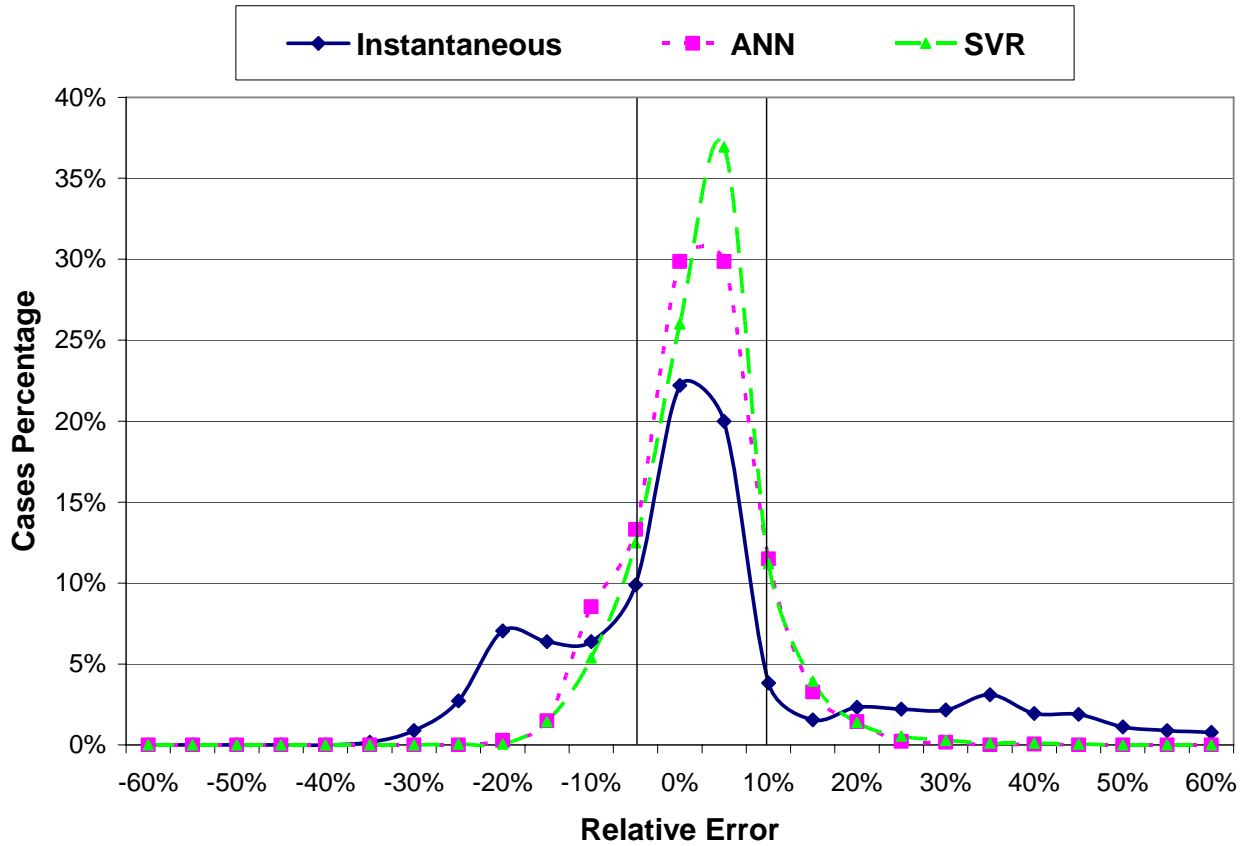


Figure 11. Categorized Relative Error Percentage of Different Travel Time Prediction Method

Table 4. Performance of VII-AI and Instantaneous Travel Time Prediction Models

Model	RMSEP	MRE	MARE	SRE
ANN	8.59%	-0.87%	5.21%	6.80%
SVR (original)	8.35%	0.13%	5.03%	2.07%
SVR (smoothed)	8.26%	0.09%	4.98%	2.05%
Instantaneous	22.95%	2.23%	13.91%	7.35%

Table 4 also shows that there was little prediction bias in the SVR model. At the same time, the instantaneous model predicted travel times 2.23 percent longer than the actual travel time. The VII-SVR also appears to be slightly superior to VII-ANN in every aspect of the selected performance measures. As can be seen, smoothing has a positive effect on the SVR model: It improves prediction accuracy and lowers variation.

To further appreciate the differences in the predictive accuracy of the different algorithms, their performance was tracked for one afternoon peak with recurrent congestion. Figure 12 shows that the instantaneous predictive model works well during non-congested conditions, although there was a lag between the actual and predicted time during congestion. This is because the instantaneous model assumes that travel times do not change over short time intervals, which is obviously not the case during congestion. In contrast, Figure 13 confirms that the SVR model is quite capable of accurately predicting travel times during both congested and non-congested conditions.

