3. Advisories of severe traffic problems on the primary freeway route were cited most often in both the July and October studies as the information that would have influenced the drivers who did not divert to use the alternative route. This unexpected result for the October studies (traffic condition information was displayed) was primarily due to the fact that some drivers failed to read or correctly interpret the message(s).
4. More than 14 percent of the 362 drivers who diverted interviewed stated that additional information on parking in the Fair Park area was desirable. Also, 9.4 percent of the drivers requested guidance on the return route, and 9.1 percent requested additional on-route guidance.

5. No drivers who had diverted during the October studies, despite the heavier volumes on the Fitzhugh Avenue route, stated that they would not follow diversion instructions in the future under similar circumstances.

ACKNOWLEDGMENTS

This study was conducted as part of a project sponsored by the Federal Highway Administration. The support and the assistance provided by the city of Dallas and the Texas State Department of Highways and Public Transportation are acknowledged. The contents of this report reflect our views; we are responsible for the facts and the accuracy of the data presented herein. The contents do not necessarily reflect the official views or policies of the Federal Highway Administration. This report does not constitute a standard, specification, or regulation.

REFERENCES


Publication of this paper sponsored by Committee on Freeway Operations.

Incident Detection: A Bayesian Approach

Moshe Levin and Gerianne M. Krause, Bureau of Materials and Physical Research, Illinois Department of Transportation

A single-feature incident-detection algorithm based on Bayesian considerations is developed. The algorithm uses the ratio of the difference between the upstream and the downstream minute occupancies and the upstream occupancy as the traffic-flow feature followed and uses historical incident information. The historical incident data used are representative of the inner lane of the outbound Kennedy Expressway between the Chicago Loop and the Edens Expressway junction during the afternoon rush period. Mathematical expressions are developed for the distributions of the ratio from incident and incident-free data. The probabilities of incidents occurring on the outbound Kennedy are developed from available incident data. The optimal threshold to be used in the incident-detection process is determined mathematically by using Bayesian concepts. The efficiency of the algorithm is evaluated in terms of its detection rate, false-alarm rate, and mean time to detect and is compared with those of the California algorithm and two algorithms developed by Technology Services Corporation. The Bayesian algorithm compares favorably with the others with regard to detection rate (100 percent) and false-alarm rate (0.0 percent). However, its mean time to detect is greater than that of the other algorithms by almost 2.5 min. A preliminary on-line evaluation comparing the Bayesian algorithm and one of the others showed no significant differences in detection rate, false-alarm rate, and mean time to detect.

Freeway incident-management systems that offer various levels of service to the motoring public have been in operation for quite some time. In essence, these systems provide some or all of the following elements:

1. Detection of traffic-flow abnormalities,
2. Incident identification,
3. Traffic management strategies and tactics through communication and control systems, and
4. Early removal of incidents and the return to normal traffic-flow conditions.

The degree of comprehensiveness of the management system and the level of sophistication of its elements determine the operational efficiency of the system and its success in achieving its objectives.

The detection of traffic-flow abnormalities on a freeway is carried out by a surveillance system, usually through an electronic detector subsystem. The availability of such a subsystem allows continuous quantification of traffic-flow characteristics, the identification of incidents, and the application of appropriate control strategies.

The process by which traffic-flow abnormalities are identified as incidents is a key element in such a management system because a positive identification normally activates the control, driver-communication, and incident-handling subsystems. Obviously, missed incidents or false alarms will affect the efficiency of the management system and its credibility.

The incident-identification process uses an incident-detection algorithm that relates measured relationships between traffic characteristics to calibrated ones and yields a decision with regard to the occurrence of an incident. Throughout the years of freeway-control research, the basic approaches to the development of
incident-detection algorithms have been used to theoretical traffic-flow considerations and the identification of consistent deviations as incidents (1, 2, 3) and

1. Pattern recognition: the comparison of current traffic patterns with those expected based on historical data or theoretical traffic-flow considerations and the identification of consistent deviations as incidents (1, 2, 3) and

2. Statistical forecasting of traffic behavior: the comparison of current traffic characteristics with forecasted ones based on time-series analysis and the identification of calibrated deviations as incidents (4, 5, 6).

