DETECTION OF FREEWAY CAPACITY-REDUCING INCIDENTS BY TRAFFIC-STREAM MEASUREMENTS

Allen R. Cook, Department of Civil Engineering, McGill University; and
Donald E. Cleveland, Department of Civil Engineering, University of Michigan

This paper investigates the feasibility of using freeway traffic-flow data compiled by electronic surveillance and control systems for the detection of accidents and other lane blockage incidents that temporarily disrupt traffic flow. Research was conducted on the John C. Lodge Freeway in Detroit where traffic data consisted of 1-minute compilations of volume and occupancy recorded by ultrasonic presence detectors. Nineteen detection algorithms, including one being used in Los Angeles, were evaluated with a sample of 50 representative afternoon peak-period incidents. The technique of exponential smoothing of occupancy or volume data to detect incident-generated shock waves was found to be the most effective. This algorithm detected 42 percent of the incidents with virtually no false alarms and every incident with an 8 percent false-alarm rate. Most of the incidents were detected within 1 minute of the onset of congestion at a detector station. Algorithm effectiveness was not affected by detector spacings ranging from 1,460 to 4,815 ft (445 to 1468 m), volumes from 1,200 to 2,000 vph per lane, occupancies from 9 percent to 45 percent, precipitation, or the particular lane blocked. The algorithms could not distinguish accidents from less serious incidents, but because they directly related each incident to its impact on traffic operations their incorporation in control systems could improve system response to incidents.

•THIS PAPER investigates the feasibility of using traffic-flow information compiled in real-time by freeway traffic surveillance, communication, and control systems for the detection of accidents, vehicular breakdowns, and other incidents that temporarily block traffic lanes and disrupt flow. Freeways of large cities regularly operate at demand levels that approach or exceed capacity, and they are particularly vulnerable to incident disruptions. Although incidents are statistically rare events, occurring once every 20,000 to 30,000 vehicle-miles (30 000 to 50 000 vehicle-km) on high-volume urban freeways, they occur with such frequency that they must be taken into account by surveillance and control systems.

MEASURES OF EFFECTIVENESS FOR DETECTION ALGORITHMS

The role of computer-supervised incident detection in a surveillance system is shown in Figure 1. Implicit in this role is the capability of implementing control measures without the inevitable time lag of detection systems involving human intervention and of relating this response directly to the magnitude of the capacity reduction. To evaluate an incident detection capability, the following measures of effectiveness were investigated: the probability of detection, the probability of false alarms, the time lag to first detection, the impact of detector spacing on algorithm effectiveness, and the probability of detecting the end of the incident. A false alarm is defined as a detection signal when no incident has occurred. Information on these measures of effectiveness was obtained

Publication of this paper sponsored by Committee on Freeway Operations.

by applying detection algorithms to traffic data compiled before, during, and after actual lane blockage incidents.

DATA COLLECTION

The John C. Lodge Freeway Corridor Control and Data System

Research on detection algorithms was conducted at the National Proving Ground for Freeway Surveillance, Control, and Electronic Traffic Aids in the John C. Lodge Freeway corridor in Detroit. The research section of the Lodge Freeway contained a closed network of ultrasonic vehicle presence detectors linked to an IBM 1800 digital computer. The system was capable of sensing fluctuations in traffic conditions that were brought about by congestion and capacity reductions and of responding to them through restrictions of ramp inputs and route diversion.

Incident data were collected and analyzed from a 2-mile (3.2-km) portion of the instrumented freeway containing four detector stations, as shown in Figure 2. Freeway sections between these stations were identified as subsystems; these varied in length from 1,460 ft (445 m) to 4,815 ft (1468 m). Data were collected during a 13-month period from December 1968 to December 1969 when this section was under continuous television surveillance. Descriptions of lane blockage incidents recorded by television observers were correlated with data from the detectors during the afternoon peak period (outbound from Detroit CBD) extending from 2:30 to 6:30 p.m. Traffic data consisted of 1-minute compilations of volume and occupancy recorded by each detector and aggregated for each station. Occupancy, a surrogate for density, is the percentage duration of activation of a presence detector.