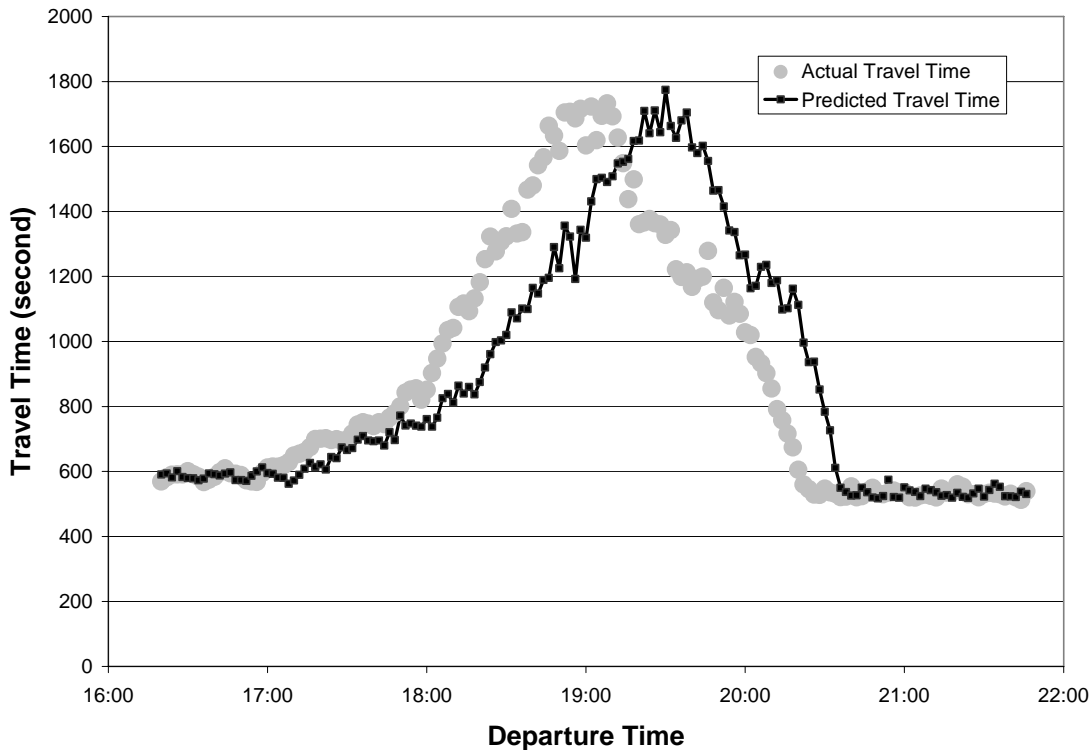
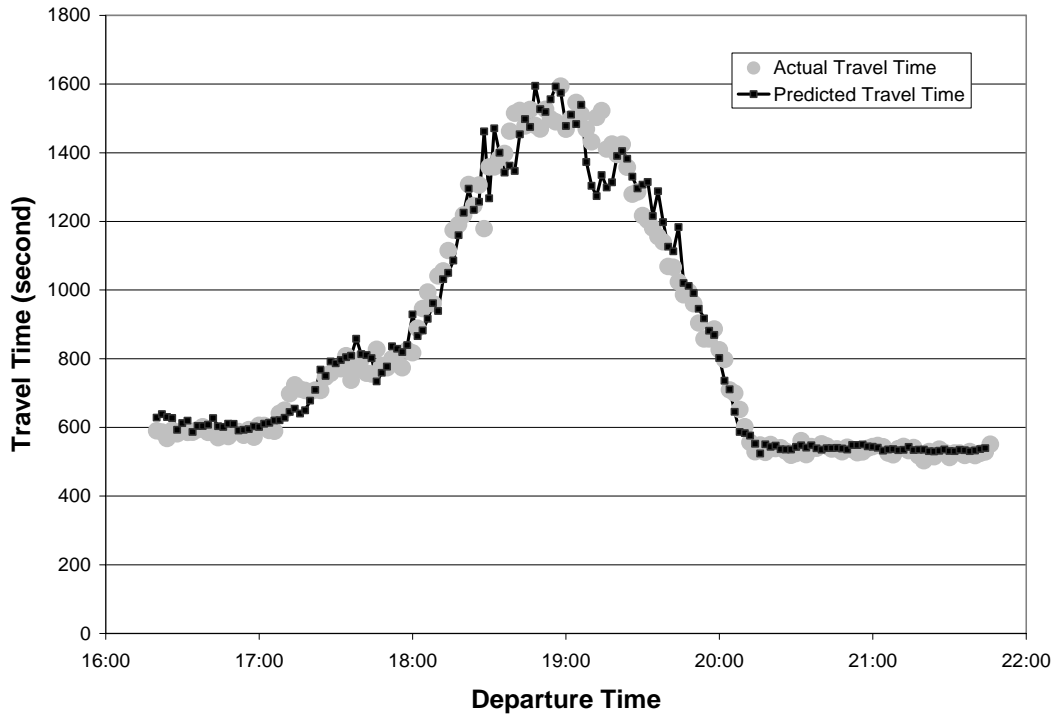
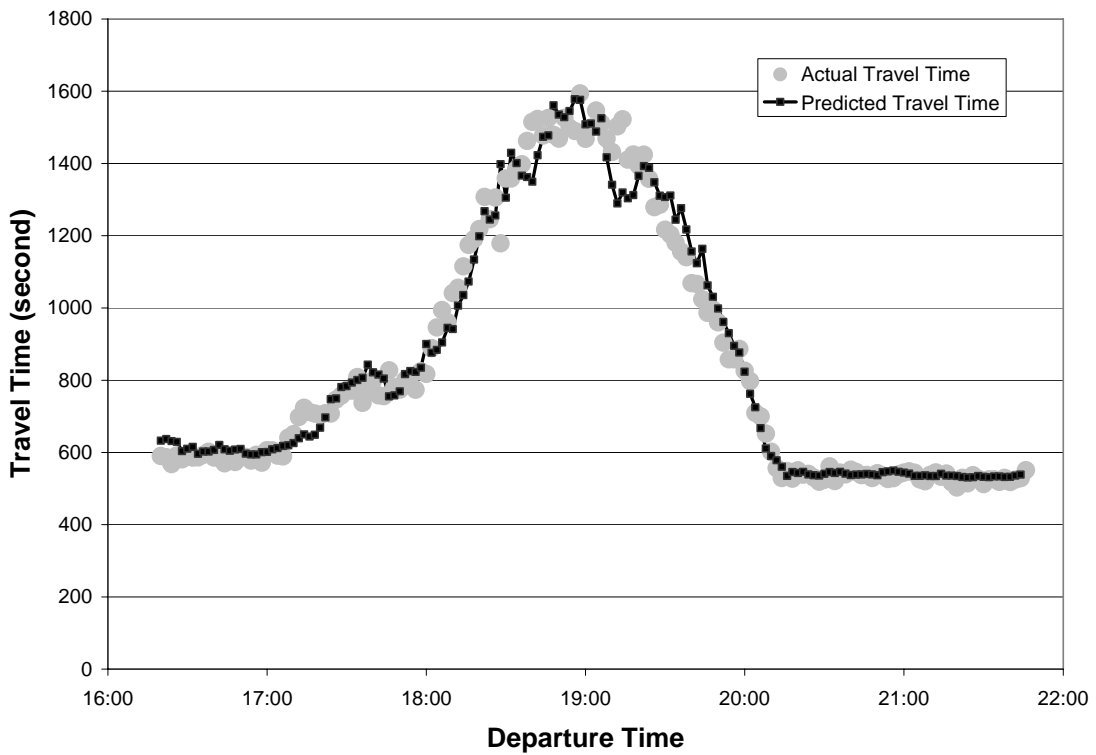