The efficiency of such algorithms can be determined by three related parameters:

1. Detection rate: the percentage of total capacity-reducing incidents occurring during a specified time period that are detected.
2. False-alarm rate: the percentage of total incident messages occurring during a specified time period that are false (on-line definition) (another definition (3) of the off-line situation is the percentage of incident messages ("1" s) out of all messages ("1" s and "0" s), where messages are produced at specific intervals (i.e., every 1 min) out of incident-free data), and
3. Mean time to detect: the mean delay between the apparent occurrence of the incident and its detection for all detected incidents occurring during a certain period of time.

The inherent positive correlation between the detection and false-alarm rates can be detrimental to the effectiveness of the incident-management system because the desired low false-alarm rate is coupled with a low detection rate. The implication of such a detrimental effect can best be illustrated by applying the detection characteristics of an existing algorithm (3), which is considered an efficient one, to the incident situation on Chicago expressways. It is estimated that the Chicago expressway system under electronic surveillance experiences approximately 20 capacity-reducing incidents/ d during the afternoon rush period. By applying an algorithm optimally calibrated to have a 0.01 percent false-alarm rate coupled with a 34 percent detection rate, it can be shown that only 7 incidents will be detected but 20 false alarms will be reported. In reality, the false-alarm rate as viewed by the incident-management decision maker would be close to 75 percent. At such a high probability of making the wrong decision, no decision will be made without more information as to the reliability of the incident message.

High message reliability can be achieved by the use of sophisticated incident-identification and verification systems (such as closed-circuit television and CB radio), which will offset the weaknesses of the detection algorithm. However, for large freeway systems, this type of verification is probably not feasible. Another way to increase message reliability is to use an algorithm that considers the likelihood of the occurrence of a capacity-reducing incident at a particular location and time period. In addition, message reliability can be improved by a time trade-off in waiting for additional incident indication(s).

The incorporation of incident historical information into a probabilistic model could be achieved by using Bayesian concepts. This approach will give the probability that an incident has actually occurred, given an incident signal or string of signals.

THEORETICAL CONSIDERATIONS

Consider a freeway section located between two detectors that have been placed on one of the section lanes. Let Z represent a certain traffic feature (characteristic) that can be measured at either the upstream or the downstream detector or at both. Let \( f(Z/U_0) \) and \( f(Z/U_1) \) represent the frequency distribution functions of feature Z during incident and incident-free situations respectively for certain environmental and traffic conditions.

The probability of an incident occurring on this section \( P(U_i) \) under certain environmental and traffic conditions can be derived based on its history of capacity-reducing incidents. The probability of not having any capacity-reducing incidents is then \( P(U_0) \). Thus

\[
P(U_0) = 1 - P(U_1)
\]

and

\[
P(U_0) \int_{a_0}^{b_0} f(Z/U_0)dZ + P(U_1) \int_{z_1}^{z_f} f(Z/U_1)dZ = 1
\]

where \( a_0, b_0, a_1, \) and \( b_1 \) are the upper and lower bounds of Z in the functions \( f(Z/U_0) \) and \( f(Z/U_1) \) respectively.

For any feature value Z (threshold), it can be shown that the probability of obtaining an incident signal \( P(I) \) can be expressed as follows:

\[
P(I) = P(U_0) \int_{a_0}^{b_0} f(Z/U_0)dZ + P(U_1) \int_{z_1}^{z_f} f(Z/U_1)dZ
\]

Similarly, the probability of obtaining a nonincident signal \( P(0) \) is

\[
P(0) = P(U_0) \int_{a_0}^{b_0} f(Z/U_0)dZ + P(U_1) \int_{z_1}^{z_f} f(Z/U_1)dZ
\]

By applying Bayesian considerations, one can develop an expression for the probability that an incident has actually occurred, given that an incident signal "1" was output. This expression is

\[
P(\text{incident}/1) = P(U_1) \int_{z_1}^{z_f} f(Z/U_1)dZ
\]

\[
= \left[ P(U_0) \int_{a_0}^{b_0} f(Z/U_0)dZ + P(U_1) \int_{z_1}^{z_f} f(Z/U_1)dZ \right]
\]

The probability that no incident has occurred when a nonincident signal "0" is output can be expressed as

\[
P(\text{no incident}/0) = P(U_0) \int_{a_0}^{b_0} f(Z/U_0)dZ
\]

\[
= \left[ P(U_0) \int_{a_0}^{b_0} f(Z/U_0)dZ + P(U_1) \int_{z_1}^{z_f} f(Z/U_1)dZ \right]
\]