Incident Characteristics

A total of 50 lane blockage incidents—18 accidents, 28 stalls and breakdowns, 2 instances of debris, and 2 short maintenance operations—were selected for analysis, with virtually every such incident occurring in the subsystems for which traffic data were available. It is believed that this sample is representative of the lane blockage incidents that take place during the peak period on the Lodge Freeway. In only one case was more than one lane blocked, and the freeway was never completely blocked. In two-thirds of the cases, the lane adjacent to the median, where there was no shoulder refuge for vehicles, was blocked. The average duration of blockage was 6.1 minutes, with times ranging from 1 to 19 minutes. None of the 18 accidents appeared serious or affected traffic flow differently from the other incidents. Therefore, it was not possible to investigate the feasibility of determining incident type by analysis of traffic data alone.

The average volumes observed before each incident took place ranged from 1,200 to 2,000 vph per lane. Prevailing occupancies ranged from 9 to 45 percent, with the great majority extending from 10 to 30 percent. The average prevailing downstream volume before the incidents, 81.4 vehicles per minute ($\sigma = 10.3$), was reduced 21 percent to an average of 64.4 vehicles per minute ($\sigma = 11.3$) during the incidents. There was considerable variability in the flow reductions, as shown in Figure 3. Similar variability was observed by Goolsby (1) with data measured at the incident site. Although downstream volumes generally decreased, there were seven exceptions where volume increased. These were attributed to congestion prevailing before the incident, where the capacity reduction appeared to have a beneficial effect on operations downstream. Six of these incidents were located upstream of the Seward Avenue entrance ramp, which was capable of admitting up to 25 vehicles per minute depending on the state of flow downstream.

DEVELOPMENT OF COMPUTER ALGORITHMS

Propagation of Disturbances Caused by Incidents

The theoretical impact of an incident on traffic operations when demand exceeds capacity is shown in the hypothetical flow-occupancy diagram of Figure 4, where point 2 is the prevailing flow state prior to the incident. After the incident, traffic upstream operates in the congested regime of point 4 and at point 5 downstream. The flow state changes are propagated through the traffic stream at a velocity equal to the slope of the chord connecting the two flow states, as hypothesized by Lighthill and Whitham (2) in their continuum theory of traffic flow. A shock wave with velocity c_{52} proceeds downstream from the incident, and a shock wave of congestion growth proceeds upstream at velocity c_{24}. Detection algorithms based on traffic-stream characteristics should signal after these waves have passed upstream and downstream detector stations and either detect their passage or recognize the joint occurrence of states 4 and 5 as being indicative of incident presence. These considerations are reflected in the various algorithms presented in the following section. The following notation applies throughout:

$\Theta(x, t)$ = occupancy in percent at detector station x and minute t,
$q(x, t)$ = volume (vehicles per minute) at detector station x and minute t,
$u(x, t) = q(x, t)/\Theta(x, t)$, surrogate for speed,
$E(x, t) = [q(x, t)]^2/\Theta(x, t)$, surrogate for kinetic energy,
x_i = upstream detector station,
x_{i+1} = downstream detector station, and
t = time in 1-minute increments.

LAAFSCP Algorithm

The algorithm used by the Los Angeles area freeway surveillance and control project (LAAFSCP) consists of three sequential tests all based on occupancy changes over short periods of time at the upstream and downstream detector stations of a subsystem (3). An incident is signaled only when the predetermined threshold values for all three variables are exceeded, indicating that the sequence of events associated with a typical capacity-reducing incident has occurred. The algorithm is applied to occupancy data compiled for the most recent minute and updated every 20 seconds.

The LAAFSCP algorithm was adapted as follows for application to Lodge Freeway data. The initial incident test, which consisted of determining whether or not the numerical difference in occupancies at two adjacent detector stations exceeded a threshold value, was dispensed with because in this study it would not affect the algorithm performance. The remaining two tests (Test 2 and Test 3 respectively) are as follows:

$$\frac{\Theta(x_i, t) - \Theta(x_{i+1}, t)}{\Theta(x_i, t)} \geq \text{Threshold } K_2$$

$$\frac{\Theta(x_{i+1}, t - 1) - \Theta(x_{i+1}, t)}{\Theta(x_{i+1}, t - 1)} \geq \text{Threshold } K_3$$

An incident is signaled if upstream occupancy becomes significantly greater than downstream occupancy (Test 2) and at the same time downstream occupancy has significantly decreased in the past minute (Test 3). Test 3 distinguishes an incident from a bottleneck situation by indicating the reduction in flow past the incident over a short period of time. Detection thresholds were determined by applying the model to 4,860 minutes of occupancy observations in each subsystem (18 peak periods containing at least 8 incidents in each subsystem). Threshold values varied from subsystem to subsystem; K_2 ranged from 0.53 to 0.61 in both dry- and wet-weather conditions, and K_3 ranged from 0.11 to 0.26 in dry weather and from 0.24 to 0.30 in wet weather. Values were selected that produced the most detections with fewest false alarms (in the authors' judgment). With these thresholds there were 81 false detections out of 14,580 applications of the algorithm, a false-alarm rate of 0.56 percent. The performance of the LAAFSCP algorithm during a typical incident is shown in Figure 5.