Figure 12. Travel Time Prediction Using Instantaneous Prediction Model



(a)



(b)

Figure 13. Original (a) and Smoothed (b) Travel Time Prediction on an Afternoon Peak Period with Recurrent Congestion

The prediction accuracy of the developed VII-ANN and VII-SVR models were compared against other travel time prediction models reported in the literature. A word of caution, however, is warranted before discussing those results. As seen in Table 5, the results include networks with different geometric characteristics; congestion levels; data sources (i.e. VII systems, loop and camera systems and probe vehicle); and training and testing data sets. Since all these factors are likely to have a significant impact on the results, comparisons among the different models may be somewhat challenging.

Table 5. Comparison of VII-AI Models with 20% Penetration Rate with Other Models in Literature

Model	MARE (%)	Network Length (mile)	Data Source	Training Data Set	Testing Data Set
VII-ANN (this study)	5.2	11	VII	10 Peaks	10 peaks
VII-SVR (this study)	5.0	11	VII	10 Peaks	10 peaks
FNN (Innamaa, 2007)	4.6-4.9	6.3-17.5	Dual loop / Camera	4 months	2-3 weeks
SSNN (Van Lint, 2006)	5.4	8.1	Dual loop	1071 peaks	118 peaks
SVR (Wu et al., 2004)	1.0-4.4	28-219	Dual loop	28 days	7 days
FNN (Huisken and Van Berkun, 2003)	4.6	6.3	Dual loop	92 days	13 peaks
Linear regression (Zhang and Rice, 2003)	6-11	6.3	Dual loop / Probe Veh.	-	20 days
Kalman filter (Park and Rilett, 1998)	6.2	17.3	AVI	131 days	100 days
Spectral FNN (Park et al., 1999)	7.2	17.3	AVI	131 days	100 days
Modular FNN (Park and Rilett, 1998)	8.1	17.3	AVI	131 days	100 days
Regular FNN (Park and Rilett, 1998)	9.0	17.3	AVI	131 days	100 days

Note: SSNN = state-space neural network; FNN = feed-forward neural network

Nevertheless, Table 5 reveals that MARE values in the range of 4-6 can be considered quite good, and the developed VII-ANN and VII-SVR models appear to satisfy such requirement. It should also be noted that the low-MARE-volume model developed by Wu et al. is not suitable for online prediction.

Sensitivity analysis was conducted in order to identify the optimal smoothing factors for the smoothing function. Figure 14 shows that the combination of 7-3-0 and 7-2-1 appear to be superior to other options. The combination 7-2-1 refers to a smoothed travel time prediction that is equal to the sum of 70 percent of the current predicted travel time, plus 20 percent of the predicted travel time for one time step before, plus 10 percent of the predicted travel time for the two previous time steps. The combination 7-2-1 yielded the highest accuracy, while the

combination 7-3-0 retained the minimum variation. The combination 7-2-1 was selected as the smoothing factor for this study.

