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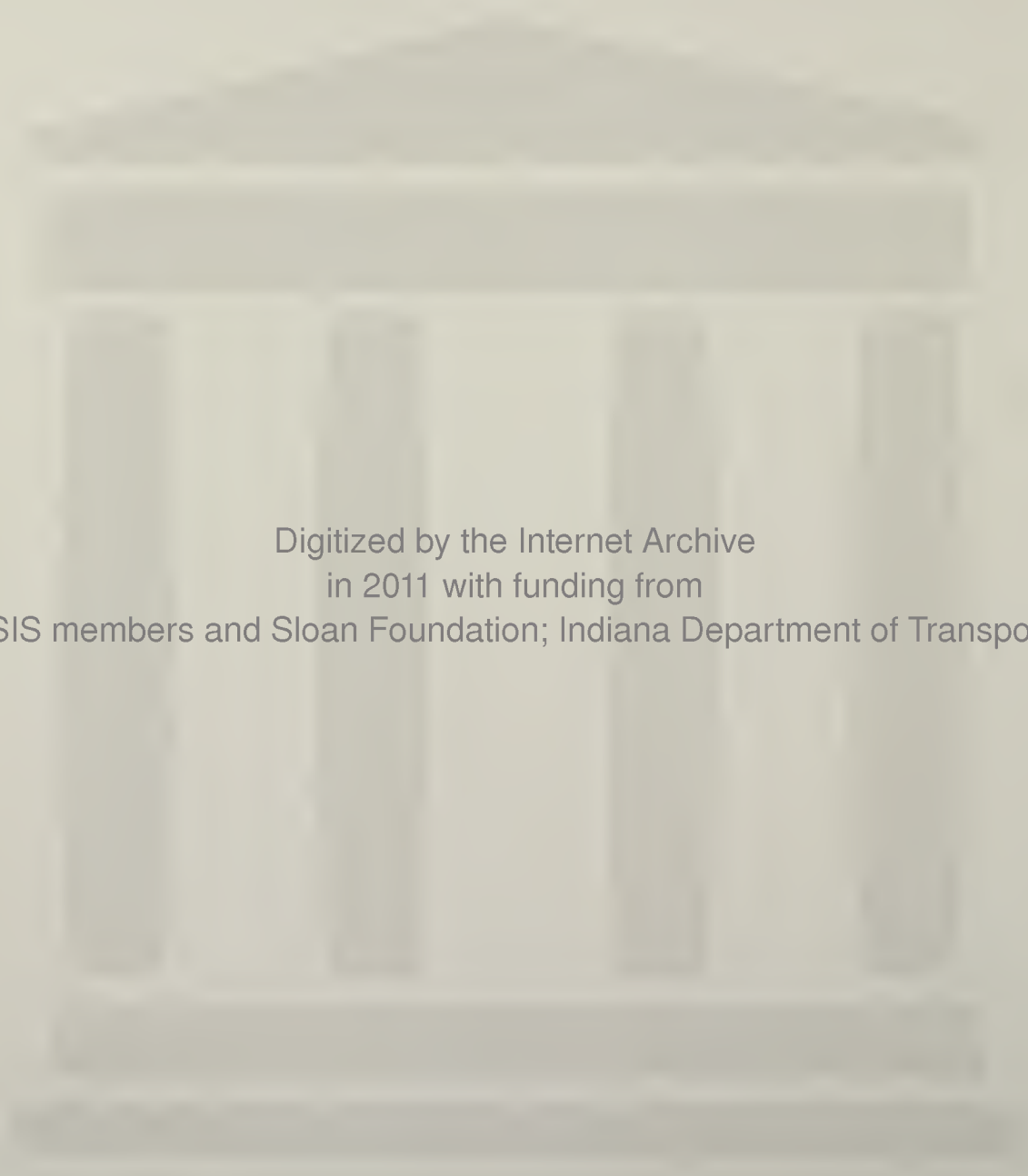
Final Report

FREEWAY INCIDENT LIKELIHOOD PREDICTION
AND RESPONSE DECISION-MAKING

Samer Madanat
Hongyu Pan
PenChi Liu
Hualiang Teng



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FINAL REPORT**

**FREEWAY INCIDENT LIKELIHOOD PREDICTION AND RESPONSE
DECISION-MAKING**

by

Dr. Samer Madanat
Associate Professor

and

PenChi Liu
Hongyu Pan
Hualiang Teng
Graduate Research Assistant

Purdue University
Department of Civil Engineering

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16. Abstract <p>This research project consisted of two parts. The first part developed a set of real-time freeway incident likelihood prediction models. The second part developed a freeway incident response decision-making methodology based on sequential hypothesis testing methods. The freeway incident likelihoods predicted by the real-time prediction models act as prior probabilities for the freeway incident response decision-making system.</p> <p>The products of this research project will be incorporated in the Advanced Traffic Management System that is being implemented on the Borman Expressway, a 16-mile segment of I-80 in northwest Indiana. The decision-making system can be used by traffic management personnel to assist in responding to various freeway incidents in a near optimal manner to minimize traffic delays and reduce the number of secondary incidents.</p>					
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IMPLEMENTATION REPORT

The product from this research is a decision-making system for integrated freeway traffic incident detection and response. This system employs sequential hypothesis testing techniques to dynamically optimize incident response decisions by systematically considering the tradeoffs between the possible costs of a delayed incident response decision and the improved decision-making capabilities which result from delaying action until additional measurements are taken. The input components to this system include traffic parameters, their distributions under different conditions, traffic delay costs due to incidents, the costs of implementing response measures, incident frequencies in time and space, and the distribution of incident durations. The outputs are optimal incident response policies for each time period. In real-time operations, the derived optimal policies can be used to select incident response decisions, given various traffic conditions.

The incident response decision-making models will be incorporated in the Advanced Traffic Management System planned for the Borman Expressway, a 16-mile segment of I80 in Northwest Indiana. The decision-making system can be used by traffic control personnel to assist in responding to various freeway incidents in a near optimal manner, to minimize traffic delays and reduce the number of secondary incidents.

1. INTRODUCTION

This research report includes descriptions of research efforts. The first research focused on the development of real-time freeway incident prediction models. The second part describes a sequential hypothesis testing-based decision-making system for freeway incident response. The freeway incident probability predicted by the real-time incident prediction model acts as a prior for the freeway incident response decision making system. The following paragraphs explain both parts in detail.