TTI Lodge Freeway Algorithms

Texas Transportation Institute (TTI) began incident detection research in 1968 as part of the Lodge Freeway corridor study program. Courage and Levin (4) developed five algorithms that used various combinations of volume and occupancy data to form

Figure 1. Role of incident detection in freeway surveillance and control.

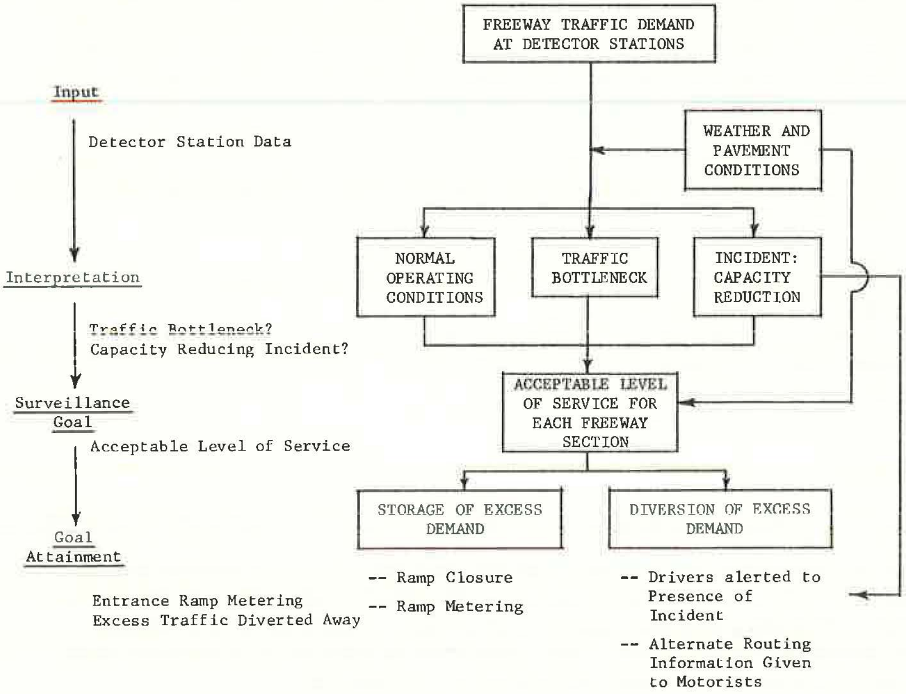


Figure 2. Lodge Freeway detection subsystems and sensing equipment.

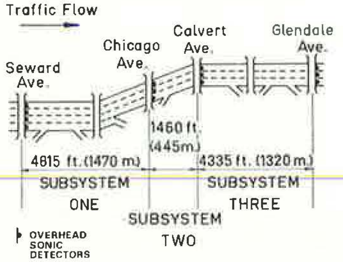


Figure 3. Effect of incidents on downstream traffic volume.

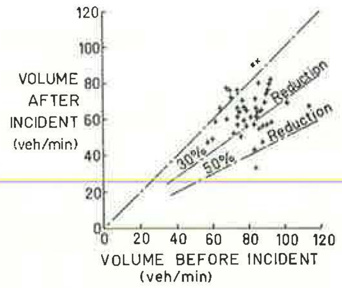


Figure 4. The fundamental diagram and kinematic wave theory.

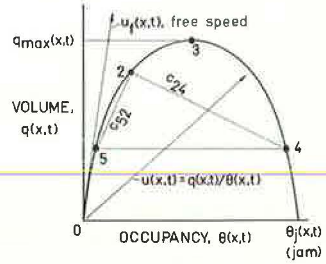


Figure 5. Performance of the LAAFSCP algorithm during an incident.

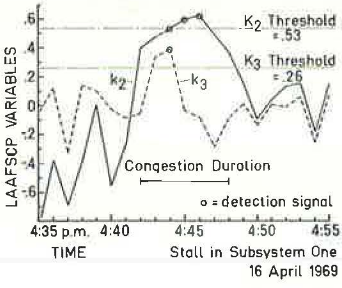


Figure 6. TTI station discontinuity performance during an incident.