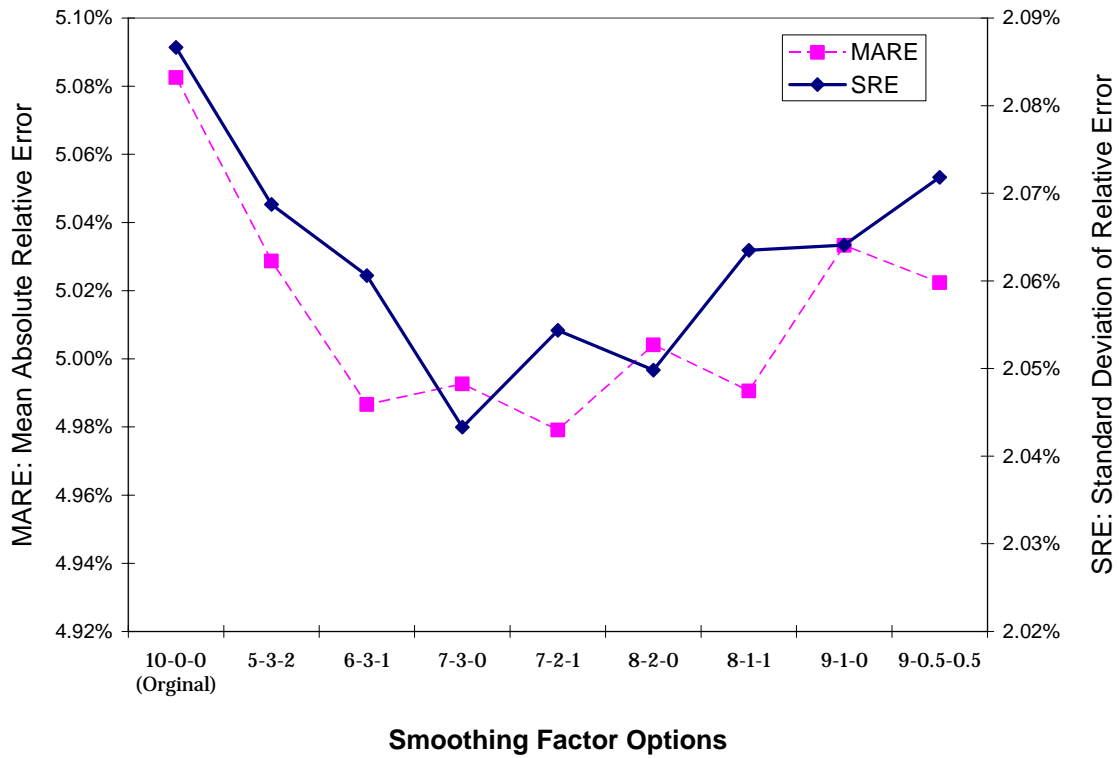


Figure 14. MARE and SRE of Travel Time Prediction with Different Smoothing Factors

An increase in the number of VII-enabled vehicles positively affects prediction accuracy and variation. At low penetration rates, the travel time and traffic volume data collected from VII-enabled vehicles is unreliable. This is because of the sample’s small size, and the measurement’s high deviation from the population. The accuracy improves as the penetration increases, but the positive effects tend to diminish as the penetration rates keep increasing. A 20-25 percent penetration rate appears to be adequate for yielding accurate and reliable travel time predictions.

Many conventional sensor-based prediction models have trouble with accurately predicting travel times during incidents. To test the SVR model’s ability to predict travel time during incidents, a scenario was created in which an accident blocking two lanes for 30 minutes was assumed to occur at 16:35. The results, shown in Figure 15, prove that the developed VII-SVR model is capable of accurately predicting travel times for normal traffic conditions and conditions during incidents. The VII-ANN model performed similarly, and its ability to predict travel for non-recurrent congestion should be credited to the real-time traffic data provided by VII. The inputs for the VII-AI framework are similar for recurrent and non-recurrent congestion. Consequently, the proposed framework performs reasonably well for the non-recurrent condition with the lack of such training data set.