The optimal threshold \( Z_1 \) can be obtained by maximizing the expression:

\[
P(\text{incident}) + P(\text{no incident})
\]

Theoretically, this optimization procedure for \( Z_1 \) can be repeated for \( f(Z/U_i) \) to give a set of optimal thresholds \( Z_i \) where \( i \) represents consecutive determined time intervals after the detection of an incident. However, by selecting a feature for which there are no statistically significant differences between \( f(Z/U_i) \) and \( f(Z/U_0) \), only one threshold value could be used in
the detection process. The use of such a feature is important because of the delay between the occurrence of an incident and its detection. In such cases, the calculated values of $Z_n, Z_{n+1}$, and so on will not represent time intervals immediately after the occurrence of the incident. Thus, by selecting one appropriate threshold, the threshold-synchronization problem is eliminated.

The application of the Bayesian concepts can also be extended to the case of strings of signals. The evaluation of the probability that an incident has actually occurred, given an n-signal string (although this forces a wait of n time intervals before making an incident-management decision) can provide the decision maker with more reliable information. Obviously, for practical reasons, n could be limited to three; thus, the signal strings of interest would be 10, 11, 100, 101, 110, and 111. The nature of the probabilities of the occurrence of an incident, given any of the above signals, can be shown to be such that

$$P(\text{incident/111}) > P(\text{incident/11})$$

and

$$P(\text{incident/100}) < P(\text{incident/10})$$

These relationships are necessary conditions if the Bayesian approach is valid.

The probabilities of the actual occurrence of an incident, given the n-signal strings shown above, are given below.

<table>
<thead>
<tr>
<th>Probability</th>
<th>Expression</th>
</tr>
</thead>
<tbody>
<tr>
<td>$P(\text{incident/1})$</td>
<td>$P(1/\text{incident}) P(\text{incident}) + [P(1/\text{incident}) P(\text{incident}) + P(1/\text{no incident}) P(\text{no incident})]$</td>
</tr>
<tr>
<td>$P(\text{incident/0})$</td>
<td>$P(0/\text{incident}) P(\text{incident}) + [P(0/\text{incident}) P(\text{incident}) + P(0/\text{no incident}) P(\text{no incident})]$</td>
</tr>
<tr>
<td>$P(\text{no incident/1})$</td>
<td>$P(1/\text{no incident}) P(\text{no incident}) + [P(1/\text{incident}) P(\text{incident}) + P(1/\text{no incident}) P(\text{no incident})]$</td>
</tr>
<tr>
<td>$P(\text{no incident/0})$</td>
<td>$P(0/\text{no incident}) P(\text{no incident}) + [P(0/\text{incident}) P(\text{incident}) + P(0/\text{no incident}) P(\text{no incident})]$</td>
</tr>
<tr>
<td>$P(\text{incident/10})$</td>
<td>$P(0/\text{incident}) P(\text{incident}) + [P(0/\text{incident}) P(\text{incident}) + P(1/\text{no incident}) P(\text{no incident})]$</td>
</tr>
<tr>
<td>$P(\text{incident/11})$</td>
<td>$P(1/\text{incident}) P(\text{incident}) + [P(1/\text{incident}) P(\text{incident}) + P(1/\text{no incident}) P(\text{no incident})]$</td>
</tr>
<tr>
<td>$P(\text{incident/100})$</td>
<td>$P(0/\text{incident}) P(\text{incident}) + [P(0/\text{incident}) P(\text{incident}) + P(0/\text{no incident}) P(\text{no incident})]$</td>
</tr>
<tr>
<td>$P(\text{incident/101})$</td>
<td>$P(1/\text{incident}) P(\text{incident}) + [P(1/\text{incident}) P(\text{incident}) + P(1/\text{no incident}) P(\text{no incident})]$</td>
</tr>
<tr>
<td>$P(\text{incident/110})$</td>
<td>$P(1/\text{incident}) P(\text{incident}) + [P(1/\text{incident}) P(\text{incident}) + P(1/\text{no incident}) P(\text{no incident})]$</td>
</tr>
<tr>
<td>$P(\text{incident/111})$</td>
<td>$P(1/\text{incident}) P(\text{incident}) + [P(1/\text{incident}) P(\text{incident}) + P(1/\text{no incident}) P(\text{no incident})]$</td>
</tr>
</tbody>
</table>

These probabilities can be computed for any particular freeway section and specific traffic and environmental conditions by using the history of capacity-reducing incidents.