Freeway Incident Likelihood Prediction Models

Traditionally, traffic management strategies implemented to mitigate operating problems such as incident congestion are "reactive" in nature. In other words, control strategies are typically activated after operating problems have been identified (Davis 1991; Stephanedes 1991). Delaying the implementation of control strategies until after congestion occurs is generally not the most efficient manner to manage highway operations. Moreover, a reactive approach to traffic control impedes the capability to fully exploit route diversion opportunities (Stephanedes 1993).

A better approach to corridor-wide traffic control is to use a system which is "proactive", rather than reactive. Under such a system, real-time predictions of incident likelihoods are performed, based on traffic stream and environmental conditions measured by surveillance sensors. Traffic control and management strategies are immediately implemented to minimize these likelihoods. Thus, strategies are activated to avoid the occurrence of incidents as well as to mitigate incident-related problems after they have occurred.

A proactive approach to traffic control will greatly enhance capabilities to improve operation through route diversion. Indeed, managing freeway traffic demand prior to congestion occurrence mandates the need for efficient route diversion. The manner in which diversion advisories are transmitted, and the extent to which traffic control devices (traffic signals and ramp meters) are adjusted to accommodate diversion, largely depend upon forecasts of diversion behavior.

Freeway Incident Response Decision-Making System

The product from this research is a decision-making system for integrated freeway traffic incident detection and response. This system employs sequential hypothesis testing techniques to dynamically optimize incident response decisions by systematically considering the tradeoffs between the possible costs of a delayed incident response decision and the improved decision-making capabilities which result from delaying action until additional measurements are taken.

The input components to this model include traffic parameters, their distributions under different traffic conditions, traffic delay costs due to incidents, the costs of implementing response measures, incident frequencies in time and space, and the distribution of the incident durations. The outputs are optimal incident response policies for each time period. In real-time operations, the derived optimal policies can be used to select incident response decisions, given various traffic conditions.

The proposed system is based on a novel approach to the incident response process. This decision process is modeled as an optimization problem in which the uncertainties in the measured traffic stream characteristics and the costs associated with incorrect decisions are considered simultaneously.

Because incident detection and response decisions are made simultaneously, this system can

be viewed as an incident detection system. Compared to conventional incident detection systems, the proposed system explicitly accounts for the presence of traffic stream measurement and interpretation errors, and simultaneously considers incident detection decisions and possible response actions such as dispatching emergency vehicles and traffic diversion to alternative routes.

2. PROBLEM STATEMENT

Freeway Incident Likelihood Prediction Models

In order to implement the type of proactive traffic control system discussed in the introduction, two types of prediction models are required:

- (i) models for prediction of incident likelihoods,
- (ii) models for prediction of driver diversion likelihoods

This research developed the first of these two categories of models, i.e., incidents likelihood prediction models. Such models will provide forecasts of incident probabilities given various environmental and traffic stream characteristics. A preliminary literature survey has not found any prior research in the area of incident prediction. A substantial body of research, on the other hand, exists in the area of incident detection(Levin 1989).

Freeway Incident Response Decision-Making System

The full potential of freeway traffic management systems has yet to be realized largely because of an inability to precisely identify when and where control measures should be implemented. To avoid the costs of needlessly responding to false alarms, freeway management personnel are reluctant to promptly initiate mitigation measures based solely on incident information generated from conventional freeway detectors. Thus, expensive surveillance

methods such as closed-circuit television must be installed to provide reliable incident information. The incident response system developed in this research decision-maker will generate optimal policies for any given freeway detection system, by properly accounting for the measurement errors associated with that system, thus reducing the need for expensive surveillance technologies.

State-of-the-art traffic incident detection algorithms can be classified into two categories: those that use a static threshold and those that use a dynamic threshold. Examples of the first class are the algorithms of Payne and Tignor (1978), Aultman-Hall et al (1991), Stephanedes and Chassiakos (1991, 1993), Ritchie and chen (1993), and Hsiao et al (1994). The algorithms developed by Dudek and Messer (1974), and cook and Cleveland (1974) belong to the second class, where threshold updating is based on historical data.

3. OBJECTIVES

Freeway Incident Likelihood Prediction Models

The first objective of this research project was to develop models which can be used to provide real-time predictions of freeway incident likelihoods. Such predictions will serve as the basis for a proactive corridor-wide traffic control system. In such a system, traffic stream and environmental conditions measured by surveillance sensors will be used as inputs for predicting incident likelihoods in near real-time. Traffic control strategies can thus be immediately implemented to reduce the probability of an incident, as well as to mitigate incident-related problems if they occur.

To prove the feasibility of this concept, it was essential to demonstrate the possibility of accurate predictions of freeway incident probabilities, based on near real-time measurements of

traffic and weather variables. As described in the following section of this report, we have successfully developed models for likelihood prediction of two critical types of freeway incidents: crashes and overheating vehicles. These models capture the influence of various traffic and weather factors on the probabilities of vehicle crash and overheating vehicle incidents. Furthermore, both models have high internal and external validity, as demonstrated by their fit to the data and their predictive accuracy, respectively.

The predictions given by the incident likelihood models can be combined with measurements obtained by loop detectors to improve the accuracy of the estimates of incident probabilities. State-of-the-art incident detection algorithms utilize only traffic information. By considering both traffic and environmental variables, it is possible to achieve a more accurate estimate of incident probability. This estimate is used as an input to the freeway incident-response decision-making system developed in the second part of this research.

Freeway Incident Response Decision-Making System

This part of the research developed and demonstrated the effectiveness of a freeway incident response decision-making system. By exploiting Sequential Hypothesis Testing techniques, the capabilities of the decision-making system extend well beyond those of conventional incident detection systems (Stephanedes, 1991). By properly accounting for the presence of measurement errors and the inherent uncertainties in interpreting measured traffic stream characteristics, the decision-making system determines if and when prevailing, real-time conditions actually warrant the implementation of incident response strategies such as dispatching emergency vehicles and initiating route diversion. All decisions generated by the system are based

upon systematic evaluation of the tradeoff between the costs associated with unwarranted responses to false alarms and the time-dependent costs of delaying needed mitigation measures until additional surveillance data confirm the freeway's operating state.

4. WORK PLAN

Freeway Incident Likelihood Prediction Models

The specific tasks performed in this part of research are listed below.

(i) Literature survey: a review of the state-of-the-art in accident modeling methods was undertaken. Although existing statistical models of traffic accidents are mostly designed to predict accident rates rather than probabilities, the basic methods used to develop these models were of some value to our research(Jara-Diaz 1986).