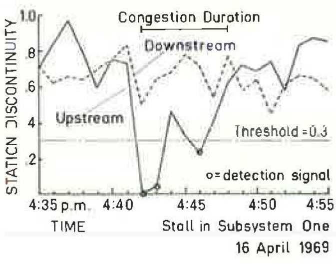
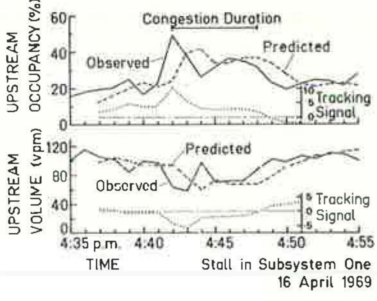


Figure 7. Exponential algorithm performance during an incident.



variables sensitive to incident situations such that each variable would exceed a predetermined threshold of detection only 1 percent of the time during incident-free operations. He concluded from an analysis of 25 peak periods containing 29 incidents that

> all models demonstrated some ability to detect incidents and may therefore merit further consideration. They did, however, exhibit a high false alarm rate, and it is felt that considerable refinement would be required to produce an operational incident detection scheme.

The variables for five alternative TTI algorithms used in this paper are described in the following paragraphs.

Station Kinetic Energy—Traffic kinetic energy $[q(x,t)]^2/\Theta(x,t)$ comes from an energy-momentum analogy between traffic flow and the flow of a compressible fluid. Significantly small variable values may indicate an incident downstream when congestion is generated upstream:

$$\text{Variable } E(x,t)/E_m(x,t)$$

This variable is normalized with the maximum kinetic energy $E_m(x,t)$ determined by fitting representative peak-period data to a linear speed-occupancy relationship (4).

Subsystem Energy—Significantly large numerical differences in normalized kinetic energy variables recorded at adjacent stations may indicate an incident presence in that subsystem:

$$\text{Variable } [E(x_i,t)/E_m(x_i,t)] - [E(x_{i+1},t)/E_m(x_{i+1},t)]$$

Subsystem Shock Wave—Significantly large numerical differences in the volume recorded at adjacent stations may indicate an incident presence in that subsystem:

$$\text{Variable } q(x_i,t) - q(x_{i+1},t)$$

Subsystem Discontinuity—The difference in flow states 2 and 4 shown in Figure 4, when transformed to the approximately linear speed-occupancy relation, may be indicative of an incident situation if it is significantly large:

$$\text{Variable}\left\{\left[\frac{u_f(x_i,t) - u(x_i,t)}{u_f(x_i,t)}\right]^2 + \left[\frac{\Theta(x_i,t)}{\Theta_j(x_i,t)}\right]^2\right\}^{1/2} - \left\{\left[\frac{u_f(x_{i+1},t) - u(x_{i+1},t)}{u_f(x_{i+1},t)}\right]^2 + \left[\frac{\Theta(x_{i+1},t)}{\Theta_j(x_{i+1},t)}\right]^2\right\}^{1/2}$$

Speed values are normalized by the theoretical free speed, $u_f(x,t)$ and occupancy is normalized by the theoretical jam occupancy, $\Theta_j(x,t)$, both obtained from an assumed linear speed-occupancy fit of data (4). This is done to make the data at adjacent stations comparable.

Station Discontinuity—This variable is based on a comparison of the kinetic energies, $E'(x_{i,j},t)$ of individual lanes, j, at a station where there are n lanes:

$$\text{Variable } \frac{(n-1)\,\{\text{Min}\,[E'(x_{i,j},t)]_{j=1}^{n}\}}{\sum_{j=1}^{n} E'(x_{i,j},t) - \text{Min}[E'(x_{i,j},t)]_{j=1}^{n}}$$

This variable can range from 0 to 1. A value of 1 would indicate an equal distribution of kinetic energy across the lanes. A value of 0 would indicate no energy in one lane, a result of either no traffic at all in the lane because it is blocked upstream or of traffic stopped altogether in the lane because of a blockage downstream. Both of these may occur while traffic in other lanes is moving. Significantly low values of the variable thus constitute an incident detection signal.

Threshold values for each variable were determined for each station or subsystem and dry- and wet-weather conditions such that false alarms were generated no more than 1 percent of the time during 8 incident-free dry-weather 4-hour peak periods and 4 incident-free wet-weather peak periods. The full set of numerical thresholds thus developed elsewhere (5). The performance of the TTI station discontinuity algorithm during a typical incident is shown in Figure 6.