For appropriate freeway sections and environmental and traffic conditions, the theoretical probabilities that an incident has actually occurred, given a certain signal string, can be correlated with actual string probabilities derived from on-line implementation of the Bayesian algorithm. Once the calibration is complete, a certain criterion value can be selected to use in making an incident-management decision.

ALGORITHM DEVELOPMENT

The process of quantifying these theoretical considerations requires the use of three data bases that were established within the framework of other incident-detection research. These are the

1. Incident data base,
2. Incident-free data base, and

The first two data bases were used to develop $f(Z/U)$ and $f(Z/U')$, respectively, and the third one was used to develop historical probabilities of capacity-reducing incidents.

The incident data base contained 122 data segments for that number of incidents and represented various locations and environmental and traffic conditions. Each data segment consisted of main-line, 20-s based, occupancy and volume data for at least 15 min before the occurrence of the incident and at least 10 min after its termination. The same traffic characteristics were collected for similar environmental and traffic conditions on the same freeway locations. Data were collected through the Chicago expressway surveillance system, which features center-lane detectors spaced every 0.8 km (0.5 mile) and fall detector coverage every 4.8 km (3 miles). These detectors are connected via leased telephone lines to a central computer that processes the raw pulses into occupancy, volume, and speed data.

The historical data base for the capacity-reducing incidents was developed by using the assistance-rendered reports submitted by emergency patrol vehicles for the years 1973, 1974, and 1975. These reports provide such information as the type of incident (e.g., accident or stalled vehicle), its location, estimated occurrence time, and environmental conditions.

Once the three data bases were available, it was possible to proceed with the selection of a study site for which the Bayesian model would be developed, the selection of the appropriate traffic-flow feature to be used in the model, and the development of historical probabilities of capacity-reducing incidents.

Study-Site Selection

Because the incident and incident-free data bases were prepared in the framework of other incident-detection research, the selection of the study site was confined to isoperational sections for which large enough samples of incident-free and incident data were available. This led to the selection of the outbound J. F. Kennedy Expressway between the Chicago Loop and the junction with the Edens Expressway. This section of the Kennedy Expressway is basically four lanes wide and has two reversible lanes that operate outbound in the afternoon rush period; it has an average daily traffic of approximately 115 000 vehicles. In 1975, the number of assists by emergency vehicles on weekdays (capacity-reducing incidents and others) was nearly 1500, and there was an average of approximately 1 capacity-reducing incident/afternoon rush period.

Feature Selection

Seven traffic features were considered in the feature-selection process. These features were taken from incident-detection algorithms developed by Payne and others (3) for Technology Science Corporation (TSC)
and have been the subject of other research (7). The seven features considered are given below:

<table>
<thead>
<tr>
<th>Name</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>OCC(t)</td>
<td>Minute-average occupancy measured at upstream detector at time t</td>
</tr>
<tr>
<td>DOCC(t)</td>
<td>Minute-average occupancy measured at downstream detector at time t</td>
</tr>
<tr>
<td>OCCRDF(t)</td>
<td>OCC(t) - DOCC(t)</td>
</tr>
<tr>
<td>OCCRDF(t)/OCC(t)</td>
<td></td>
</tr>
<tr>
<td>SPEED(t)</td>
<td>Minute-average speed measured at upstream detector at time t</td>
</tr>
<tr>
<td>DOCCDT(t)</td>
<td>[DOCC(t - 2) - DOCC(t)]/DOCC(t - 2)</td>
</tr>
<tr>
<td>SPDSTDFT(t)</td>
<td>[SPEED(t - 2) - SPEED(t)]/SPEED(t - 2)</td>
</tr>
</tbody>
</table>

The criteria for selecting a feature were that it have

1. Considerable difference between its values before and during the incident.
2. Stability of this difference during the incident.

High stability would allow the use of a single threshold throughout the detection process.