(ii) Development and validation of preliminary models using existing databases (the Hoosier Helper accident reports). In developing these models, care has been taken to utilize, as explanatory variables of incident likelihoods, those factors which can be measured by a freeway surveillance system such as flow rates, speed variances across lanes, time of day, etc. The specific statistical methods used in model development included logit and probit modeling techniques and discriminant analysis.

(iii) Once the models were refined and validated, they were incorporated in a computer program that can be used to provide realtime predictions of incident probabilities. This program can later be incorporated in a real-time traffic controller to optimally select control strategies in a proactive manner.

Freeway Incident Response Decision-Making System

This part of the research was conducted in three tasks. Tasks 1 and 2 entailed development and implementation of the decision-making system. The system was demonstrated and evaluated in the third task. The specific work plan is described below:

Task 1: Model Formulation

The example traffic network used in the model formulation is illustrated in Figure 1. The simple network consists of a homogeneous freeway link and a uni-directional surface street. A pretimed traffic signal controls the junction of the on-ramp and surface street, while the junction of the off-ramp and the street is uncontrolled. The only freeway traffic management strategy used in this study is route diversion to the surface street via the dissemination of incident information to freeway users.

It is assumed that loop detectors are located on the freeway section between points X_1 and X_2 . When a disturbance in traffic flow is detected, the freeway control center faces the decision of whether to declare an incident and respond to it. This decision-making process is formulated as a sequential hypothesis testing problem. At the beginning of each time period, the traffic control center obtains measurements of freeway traffic conditions from the surveillance system and thus is confronted with two mutually exclusive hypotheses, defined as:

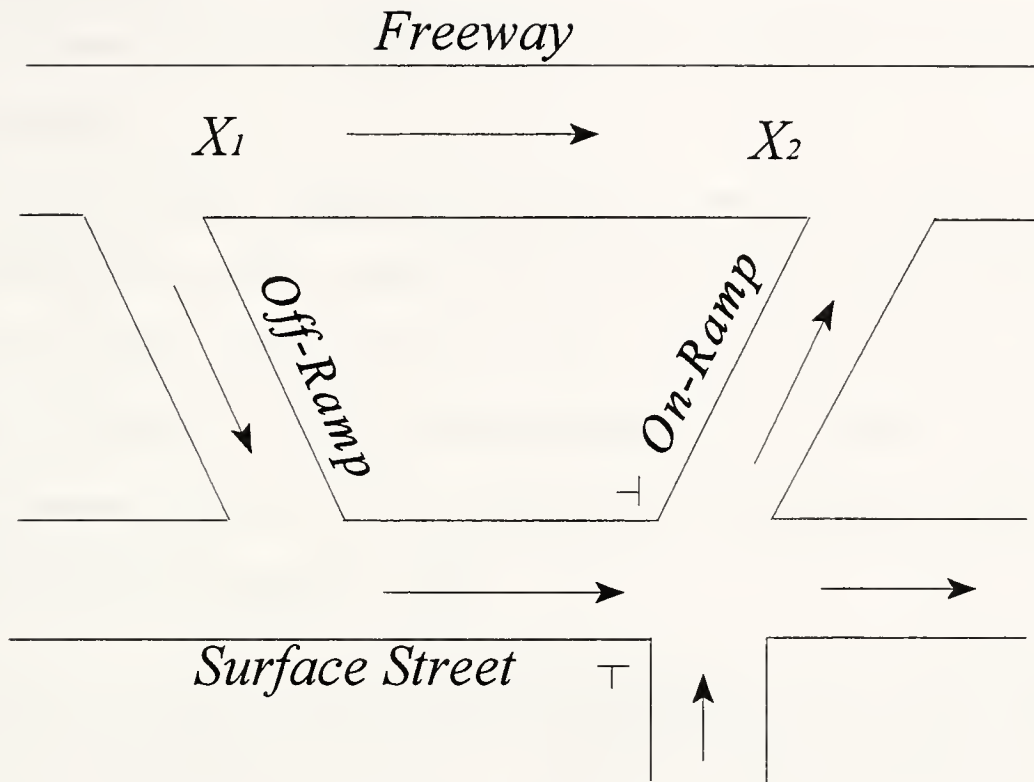


Figure 1 Example Traffic Network

H_0 : no incident has occurred on the freeway section between X_1 and X_2 and,

H_1 : an incident has occurred on the freeway.

After each observation, the decision-making system will either:

- (1) accept H_0 and implement no response,
- (2) accept H_1 and initiate route diversion from the freeway to the surface street, or
- (3) delay the decision to accept either hypothesis for an additional measurement period.

The decision of whether to accept either hypothesis or to delay the acceptance is based on the

expected losses associated with these decisions; these losses are:

- (1) the loss incurred if the traffic control center accepts H_0 when there is, in fact, an incident (a non-response),
- (2) the loss incurred if the traffic control center accepts H_1 when there is no incident (a false alarm), and
- (3) the cost incurred by waiting for one additional measurement period if there is an incident.

The objective of the decision-making system at each time period is to select the decision that minimizes the expected losses for the current and future time periods. The expected losses are computed on the basis of the current non-incident probability. This probability is a function of previously measured traffic conditions and the probability distributions of these measurements under incident and non-incident situations, as follows:

$$p_t = \frac{p_0 f_0(z_1) \dots f_0(z_t)}{p_0 f_0(z_1) \dots f_0(z_t) + (1-p_0) f_1(z_1) \dots f_1(z_t)}, t=1,2(1)$$

where

p_t : non-incident probability at time t ;

$f_0(z)$, $f_1(z)$: probability density functions (pdfs) of the traffic measurements under non-incident and incident conditions, respectively;

z_t : traffic measurements obtained at the beginning of period t ; examples of traffic measurements include occupancy, speed and flow.

p_0 : the prior non-incident probability; this probability is the output of the incident likelihood prediction model developed in the first part of the research.

The current non-incident probability can be obtained recursively by Bayesian updating as follows:

$$P_t = \frac{P_{t-1} f_0(z_t)}{P_{t-1} f_0(z_t) + (1-P_{t-1}) f_1(z_t)}, t=1,2,\dots \quad (2)$$

The Bayesian updating formula has the advantage of fast computation of the non-incident probability. The probability density functions $f_0(z)$ and $f_1(z)$ must be calibrated from field data for specific locations.