Exponential Algorithms

The sudden flow-state changes observed during incidents suggest the application of short-term forecasting techniques for detecting irregularities in a time series of traffic data $z(x,t)$. Whitson et al. (6) proposed the use of a moving average of the most recent 5 minutes of volume data as the forecast variable with confidence limits determined from the variance of the data. In this research, the double exponential smoothing algorithm described by Brown (7) was investigated as a means for incident detection. With this technique, the forecast traffic variable $\hat{z}(x,t)$ is a function of the past data observations geometrically discounted back in time. Incident detection is accomplished through use of a tracking signal, which is the algebraic sum to the present minute of all the previous estimate errors divided by the current estimate of the standard deviation. The tracking signal should dwell around zero because the predictions either match the data or compensate for errors in succeeding time periods. A detection is indicated by a significant deviation of the signal from zero, the threshold deviation being either a function of the variability of the data or the likelihood of false alarms.

For computational efficiency the standard deviation of the traffic data was estimated by the mean absolute deviation $m(x,t)$, which Brown (7) has shown to be proportional to the standard deviation. The mean absolute deviation is obtained by single exponential smoothing of the absolute values of the prediction errors, using a smoothing constant of 0.1:

$$m(x,t) = \alpha|e(x,t)| + (1-\alpha)\, m(x,t-1) = \text{mean absolute deviation}$$

where

$e(x,t)$ = error of prediction, $z(x,t) - \hat{z}(x,t)$ and
α = smoothing constant.

The variable forecast $\hat{z}(x,t)$ is computed by double exponential smoothing with a smoothing constant of 0.3, and the tracking signal is found as follows:

$$TS(x,t) = y(x,t)/m(x,t-1)$$

where $y(x,t) = y(x,t-1) + e(x,t)$ = cumulative error.

Several values of the smoothing constant other than 0.3 were tried on data for several peak periods, but higher values were insensitive to incidents, and lower values greatly increased false alarms. A smoothing constant of 0.1 was used for $m(x,t)$ to make it less sensitive to recent changes in data variability.

Initial estimates for the algorithm parameters were based on the mean and standard deviation of the first 6 minutes of variable observations in each incident data stream. An initial $m(x,t-1)$ was found from the sample standard deviation, σ_z, as follows:

$$m(x,t-1) = [\sqrt{2/\pi}\,\sqrt{2/(2-\alpha)}]^{\sigma_z}$$

A total of 13 traffic variables were investigated with the exponential smoothing algorithm, including all five variables used with the TTI algorithm; they are as follows:

1. Station volume, $z_1(x,t) = q(x,t)$.
2. Station occupancy, $z_2(x,t) = \Theta(x,t)$.
3. Station speed, $z_3(x,t) = q(x,t)/\Theta(x,t) = u(x,t)$.

4. Station volume-occupancy, where the chord connecting flow states 2 and 4 in Figure 4 is treated as the forecast error and where the forecast variable is the joint volume-occupancy flow state,

$$z_4(x,t) = \{q(x,t),\ \Theta(x,t)\}$$

$$e_4(x,t) = \sqrt{[q(x,t) - \hat{q}(x,t)]^2 + [\Theta(x,t) - \hat{\Theta}(x,t)]^2}$$

5. Station speed-occupancy, which is analogous to volume-occupancy,

$$z_5(x,t) = \{u(x,t),\ \Theta(x,t)\}$$

$$e_5(x,t) = \sqrt{[u(x,t) - \hat{u}(x,t)]^2 + [\Theta(x,t) - \hat{\Theta}(x,t)]^2}$$

6. Station kinetic energy, $z_6(x,t) = E(x,t)$.
7. Station discontinuity, which is the same variable used in the TTI station discontinuity algorithm, $z_7(x,t) = SD(x,t)$, where $SD(x,t)$ is the station discontinuity variable.
8. Subsystem volume, $z_8(x,t) = q(x_i,t) - q(x_{i+1},t)$.
9. Subsystem occupancy, $z_9(x,t) = \Theta(x_i,t) - \Theta(x_{i+1},t)$.
10. Subsystem speed, $z_{10}(x,t) = u(x_i,t) - u(x_{i+1},t)$.
11. Subsystem kinetic energy, $z_{11}(x,t) = E(x_i,t) - E(x_{i+1},t)$.
12. Subsystem volume-occupancy discontinuity,

$$z_{12}(x,t) = \sqrt{[q(x_i,t) - q(x_{i+1},t)]^2 + [\Theta(x_i,t) - \Theta(x_{i+1},t)]^2}$$

13. Subsystem speed-occupancy discontinuity,

$$z_{13}(x,t) = \sqrt{[u(x_i,t) - u(x_{i+1},t)]^2 + [\Theta(x_i,t) - \Theta(x_{i+1},t)]^2}$$

Subsystem variables 8 through 13 are compiled from adjacent detector stations upstream i and downstream i + 1.