The feature OCCRDF(t) was selected for the Bayesian model. However, because theoretically, \( \approx = \approx \)OCCRDF(t) \( \approx = \approx \), the feature \( Z = 1 - \) OCCRDF(t), where \( 0 < Z < 1 \), was introduced for mathematical convenience.

The next step was to develop mathematical expressions for \( f(Z/Uo) \) and \( f(Z/U1) \). These functions were developed for the data collected on the study site for the afternoon rush period of dry-weather weekdays. Statistical analysis by using the Kolmogorov-Smirnov test at the 5 percent level of significance confirmed the following truncated shifted gamma distributions.

\[
f(Z/Uo) = 21.6(21.6(Z + 0.4))^{1.64} \times \exp[-21.6(Z + 0.4)] + 0.9931(17.1) \tag{10}
\]

\[
f(Z/U1) = 1.082(1.082(Z - 0.821))^{0.711} \times \exp[-1.082(Z - 0.821)] + 0.991(0.289) \tag{11}
\]

**Probabilities of Capacity-Reducing Incidents**

Once the study site was selected, the number of capacity-reducing incidents was determined through correlation of the assistance-rendered reports with the flow abnormalities indicated by available occupancy contour maps. The average number of incidents occurring on dry-weather weekdays during the afternoon rush period (2-6 p.m.) was found to be 1.04.

The probability of an incident occurring at a given detector at a specified minute in time is given by the ratio \( A:B+C \), where \( A = \) average number of incidents occurring on the study section in the total time period, \( B = \) total number of detectors in the study section, and \( C = \) number of minutes in the time period. Hence

\[
P(\text{incident}) = 1.04/(15 \times 240) = 0.00027 \tag{12a}
\]

and

\[
P(\text{no incident}) = 0.99973 \tag{12b}
\]

**Derivation of Optimal Threshold**

Expressing \( P(Uo) \), \( P(U1) \), \( f(Z/Uo) \), and \( f(Z/U1) \) mathematically allowed the graphical derivation of the optimal threshold \( Z \) that maximizes Expression 7. The optimal threshold was found to be \( Z_1 = 0.57 \), which gives \( \text{OCCRDF}(t) = 1 - Z_1 = 0.43 \).

**Algorithm Evaluation**

The effectiveness of the algorithm was evaluated by determining its detection rate, false-alarm rate, and mean time to detect by running it through incident and incident-free data related to the study site. Also, these results were compared with those obtained by applying three other algorithms to the same data.

The threshold value of the traffic feature OCCRDF was compared with minute values of this feature for the incident and incident-free data. Any time the value of OCCRDF was greater than the threshold value, a "1" signal was output. A "0" signal was output when the threshold value was not exceeded. The first "1" signal was considered to be an indication of a tentative incident for both the incident and the incident-free data.

A string of four consecutive "1"s was required to signal a confirmed incident. Detection time was defined as the difference between the time the fourth consecutive "1" signal was output and the apparent occurrence time of the incident.

A total of 17 incidents representing the afternoon rush period on dry-weather weekdays and 2 h of incident-free data taken at 15 subsystems were analyzed. The detection rate (percentage of incidents detected), false-alarm rate (percentage of "1111" signal strings in incident-free data), and mean time to detect found were as follows:

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Detection rate</td>
<td>100</td>
</tr>
<tr>
<td>False-alarm rate</td>
<td>0.0</td>
</tr>
<tr>
<td>Mean time to detect</td>
<td>3.9</td>
</tr>
</tbody>
</table>

Note that the structure of the algorithm requires that the mean time to detect be at least 4 min. Thus, the mean time to detect actually achieved is as good as can be expected from this algorithm. (The slight discrepancy between 3.9 min and 4 min is due to inaccuracies in determining the apparent time of occurrence of the incident.)