The decision-making process proceeds as follows. At the beginning of each period t , the response decision-making system uses the new traffic measurements z_t to update the non-incident probability by Equation (2) and then selects, among the three available alternatives, the one that minimizes the sum of present and future expected costs. If either of the two hypotheses is accepted, the corresponding action is taken. If the optimal decision is to take an additional measurement, then the same process is repeated in the following time period, $t+1$. The optimal response decision can be solved using dynamic programming (Bertsekas 1987). For every time period t , the dynamic programming recursion is given by:

$$J_t(p_t) = \min \{ (1-p_t) L_0, p_t L_1, (1-p_t) C + E_{z_{t+1}} [J_{t+1}(p_{t+1})] \} \quad (3)$$

where: $J_t(p_t)$: minimum expected cost-to-go function for time period t and state variable p_t ;

L_0 : loss resulting when no response is made to an incident; given by the expected difference between the delay incurred with and without diversion.

L_1 : loss associated with a false response; given by the expected total travel time increase due

to unwarranted traffic diversion from the freeway to the surface street.

C : cost associated with waiting one more period before making a response, if an incident has indeed occurred on the freeway. This cost is incurred by the drivers who pass location X_2 in Figure 1 during one time period.

The optimal policy can be shown to be stationary if the predicted costs L_0 , L_1 and C are constant, and if the analysis period is sufficiently long. This optimal policy is defined by the closed-form expression given below (Bertsekas 1987):

$$\begin{aligned}
 &\text{accept } H_0, && \text{if } p_t \geq \alpha = 1 - \frac{(1-p_t)C}{L_0} \\
 &\text{accept } H_1, && \text{if } p_t \leq \beta = \frac{(1-p_t)C}{L_1} \\
 &\text{wait for an additional period,} && \text{if } \beta < p_t < \alpha . \tag{4}
 \end{aligned}$$

This stationary optimal policy is known in the statistics literature as the Sequential Probability Ratio Test (SPRT).

Task 2: Algorithmic Implementation

Based on the model formulated in Task 1, a computer algorithm for optimal incident response was developed and implemented. In developing the computer algorithm, the critical factor was computational running time, due to the real-time constraints that this algorithm must satisfy.

One restriction of the SPRT algorithm is the assumption of constant costs. The cost components in the formulation are assumed constant for all time periods, which is not true for traffic

delays. On the other hand, this assumption produces a closed-form optimal policy which has the property of minimal computational complexity, a benefit in on-line traffic management. To exploit this property while accounting for the dynamic nature of traffic delays, a rolling-horizon implementation (Gartner 1982) of the decision-making algorithm was used. In this implementation, illustrated in Figure 2, the predicted costs are assumed constant for the duration of each projection horizon which makes it possible to use the SPRT policy. This policy is applied only to the first period of each horizon. At the end of that period, the projection horizon rolls forward, and the cost functions are updated on the basis of the latest traffic measurements. Thus, at the beginning of each

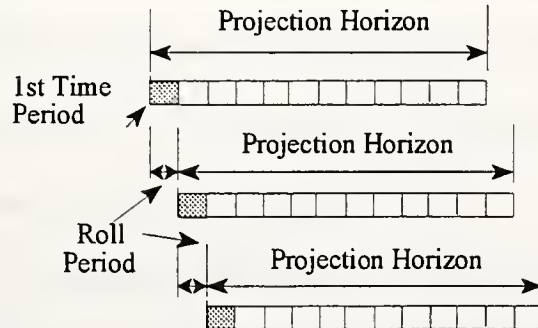


Figure 2. Rolling Horizon Implementation

projection horizon, a new incident response policy is derived for that horizon, but applied for the first time period only. The resulting optimal policy is therefore time-varying because a different stationary policy is applied to each time period.

Task 3: Parametric Analysis (Laboratory Testing)

The Optimal Incident Response algorithm was tested and validated through extensive laboratory simulations. In these experiments, a range of incident locations, traffic volumes and speeds, and measurement precision was simulated. For each combination of these inputs, the performance of the algorithm was evaluated. This performance was compared to that of a classical state-of-the-art incident detection algorithm, for the same range of input parameters.

This exhaustive parametric analysis serves two main purposes:

- to identify the ranges of input values, for which the proposed methodology outperforms state-of-the-art algorithms; this has important implementation implications,
- to determine the impact of certain input parameters, this will answer important questions regarding the design of freeway surveillance systems.

The following cost functions were used in the simulation experiments.

Cost of not responding to an incident, L_0

Figure 3 is a queueing diagram (Newell 1991) describing incident conditions with and without response. The slope Q_1 is the bottleneck capacity for the (undetected) incident; present for duration t_{ID} . Q_c is the freeway section capacity at X_2 following incident removal. Demand (i.e., "desired" arrival rate) to the restriction in the absence of response is labeled q_1 . Slope q_2 is the demand to the restriction assuming response is immediate and continues for the duration of congestion. The restoration times after the incident is cleared with and without incident response are r and r' , respectively. The delay to freeway vehicles with and without response, d_r and d_r' , respectively, are

the areas of the triangular regions bounded by the arrival and departure curves.

The loss (i.e., added delay) from not responding to the incident is the difference between total freeway and surface street travel times incurred with and without incident response. The latter is defined as:

$$\frac{L_f}{V_f} q_1 (t_{ID} + r') + d_{r'} + \frac{L_s}{V_s} q_{so} (t_{ID} + r) + W_1 \frac{(t_{ID} + r)}{Y} q_{so} (t_{ID} + r) \quad (5)$$

The first two terms in (5) describe total freeway travel time, the remaining terms compute total travel time on the surface street, where:

L_f : length of the freeway segment;

V_f : average (free-flow) speed on the freeway segment;

L_s : length of the surface street;

V_s : average (free-flow) speed on the surface street;

q_{so} : surface street traffic flow prior to diversion;

W_1 : the average vehicle delay due to signal control, computed by Webster's formula (1958).

Y : traffic signal cycle length;

Total travel time on the network with incident response is:

$$-q_2 (t_{ID} + r) + d_r + \frac{L_s}{V_s} (q_{so} + q_1 - q_2) (t_{ID} + r) + W_2 \frac{(t_{ID} + r)}{Y} (q_{so} + q_1 - q_2) (t_{ID} + r) \quad (6)$$

where W_2 is the average vehicle delay due to signal control; it is larger than W due to diversion to the surface street. This assumes no added delay in the surface street due to traffic

diversion.