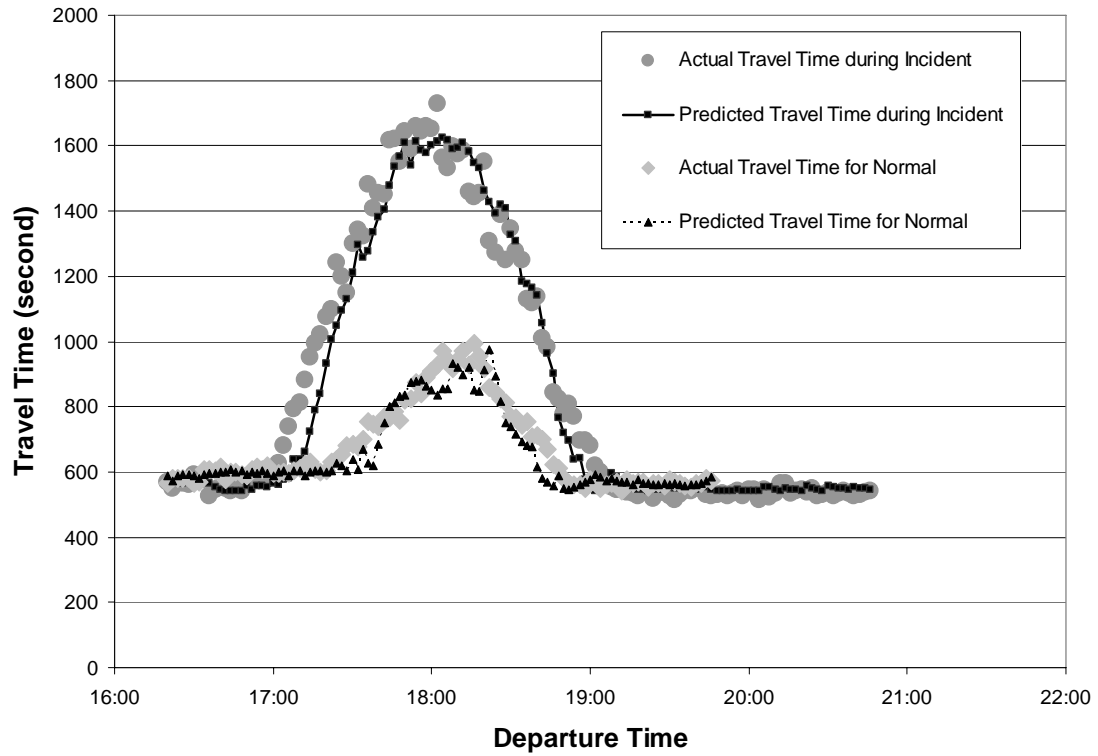


Figure 15. Travel Time Prediction in Both Normal Traffic Conditions and During Incident

TRANSFERABILITY TEST

The transportability of the VII-SVM incident detection system was tested in a simulation based on a portion of Interstate 83 in Baltimore, Md.

As shown in Figure 16, the first steps in this process were the selection of the test networks and the development of a detailed microscopic simulation model for each. After calibration and validation, the traffic simulation model for the original network was utilized to generate training cases for both incident and non-incident scenarios. The development of modules for estimating in-vehicle travel experiences involved designing the vehicle-kinetics data collection plan, and cross-validating the training sets and grid searching of optimal parameters for the SVM model.

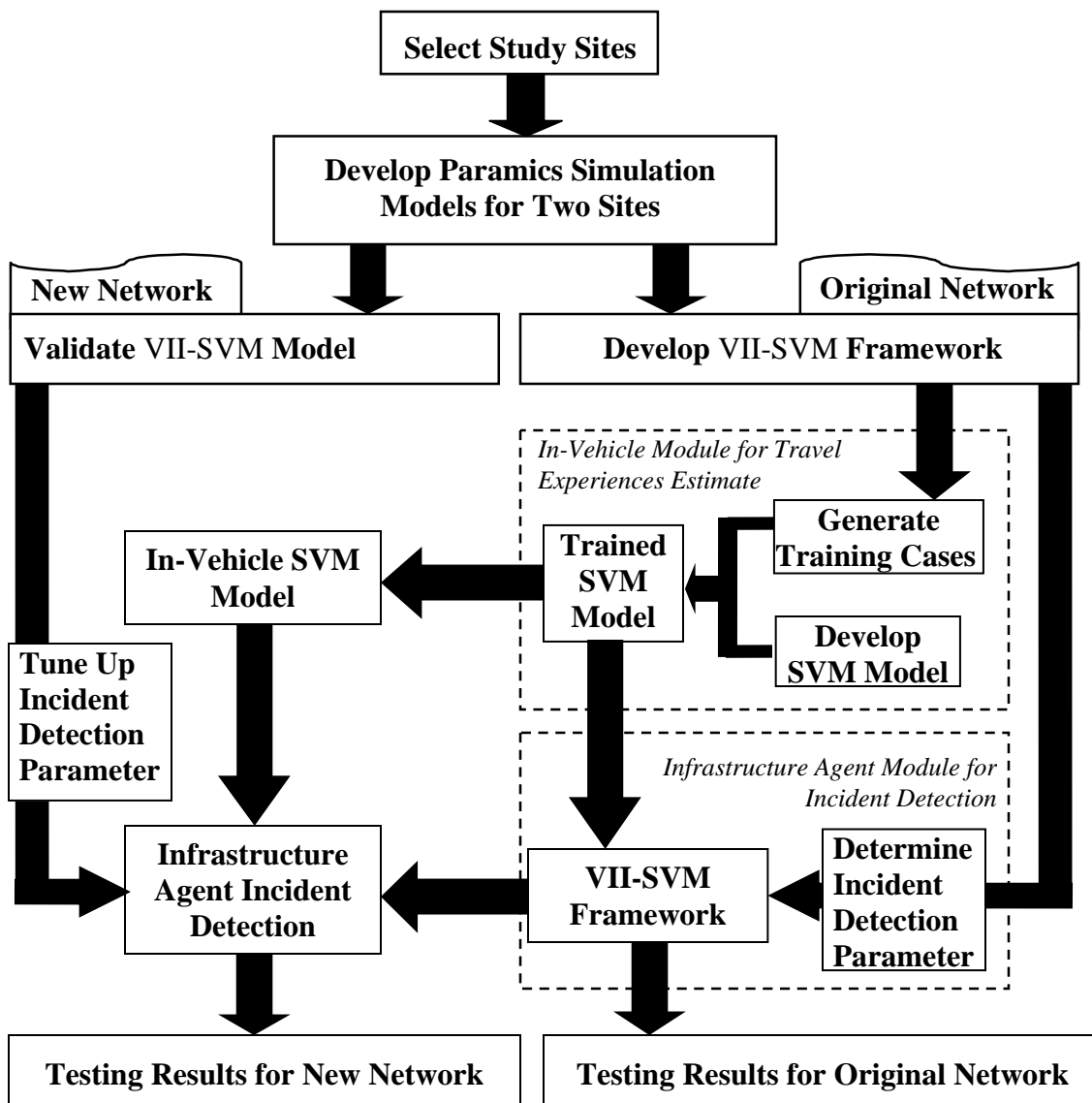


Figure 16. Study Approach for VII-SVM Incident Detection Framework

The trained SVM model continuously fed the vehicle travel experiences to the incident-detection-algorithm implemented in infrastructure agents. Portions of I-85 and I-26 in Spartanburg, S.C., were chosen to generate the cases required for training the SVR model. This site was modeled with Paramics, and the models were carefully calibrated and validated.