The Bayesian algorithm was compared with the California algorithm (TSC-2) and the TSC algorithms 7 and 8 (3). The structure of these algorithms is shown in Figures 1, 2, and 3. The structure of the Bayesian algorithm is shown in Figure 4. By using the optimization routine developed by TSC for any chosen detection rate, a set of optimal thresholds for each of the TSC algorithms was established. This set yielded the minimum false-alarm rate for the particular detection rate. A comparison among the four algorithms by using the incident and incident-free data obtained at the study site is given below:

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Detection Rate (%)</th>
<th>False-Alarm Rate (%)</th>
<th>Mean Time to Detect (min)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bayesian</td>
<td>100</td>
<td>0.0</td>
<td>3.9</td>
</tr>
<tr>
<td>California</td>
<td>100</td>
<td>0.11</td>
<td>1.5</td>
</tr>
<tr>
<td>TSC 7</td>
<td>100</td>
<td>0.0</td>
<td>1.5</td>
</tr>
<tr>
<td>TSC 8</td>
<td>100</td>
<td>0.0</td>
<td>1.5</td>
</tr>
</tbody>
</table>

The Mann-Whitney U-test was conducted to determine the significance of the differences in mean time to detect between the Bayesian algorithm and each of the others. At the 5 percent level of significance, such difference was found.

From these results it can be seen that, for the 17 incidents on the outbound Kennedy Expressway, the Bayesian algorithm compared favorably with others tested. In some cases, a difference of 2-2.5 min in detecting an incident might not be particularly significant.
This could be the case if the variability in response time of the incident-handling subsystem is quite considerable or traffic messages are given by commercial radio frequently during the rush period. Also, a delay of such magnitude in implementing ramp-control strategies for incident situations should not be detrimental, especially if there is a dynamic control system that is responsive to flow changes.

Probabilities of Incidents Given Various Signal Strings

As discussed above, theoretical probabilities for the actual occurrence of incidents given certain signal strings can be developed once \( f(Z/U_0) \), \( f(Z/U_1) \), \( P(U_0) \), and \( P(U_1) \) are defined quantitatively. Moreover, such values can be computed by considering the number of capacity-reducing incidents that occurred during the particular time slice just before the incident under consideration. These values are given below.

\[
\begin{array}{ccccccccc}
\text{Signal String} & \text{Probability of incident} \\
\hline
\text{P(incident/1)} & 0.00305 \\
\text{P(incident/10)} & 0.00104 \\
\text{P(incident/11)} & 0.28209 \\
\text{P(incident/110)} & 0.01166 \\
\text{P(incident/111)} & 0.01166 \\
\text{P(incident/1110)} & 0.00354 \\
\text{P(incident/1111)} & 0.81662 \\
\end{array}
\]

This table shows that, once a signal "1" is output,
the probability that an incident has occurred is 0.00305 and the probability of making a wrong incident-management decision is close to 100 percent. The probabilities of the actual occurrence of an incident do not improve significantly for two or three consecutive signals. For a string of four "1" signals, this probability increases to 0.817; obviously the longer the string of "1" signals, the higher the probability of actual occurrence of an incident. However, the decision about the appropriate string size to operate should come after an on-line evaluation.

Preliminary On-Line Evaluation

A preliminary on-line evaluation comparing the Bayesian algorithm with algorithm 7 was conducted on the Eisenhower Expressway (inbound and outbound) during the afternoon rush period on dry-weather weekdays.

In calibrating the Bayesian algorithm for use on the Eisenhower test section, P(incident) and P(no incident) were calculated by using incident data obtained in a previous study. Based on 25 days of data, it was found that, during the afternoon rush period on the Eisenhower Expressway P(incident) = 0.00054 and P(no incident) = 0.99946. By using the Bayesian criterion, the optimal threshold was determined to be 0.43.

In the on-line evaluation, algorithm 7 was run by using a pair of threshold sets—the first applied to typical freeway sections and the second applied to sections that had geometric anomalies such as bottlenecks. This fine tuning of algorithm 7 improved the false-alarm rate, which had been quite high at these geometric problem areas. This pair of thresholds was used for the entire 5-d evaluation period.

The Bayesian algorithm was run by using a threshold of 0.43 for the first 3 d of the evaluation. Inspection of the data indicated that increasing the threshold to 0.6 would substantially improve the false-alarm rate without affecting the detection rate. Thus, for the two remaining days of the study, the Bayesian algorithm was run by using a threshold of 0.60. Table 1 presents the comparison between the two algorithms. A t-test performed on the first 3 d of data showed no significant differences in detection rate, false-alarm rate, and frequency of false alarms. However, a significant difference in the number of false alarms exists at the 10 percent level of significance. No significant difference between the mean time to detect of incidents detected by both algorithms was found at the 5 percent level of significance. The increase in the Bayesian threshold in the next 2 d reduced the number of false alarms but also reduced the detection rate.