Subtracting (6) from (5), the loss due to not responding to an incident becomes:

$$d_{nr} + \frac{L_f}{V_f} Q_c (r' - r) - \frac{L_s}{V_s} (q_1 - q_2) (t_{ID} + r) - [W_2 (q_{so} + q_1 - q_2) - W_1 q_{so}] \frac{(t_{ID}}{(7)}$$

where d_{nr} denotes the difference between d_r and d_r , the area of triangle AC'CA in Figure 4.

Cost of a false response, L_1

The total network travel time resulting from a (false) response in the absence of an incident can be expressed as:

$$\frac{L_f}{V_f} q_2 t_d + \frac{L_s}{V_s} (q_{so} + q_1 - q_2) t_d + W_2 \frac{t_d}{Y} (q_{so} + q_1 - q_2) t \quad (8)$$

where t_d is the diversion period.

Total network travel time in the absence of both incident and response is:

$$\frac{L_f}{V_f} q_1 t_d + \frac{L_s}{V_s} q_{so} t_d + W_1 \frac{t_d}{Y} q_{so} t \quad (9)$$

Subtracting (9) from (8), we obtain the loss resulting from a false diversion decision:

$$L_1 = \frac{L_s}{V_s} (q_1 - q_2) t_d + \frac{t_d^2}{Y} [W_2 (q_{so} + q_1 - q_2) - W_1 q_{so}] - \frac{L_f}{V_f} (q_1 - q_2) t \quad (10)$$

Cost of postponing the decision for one additional time period, C

The queueing diagram in Figure 4 illustrates freeway conditions when incident response is initiated. Curve ABC defines vehicle departures past location X_2 due to the incident of duration t_D .

Curve AEC illustrates vehicle demands to location X_1 assuming an "immediate" incident response (i.e. a response made in the current period) which continues for a diversion period t_d . Curve AA'E'C defines the demand rate when initiation of response is postponed for one interval.

Thus, the cost of postponing the decision by one time period is :

$$C = d_p - d_c = (q_1 \Delta t) t_d \quad (11)$$

Where: Δt denotes the length of one period

All the variables used in computing C , L_0 and L_1 at the beginning of every period can be obtained using on-line measurements. Traffic flow and speeds for the projection horizon can be predicted using time-series forecasting techniques such as auto-regressive or moving-average processes. In this study, we used moving-average techniques to predict both traffic flows and speeds.

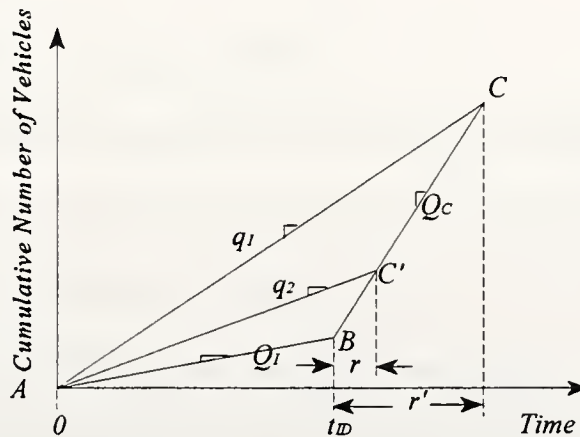


Figure 3. Queueing Diagram for Computation of L_0

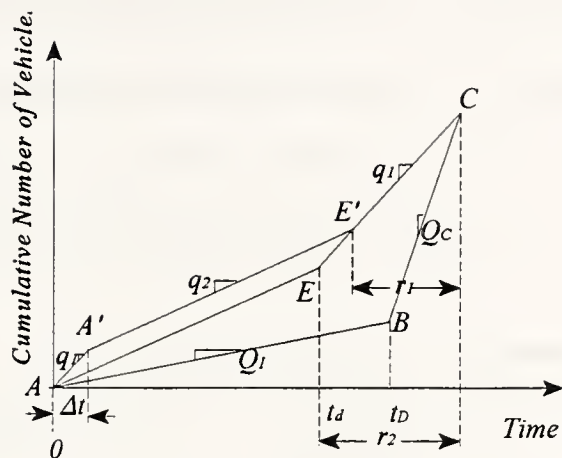


Figure 4. Queuing Diagram for Computation of C

5. ANALYSIS OF DATA

Freeway Incident Likelihood Prediction Models

Eight-and-a-half months of incident, traffic and weather data for the Borman expressway were used for model development. We sampled non-incident data from the non-incident population which comprises those time periods in which no incidents were observed. Therefore, our sample is a stratified random sample with two strata, incidents and non-incidents.

Two binary logit incident prediction models are presented in the following paragraphs. These are models for two types of incidents: (i) overheating vehicles, and (ii) crashes. In Tables 1 & 2 the column entitled "Independent Variable" lists the explanatory variables used in the model. The "Estimated Coefficient" column shows the contribution of each explanatory variable to the probability of that type of incident and the "t-Statistic" column displays the statistical significance of that variable.

A t-statistic larger than 1.65 in absolute value means that the variable is a significant predictor of that type of incident at the 90% confidence level. The goodness of fit of each model is represented by ρ^2 ; the larger the value of ρ^2 , the better the fit of the model to the data. In binary logit models, the statistic "percent correctly predicted" provides an estimate of the predictive accuracy of each model.

For the overheating vehicle incident likelihood model, the variables peak, merge, temp (temperature), rain, and spv (speed variance) were found significant.

Table 1 Incident Likelihood Model for Overheating Vehicles

Independent Variable	Estimated Coefficient	t-Statistic
constant	-2.45	-5.25
peak	0.40	1.62
merge	0.51	2.19
temp	0.03	4.63
rain	-1.06	-2.29
spv	-0.05	-2.37
number of observations	427	
percent correctly predicted	73.53	
ρ^2	0.21	

The coefficient for the variable peak has a positive sign, which suggests that an overheating vehicle incident is more likely to occur in a peak period than a non-peak period. This is expected because traveling speeds are slower during the peak period. This variable is not significant at the 90% confidence level, as can be seen by the value of its t-statistic (1.62), possibly because the peak

period on the Borman expressway is widely spread out. The coefficient of the variable merge represents the effect of location relative to on/off ramps on the likelihood of an overheating vehicle incident. The positive sign of this coefficient indicates that an overheating vehicle incident is more likely to occur in a merge section than a mid-section. The value of the t-statistic (2.19) suggests that this effect is significant. The coefficient of the variable temp shows the effect of temperature on the likelihood of an overheating vehicle incident. The positive sign suggests that an overheating vehicle incident is more likely to occur in high temperature conditions than low temperature conditions, because high temperatures aggravate engine overheating. The high t-statistic (4.63) strongly supports this explanation. The coefficient of the variable rain has a negative sign which indicates that an overheating vehicle incident is more likely to occur in sunny (non-rainy) conditions than in rainy conditions. The t-statistic (-2.29) shows a significant effect for the variable rain. The coefficient of the variable spv represents the effect of speed variance between lanes on the likelihood of an overheating vehicle incident. The negative sign means that an overheating vehicle incident is more likely to occur in lower speed variance conditions than higher speed variance conditions. This is because when the speed variance is low, there are less overtaking opportunities, which increases the likelihood of an overheating vehicle incident. The t-statistic (-2.37) suggests that this result is significant. Overall, this model demonstrates good fit to the data, as can be seen from the value of ρ^2 (0.21), and high predictive accuracy, as measured by the high percentage of observations correctly predicted (74%).