The aforementioned portion of Baltimore’s I-83 was also modeled with Paramics, carefully calibrated, and then used to test the VII-SVM model. A few of the incident detection parameters used by infrastructure agents in the Spartanburg network were adjusted when applied to the Baltimore network. Incident detection performance measures — such as the detection rate, false alarm rate, and detection time — were collected for the two sites, respectively.

Interstate 83, also referred to as the Jones Falls Expressway or JFX, is the major artery that connects northern Baltimore to downtown Baltimore. This section was chosen for testing the transportability of the VII-SVM incident detection framework because of the severe congestion it experiences during the simulated weekday morning peak periods.

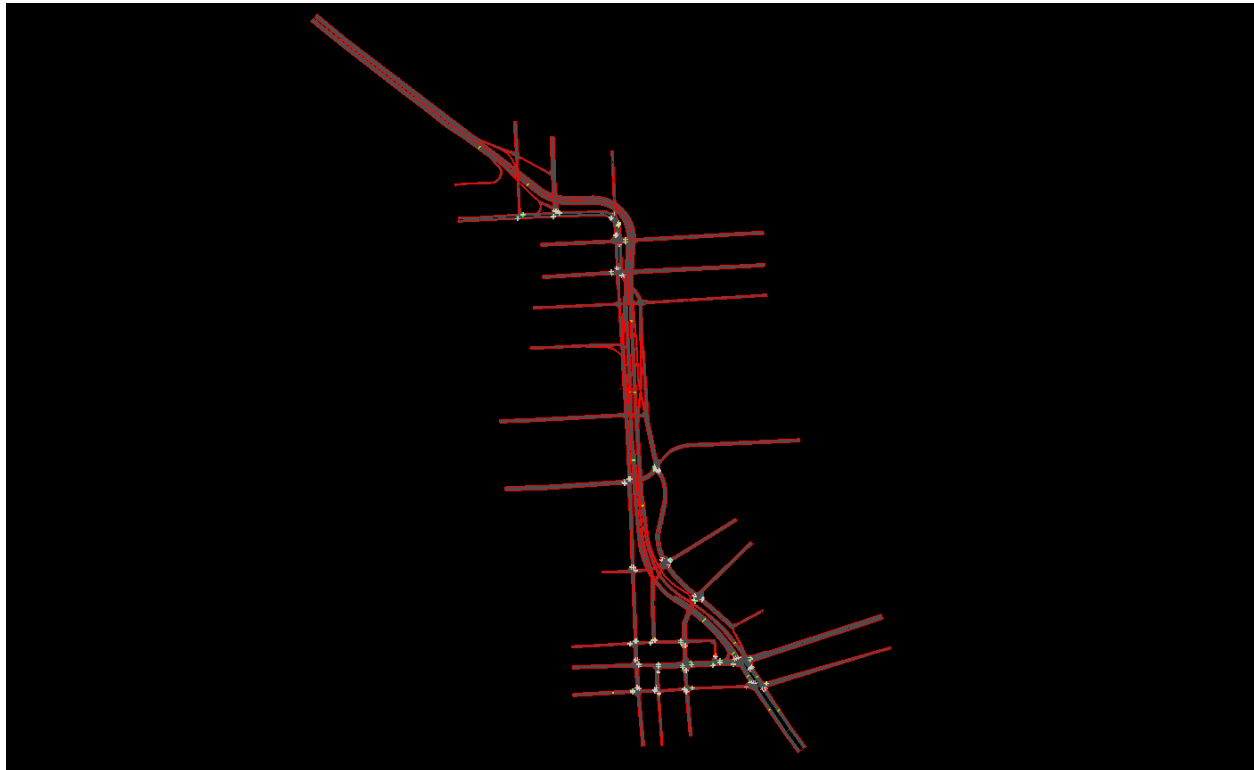


Figure 17. Paramics Layout of the Test Sites, Baltimore, Md.

As shown in Figure 18, a 20 percent penetration rate in the VII-SVM system produced similar detection and false alarm rates for the Baltimore and Spartanburg networks, however the Spartanburg network gives slightly better results. In both networks, the detection rate approached 100 percent at the cost of increased false alarm rate, while the satisfactory detection rate (e.g. 95 percent) was achieved with a low false alarm rate. The incident detection performance in the original network appears to be superior to that in the new network, which is more congested.