CONCLUSIONS

Based on the analyses presented in this paper, the single-feature Bayesian algorithm compared favorably with multifeature algorithms with respect to detection rate and false-alarm rate. There was an apparent difference of 2-2.25 min in mean time to detect between the TSC algorithm 8 and the Bayesian algorithm in the off-line evaluation. The preliminary on-line evaluation, however, showed no significant difference in mean time to detect between the Bayesian algorithm and the TSC algorithm 7.

The simplicity of the Bayesian algorithm allows one to estimate the likelihood that an incident signal will be a false alarm or an actual incident. Operationally, one is not limited to receiving only two possible messages—incident occurred or incident free. It would be easy to receive a printout of a string of feature values so that the operator could judge the severity of the situation. For example, if the string consists of low values close to 0.43, one may wish to wait for further evidence before responding to the message. On the other hand, if the string has extremely high values, it could be judged highly indicative of incident conditions. The Bayesian algorithm presents the operator with a set of incident signals to which he or she can apply other resources and so reduce the false-alarm rate.

Clearly, more complicated multifeatured algorithms do not permit the operator such flexibility.

The use of historical incident information in the Bayesian model allows the development of probability values that can be used in determining the occurrence of an incident at a particular location and time.

The Bayesian model could be used when the occurrence of nearly simultaneous incidents required the allocation of limited resources.

At this time, there should be a more comprehensive on-line evaluation of the Bayesian and other algorithms.
ACKNOWLEDGMENT

The research reported in this paper was conducted within the framework of the Illinois Department of Transportation Highway Planning and Research Program. We wish to acknowledge the support of the staff of the Chicago Area Expressway Surveillance Project in the data-collection phase. The opinions, findings, and conclusions expressed in this paper are ours and not necessarily those of the sponsoring agencies.

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Distance Requirements for Frontage-Road Ramps to Cross Streets: Urban Freeway Design

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Heavy ramp volumes on urban freeway frontage roads can cause operating problems at adjacent diamond interchanges if the spacing between the cross street and the ramp is not adequate. Spacing requirements from diamond interchanges were studied for both exit ramps and entrance ramps. Exit ramps should provide sufficient storage for the vehicles queued at the cross street as well as an adequate distance for the weaving and braking maneuvers performed by exiting vehicles. Entrance ramps should provide sufficient spacing to prevent queueing through the cross-street intersection. Studies were made on several Texas freeways to provide data to be used to determine spacing requirements. Volume and queue counts were conducted to determine realistic volumes. These studies were used to determine design criteria and to further justify the analytic exit- and entrance-ramp models presented.

The modern urban freeway is conceived and constructed to move large numbers of persons and goods safely and efficiently over considerable distances. The basic design objective is to provide a high level of service in an economical manner. One of the consequences of this design objective is that the spacings of ramps and interchanges are relatively long because this minimizes the effects of weaving on the freeway flow. Apparently, little attention has been given to the resulting negative effects on the connecting ramps and frontage roads. Neither AASHO (1) nor Leisch (2) discuss this question. The traffic engineer currently has a number of design criteria or procedures available to use in selecting ramp spacings. Some designers have used rule-of-thumb procedures—e.g., 152 m (500 ft) for exit ramps and 229 m (750 ft) for entrance ramps.

Significant operating problems have been observed on urban freeway ramps and frontage roads near diamond interchanges, especially those where ramp-metering systems are in operation. In most cases, these problems on connecting exit and entrance ramps are directly related to insufficient ramp spacings. These problems are of three different types:

1. Signal queues at interchanges that block merge areas of exit ramps and the frontage road (see Figure 1),
2. Signal queues at interchanges that back into freeway main lanes, and
3. Ramp-metering queues that back into cross-street intersections (see Figure 2).

Freeway exit ramps should be long enough to store enough vehicles to prevent the spillback of the vehicles onto the freeway. The dangerous condition of spillback should not be tolerated as a recurring event and should occur only as a result of unusual circumstances. Freeway entrance ramps should be long enough to minimize queue spillback into the adjacent cross-street intersection because of ramp metering. The installation of ramp metering is a frequently used solution to the problem of congestion on urban freeways, even newly constructed ones.

The objective of this study was the investigation of the locations of entrance and exit ramps with respect