For the crash model, the variables merge, visi (visibility), and rain are found significant. In Table 2, the coefficient of the variable merge has a positive sign, which suggests that a crash is more likely to occur in a merge section than a non-merge section. Though the t-statistic (1.46) indicates

that this variable is not strongly significant at the 90% confidence level, it has the correct sign, because there are more vehicle interactions and therefore a higher crash probability in the merge sections, where traffic flow is not as smooth as in the mid-sections. The coefficient of the variable *visi* has a negative sign, which indicates that a crash is more likely to occur in low visibility conditions, as expected. This variable is not strongly significant, as can be seen by its t-statistic (-1.02) possibly because, in our dataset, visibility is measured in miles, a unit which is not sufficiently precise to capture the effect of low visibility on drivers. The coefficient of the variable *rain* has a positive sign, which means that a crash is more likely to occur in rainy conditions than

Table 2 Incident Likelihood Model for Crashes

Independent Variable	Estimated Coefficient	t-Statistic
constant	-0.76	-2.23
merge	0.31	1.46
visi	-0.02	-1.02
rain	1.48	3.45
number of observations	434	
percent correctly predicted	71.19	
ρ^2	0.14	

non-rainy conditions. This is because the presence of rain reduces visibility and lowers pavement skid resistance. The high t-statistic (3.45) supports this explanation. The fit of this model is satisfactory, as shown by its ρ^2 value (0.14), as is its predictive accuracy (71% of observations correctly predicted).

It should be noted that the estimated coefficients in these models are unbiased regardless of the use of a stratified random sampling scheme in which incidents are oversampled. The only correction that must be made is for the constant, using the method described in (Ben-Akiva and Lerman). The effect of this correction is to reduce the probability of an incident by a factor proportional to the log of the fraction of incident observations in the sample divided by the fraction of incident observations in the population.

The effects of various attributes of the incident likelihoods are shown in Figures 5 to 8.

Overheating vehicle incident likelihood model

As can be seen in Figure 5, there is no major difference between actual and historical likelihood in the low temperature range. However, when the temperature rises above 50 F, the incident probability curve for extreme conditions deviates upward quickly from the historical probability.

case 1: historical probability (independent of all conditions)

case 2 (extreme conditions): peak hour, merge section, and no rain

case 3 (favorable conditions): off-peak, mid section, and rain

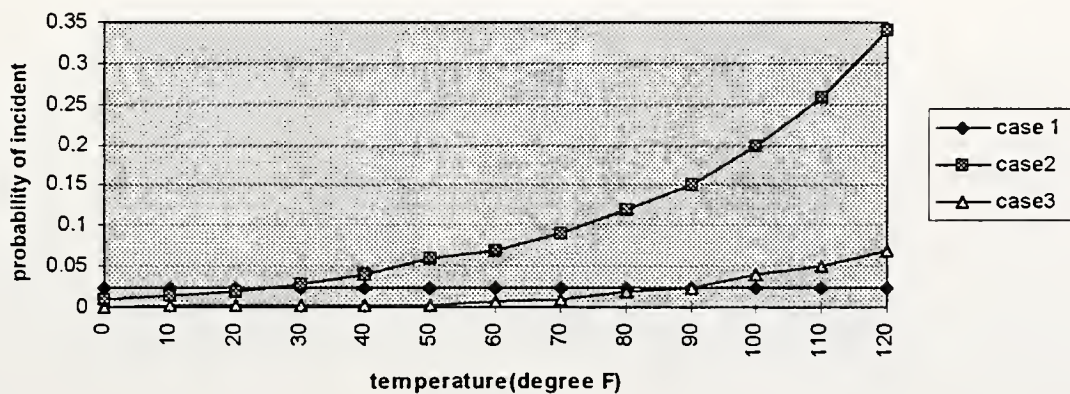


Figure 5. Effect of temperature on the probability of an "overheating vehicle" incident

In Figure 6, it can be seen that for a realistic range of speed variances, the incident probabilities under extreme conditions are higher than the historical incident probabilities and those under favorable conditions, though the differences are not significant

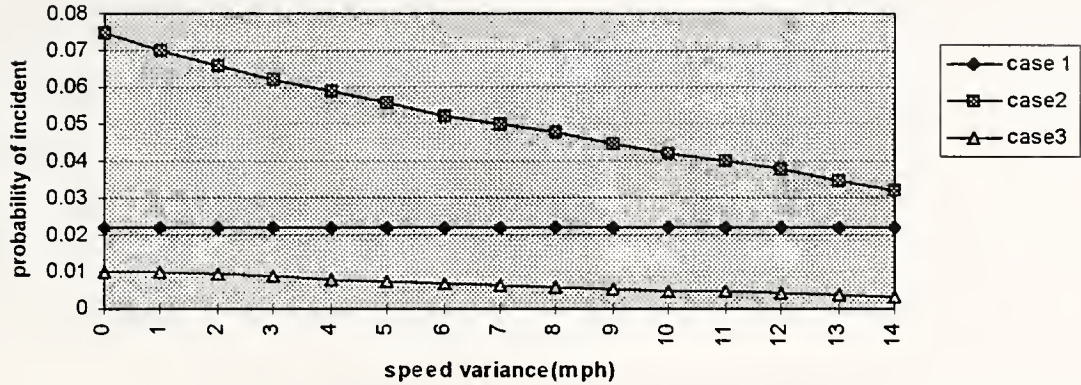


Figure 6. Effect of speed variance on the probability of an "overheating vehicle" incident