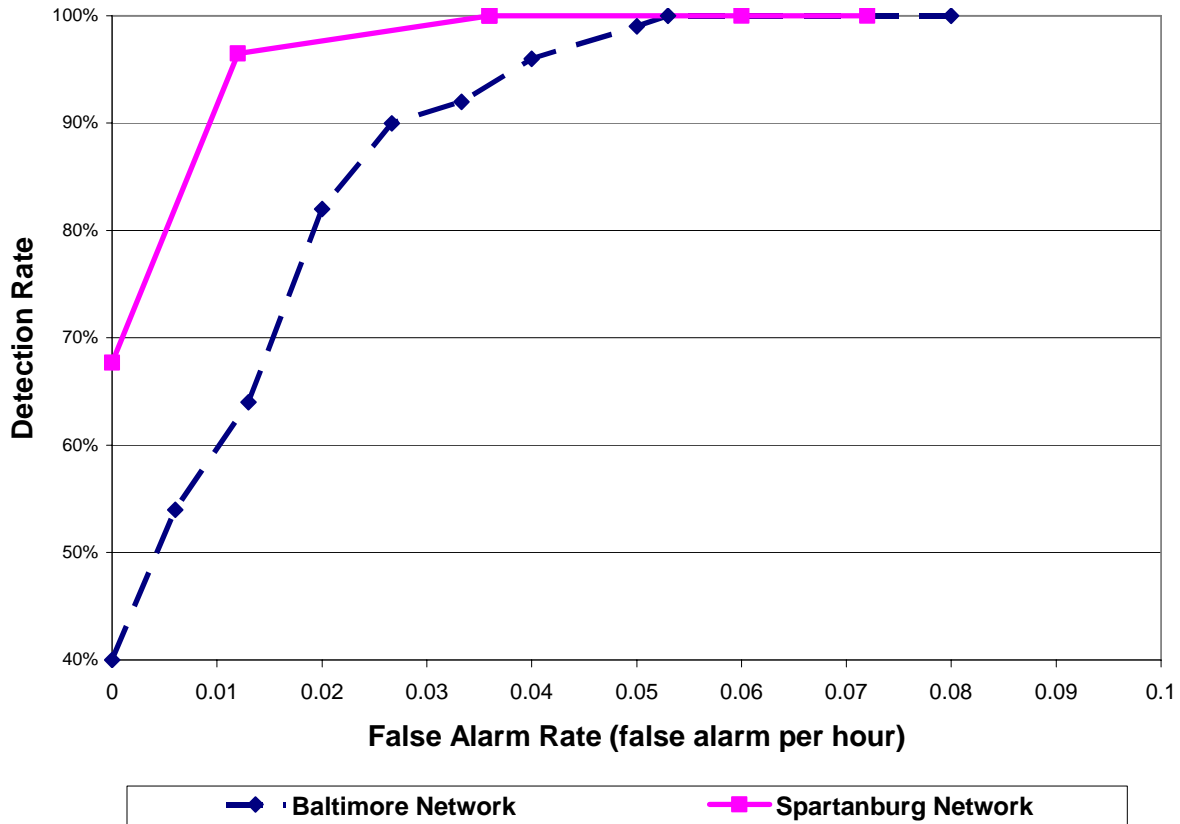


Figure 18. Comparison of Detection Rate and False Alarm Rate for the VII-SVM System with 20% Penetration Rate in Spartanburg and Baltimore Network

Table 6 presents how the VII-SVM system’s detection and false alarm rates change when different penetration rates are used and the number of incident-blocked lanes increases from one to three. For penetration rates of 5-15 percent, the Baltimore network produced detection and false alarm rates similar to those for the Spartanburg network (see Table 3). However, penetration rates higher than 25 percent delivered detection rates in the Baltimore network that were lower than in the Spartanburg network. Detection parameters, such as the incident-detection segment length and thresholds to detect incidents, were adjusted to maintain low false alarm rates. The resulting decreased detection rates were the trade-off of such adjustments.

Table 6. Detection Rate and False Alarm Rate in Baltimore Network

		Penetration Rate					
		5%	10%	15%	20%	25%	30%
Detection Rate	1 lane blocked Incidents	86%	87%	100%	73%	85%	92%
	2 lanes blocked Incidents	100%	100%	100%	93%	100%	100%
	3 lanes blocked Incidents	100%	100%	100%	93%	100%	100%
False Alarm Rate (false alarms per hour)		0.02	0.01	0.03	0.02	0.03	0.03

Figure 19 shows how the Baltimore network can quickly detect incidents blocking two and three lanes. However, the detection times for incidents blocking one lane were generally higher than in the Spartanburg network. This is because the increased traffic volumes make it difficult to maintain low false alarm rates. The detection times were traded off to minimize these false alarm rates. When the penetration rate exceeded 20 percent, traffic congestion led to considerable variation in the detection time for incidents blocking one lane.

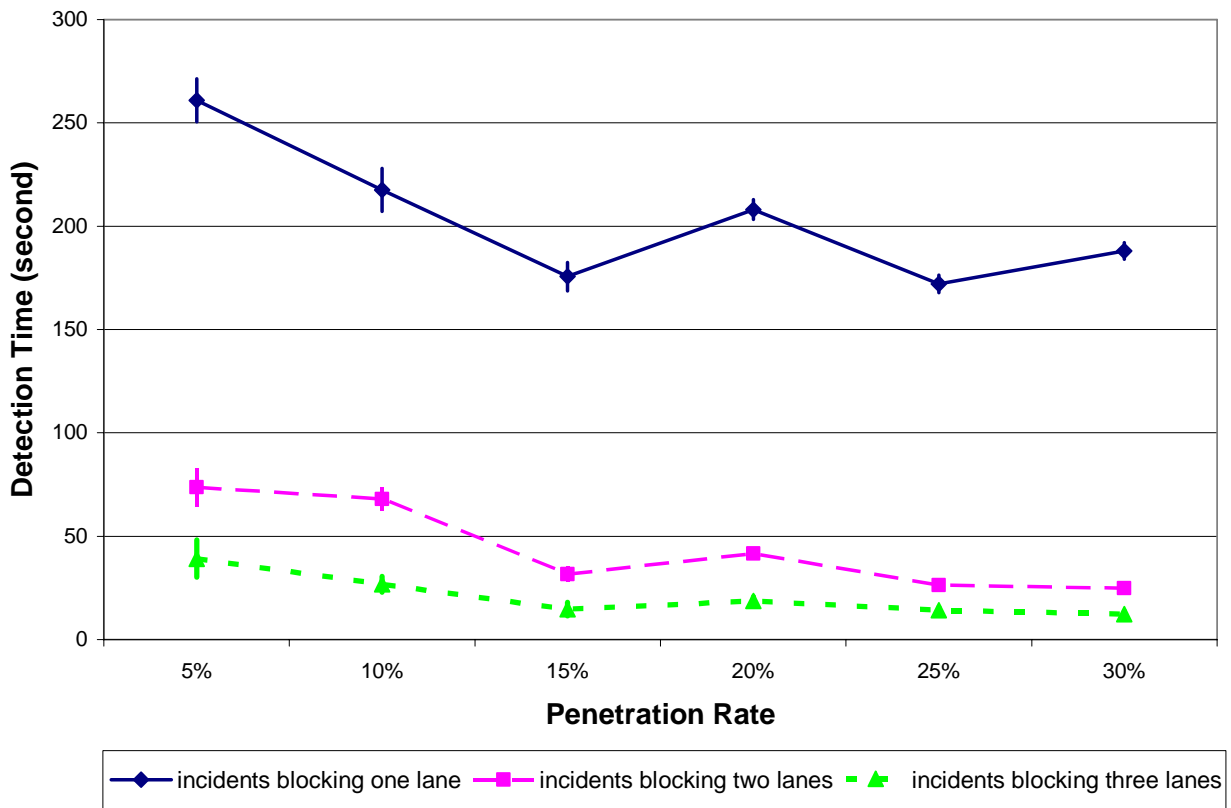


Figure 19. Detection Time of the VII Incident Detection System in Baltimore Network

The proposed VII incident detection system successfully identifies incident locations. When incidents blocked one or two lanes and the penetration rate exceeded 10 percent, the

system was able to identify incident sites within 500 feet of their true location 84-90 percent of the time. For incidents blocking all lanes, 95-100 percent of the locations reported by the system were within 500 feet of the actual position.

CONCLUSIONS

Evaluation of the VII-SVM algorithm revealed that it can successfully classify traffic conditions into three categories — normal, passing an incident, and stopped in a queue — through the use of vehicle kinetics data.

The model was trained on a network based on a freeway segment in Spartanburg, S.C., and its transportability was tested on a network based on Baltimore's I-83. The original and new networks both produced accurate detection and false alarm rates. However, several incident detection parameters must be adjusted in order to apply the SVM model in the original network to the new network. Prototype applications also indicate that maintaining low false alarm rates slows detection performance in urban areas more than in rural locations.

The study also found that a penetration rate as low as 15 percent in both networks delivered a detection time for the prototype that was comparable or superior to most existing AID algorithms. In the original network, detection time decreases as the penetration rate increases, but the extra benefits diminish when the proportion of VII-enabled vehicles exceeds 25 percent. Penetration rates over 15 percent did not improve the detection times in the new network.

This research also developed an online highway-travel-time prediction framework that uses VII with ANN or SVR algorithms. Evaluation of the VII-ANN and VII-SVR models revealed that the VII-AI algorithms successfully predicted the travel time based on traffic measurements derived from the VII-enabled vehicles. In addition, the developed travel-time prediction models outperformed the instantaneous algorithm that served as a baseline.

In terms of MARE, the accuracy of the VII-ANN and VII-SVR models were among the best of the results reported in literature when the penetration rate was as low 20 percent. For the SVR model, a smoothing function was beneficial for both increasing accuracy and limiting the variation of the travel-time prediction model.

Additionally, unlike other sensor based models, the proposed VII-ANN and VII-SVR models perform well during non-recurrent congestion conditions.

Recommendations

Although the results of this research are quite encouraging, there are several potential limitations that warrant the attention of future researchers and practitioners. One must remember that evaluation of the proposed framework was conducted in a simulation environment. In a real-world implementation, the performance of the models developed in this study may vary due to factors not considered in a computer simulation. The performance of the proposed VII framework was found to be quite sensitive to the penetration rate of the VII-enabled vehicles, and future research should include experiments that vary the percentage of the VII-enabled vehicles in the traffic population.

Additionally, further study should be conducted regarding the online learning ability of the VII-AI framework and how this could be utilized to improve its performance over time. The

communication system that supports the information exchange between vehicles and infrastructure devices in the VII system also requires careful study and design in order to fulfill the requirements of a real-world implementation.

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