Vehicle crash incident likelihood model

In Figure 7, it can be seen that the probability of crash under extreme conditions is significantly higher than under favorable conditions, which is about the same as the historical probability

case 1: historical probability (independent of all conditions)

case 2 (extreme conditions): merge section, and rain

case 3 (favorable conditions): mid section, and no rain

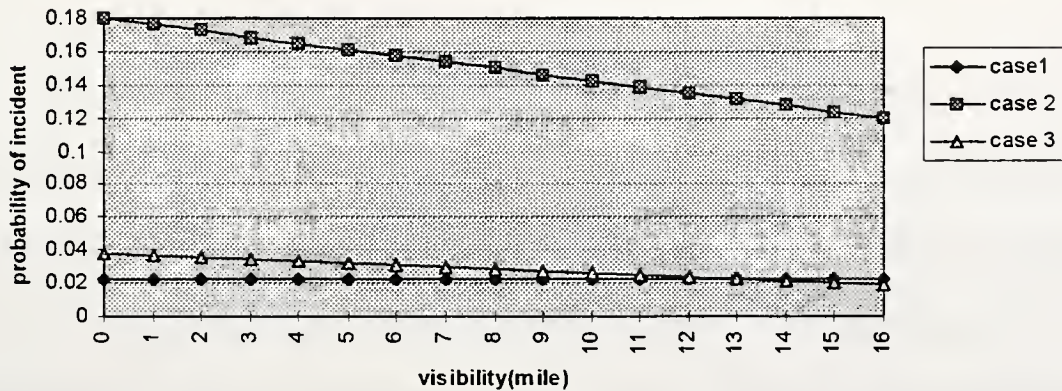


Figure 7. Effect of visibility on the probability of a "vehicle crash" incident

Other incident types likelihood

For other incident types, no traffic or environmental variables were found to be significant

explanatory variables of incident likelihood. Figure 8 demonstrates the probability for other five types of incidents

- type 1 abandoned vehicles
- type 2 debris on the roadways
- type 3 other mechanical problems
- type 4 driver pulled over
- type 5 tire repair

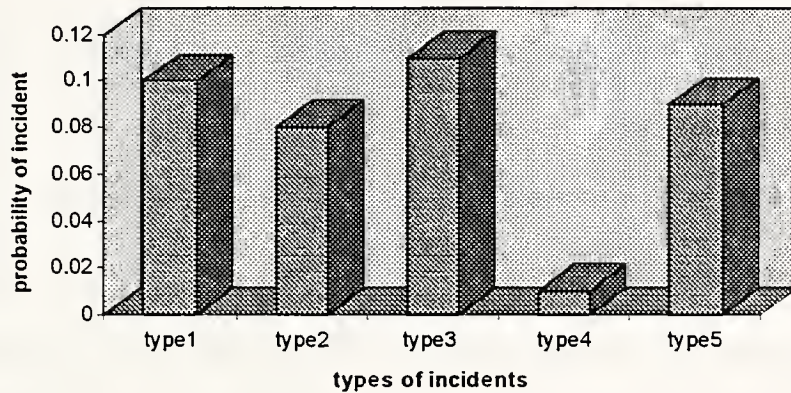


Figure 8. Historical probabilities of other five types of incidents

Freeway Incident Response Decision-Making System

An evaluation of the SPRT incident response algorithm was carried out by comparing it with a typical sequential incident response algorithm, in which incident detection is based on the Bayesian algorithm (Levin and Krause 1972), and the response decision is made only after some verification by using repeated measurements. It is assumed that the verification time is 120 seconds (Jones et al 1991). The incident detection threshold used in the Bayesian algorithm is set to maximize the probability of correct decisions for both incident and non-incident conditions. Employing Bayesian concepts, the correct decision probability is expressed as follows:

$$p(H_0|non\text{-}incident) + p(H_1|incident) =$$

$$\frac{(1-p_0) \int_{z_c}^{\infty} f(z|H_1) dz}{\int_0^{\infty} f(z|H_0) dz + (1-p_0) \int_{z_c}^{\infty} f(z|H_1) dz} + \frac{p_0 \int_0^{z_c} f(z|H_0) dz}{p_0 \int_0^{z_c} f(z|H_0) dz + (1-p_0) \int_0^{z_c} f(z|H_1) dz}$$

(12)

where the first term is for the correct decision under normal conditions, and the second term is for incident conditions. The value z_c , which maximizes expression (12) is calibrated off-line based on historical data. An incident is declared whenever the traffic measurements exceed this threshold.

In the evaluation, the required traffic measurements are generated from the INTRAS freeway simulation model (Wicks 1980). The following parameters in the models used by the SPRT algorithm are kept constant throughout the evaluation: the diversion period (set to 10 minutes), the mean incident duration (15 minutes) and the bottleneck capacity (2000 vph). The evaluation procedure is illustrated in Figure 9. The inputs to INTRAS consist of traffic flow, geometric data and incident related data such as incident type, location and duration. Given these inputs, INTRAS simulates occupancy readings at specified detector locations, in 20 second intervals. These occupancy readings are then used as inputs for the SPRT and Bayesian algorithms. The evaluation is based on three criteria: response time, non-response rate, and false response rate.

In the evaluation we investigate the performance of the algorithms under various flows and incident locations downstream of the loop detector. The ability of these two algorithms to deal with the uncertainty in traffic measurements is evaluated. The incidents are

specified to occur at 1800 feet and 2600 feet downstream of the loop detector respectively. The freeway traffic flows are varied from 3000 vph to 5000 vph. The variances of the probability density functions $f_0(z)$ and $f_i(z)$ indicate the uncertainty in the traffic measurements. By changing these variances, it is possible to observe the performance of the algorithms under different levels of uncertainty. The combinations of the above mentioned three factors result in twelve incident scenarios as shown in Table 3.

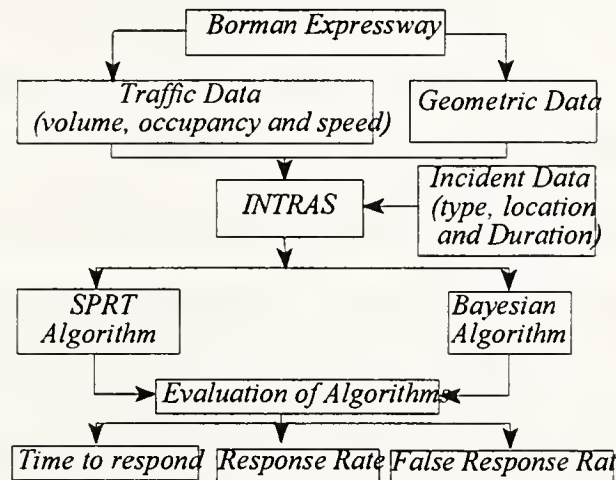


Figure 9 Simulation Evaluation Framework

Corresponding to each incident scenario, a non-incident situation was simulated with the same traffic flow and occupancy probability density functions. The statistics, shown in Table 3, for mean response time and non-response rate were computed using 100 simulation runs under incident scenarios, whereas those for false response rate were obtained from an equal number of simulation runs for the non-incident scenarios.

Table 3 clearly shows that for both algorithms, the longer the distance between the incident site and the detector, the longer the response time, because the incident shock wave takes

longer to reach the detectors. The influence of distance on both algorithms is of the same order of magnitude, as can be seen from the results in Table 3. Table 3 also indicates that under high traffic flow, incident response is faster. This is due to more drastic changes in the measured values of occupancy. The influence of traffic flow on both algorithms is also of the same order of magnitude. It can also be seen that, for both algorithms, incident response is faster for low uncertainty conditions.

Both algorithms have similarly low false response rates (0% to 4%); this result is typical for simulation tests. On-line tests usually reveal higher false-alarm rates. Table 3 also shows that the mean response time of the SPRT algorithm is lower than that of the Bayesian algorithm under all conditions. Moreover, it can be seen that the Bayesian algorithm does not respond at all to incidents when measurement uncertainty is high. The reason is that under high variance, the threshold z_c calibrated off-line in the Bayesian algorithm increases, to reduce the false-alarm rate, thus making it less likely to be exceeded by the measured occupancies. This results in no detection of the simulated incidents, and thus no response. On the other hand, the SPRT algorithm only misses 5% of incidents under high variance conditions.

In summary, two conclusions can be made. First, the SPRT algorithm has a significantly lower non-response rate than the Bayesian algorithm, because the high expected cost associated with a non-response is explicitly accounted for in the decision-making procedure, and the appropriate threshold adjusted accordingly. Second, the SPRT algorithm achieves shorter response time than the Bayesian algorithm, because the number of observations required for incident verification is optimized online, on the basis of the loss associated with waiting for these observations, rather than being predetermined. While on-line testing must be performed before

firm conclusions can be made, the results presented in this research indicate that the Sequential Hypothesis Testing based incident response algorithm is promising.

6. CONCLUSIONS

In this research, we have developed a new methodology for freeway incident response decision-making. This methodology, which is based on the Sequential Hypothesis Testing framework, explicitly accounts for the losses associated with incorrect detection and response decisions and optimize the tradeoffs between these expected losses. To facilitate the application of the decision-making methodology within the constraints of on-line traffic management, a rolling-horizon implementation was used. Results obtained by simulation indicate that the new decision-making system has a better ability to handle the uncertainty in the traffic measurements, without increasing the false-alarm and non-response rates. Moreover the SPRT response algorithm achieves shorter response time than the traditional incident detection algorithm. This superior performance can be attributed to the fact that the new system explicitly minimizes the sum of the expected losses associated with the response decisions.

7. RECOMMENDATIONS

This section discusses some of the implementation issues for the incident response decision-making system developed in this research. These issues include: off-line data requirements, on-line input requirements and computational needs. To date, our decision-making system was calibrated for on-line inputs received from loop detectors. To accommodate outputs from other types of detectors, the system's models must first be calibrated off-line using historical data. Using

multiple detector types within the response algorithm is expected to increase the efficiency of the decision-making system.

Currently, the decision-making system is operational for a single freeway section as described in Figure 1. Therefore, the following discussion will emphasize implementation issues for a single freeway section including the associated on-ramp, off-ramp and corresponding surface street section. The implementation of the current version of the decision-making system requires the presence of three loop detectors: one detector located immediately downstream of the off-ramp, one located immediately upstream of the on-ramp, and one located on the off-ramp. If a single measurement of traffic occupancy is used in the SPRT algorithm, the occupancy data is measured at the first detector. This detector also provides measurements of traffic flow and speed for cost computation and prediction at the beginning of each control interval. The second detector provides measurements of traffic flow and speed downstream of the bottleneck, which are used for cost computation. The traffic volume obtained from the off-ramp detector is used for measuring and updating the traffic diversion rate from the freeway onto the surface street.

The following parameters must be specified off-line, prior to the operation of the decision-making system.

- 1) The type of traffic measurements used; currently, our decision-making system accepts two types of traffic measurement: upstream detector occupancy or relative spatial occupancy difference between upstream and downstream freeway detectors.
- 2) The time interval between two observations; in the parametric analysis performed in this study, we use 20 seconds.
- 3) The prior probability of non-incident; this is the output of the incident likelihood

prediction models.

- 4) The length of the freeway section.
- 5) The capacity of the freeway section.
- 6) The free flow speed of the freeway section.
- 7) The length of the surface street section.
- 8) The uncongested speed on the surface street section.
- 9) The existing surface street flow.
- 10) The initial fraction of freeway traffic that diverts in incident conditions; this quantity is updated using the moving average method at the beginning of each control interval, after obtaining new measurements from the off-ramp loop detector.
- 11) The initial estimate of the length of time period for which diversion from freeway to surface street is performed.
- 12) The signal cycle length on the surface street.
- 13) The signal green time on the surface street for the traffic stream traveling in the direction parallel to the freeway section.

The decision-making system uses the following on-line inputs, measured by the three loop detectors, and updated at the start of each control interval:

- 1) Traffic flow at upstream detector.
- 2) Average vehicle speed at upstream detector.
- 3) Upstream detector occupancy.
- 4) Traffic flow at downstream detector.
- 5) Average vehicle speed at downstream detector.

6) Downstream detector occupancy.

To extend the decision-making system to a freeway system consisting of multiple sections, each equipped with the three detectors described above, the SPRT algorithm can be applied sequentially one section at a time starting at the downstream end of the freeway system. The derivation of the incident response decision for each section involves simple algebraic operations, due to the closed form response policy. Solving for the optimal incident response for one section took a fraction of a second, when the algorithm was implemented on a Pentium personal computer during the simulation-testing experiments performed as part of this research project. Therefore, the computation time required for running the algorithm in the case of a freeway system consisting of N sections is less than N seconds. In on-line operations, the optimal response decision for each freeway section can be activated as soon as it has been solved for, and before the policies of the upstream sections have been obtained. This means that the SPRT algorithm can be applied to a freeway system of any length with the use of the standard computational resources available to Traffic Operations Centers, namely stand-alone Pentium PCs or Workstations.

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