The performance of the algorithm with volume and occupancy as the variables during the incident of Figure 5 is shown in Figure 7. Forecasts are observed to correct for trends in the data within several minutes, and it is evident that the most effective variables for detection will be those that respond sharply and promptly to the passage of an incident shock wave. The sensitivity of the algorithm to incident situations was explored for each variable by varying the detection thresholds for the tracking signal from ±1.5 to ±10.0 (-1.0 to -8.0 for variable 7) in increments of 0.5. The resulting operating characteristic curves relating detection effectiveness to false alarms are presented in the following section.

RESULTS

Detections and False Alarms

Figure 8 shows the operating characteristic curves for the three best exponential station algorithms: station occupancy, station volume, and station discontinuity. More detections were achieved at the expense of more false alarms. The exponential station occupancy variable dominated the others in performance and detected all 50 incidents at a 6 percent false-alarm rate. The operating points for the five TTI algorithms and the LAAFSCP algorithm are included in the figure, and none was observed to exceed the performances of the best exponential algorithms. Moreover, they tended to generate more false alarms than anticipated. This may indicate that the incident data contained more false-alarm situations than would be found in typical traffic operations, but it also indicates that the false-alarm rate for these algorithms may vary according to the state of the traffic (an undesirable characteristic).

The differences in total detections achieved by individual algorithms in a similar false-alarm range, about 1 percent to 2 percent, were investigated by means of chi-

Figure 8. Operating characteristic curves for exponential station incident detection algorithms.

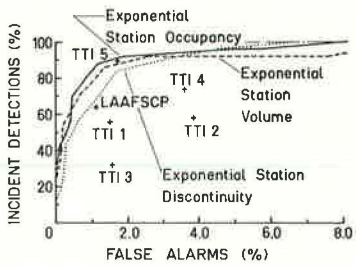


Table 1. Detection performance of the most effective algorithms at three false-alarm levels.

	False-Alarm Level					
	Low		Medium		High	
Incident Detection Algorithm	Incident Detections[a]	False Alarms[b]	Incident Detections[a]	False Alarms[b]	Incident Detections[a]	False Alarms[b]
Exponential station occupancy	48	0.26	92	1.87	96	5.73
Exponential station volume	54	0.19	90	1.90	92	6.37
Exponential station discontinuity	44	0.26	84	1.67	100	6.5
TTI station discontinuity	30	0.19	90	1.74	94	6.18

[a]Percentage of incidents detected, sample size of 50 lane-blockage incidents.
[b]Percentage of false alarms, sample size of 1,554 minutes of incident-free operations.

Table 2. Tracking signal thresholds for the most effective exponential algorithms at three false-alarm levels.

	False-Alarm Level		
Incident Detection Algorithm	Low	Medium	High
Exponential station occupancy	±8.0	±4.0	±2.75
Exponential station volume	±6.0	±3.75	±2.75
Exponential station discontinuity	-5.0	-3.0	-1.5

Table 3. Discontinuity thresholds for TTI station discontinuity algorithm at three false-alarm levels.

	False-Alarm Level					
	Low		Medium		High	
Station	Dry	Rain	Dry	Rain	Dry	Rain
Seward Avenue	0.05	0.05	0.30	0.16	0.44	0.36
Chicago Avenue	0.05	0.05	0.33	0.25	0.41	0.35
Calvert Avenue	0.05	0.10	0.31	0.30	0.43	0.45
Glendale Avenue	0.05	0.15	0.23	0.28	0.38	0.42

Table 4. Mean time lags (minutes) to detection for the most effective algorithms at three false-alarm levels.

	False-Alarm Level		
Incident Detection Algorithm	Low	Medium	High
Exponential station occupancy	1.46 (2.78)	0.74 (1.40)	0.35 (0.81)
Exponential station volume	2.18 (3.09)	0.82 (1.58)	0.30 (0.66)
Exponential station discontinuity	0.82 (1.19)	1.14 (1.78)	0.64 (1.67)
TTI station discontinuity	3.13 (5.62)	2.07 (4.05)	0.83 (1.11)

Note: Standard deviations are in parentheses.

square tests using the null hypothesis that the expected detection performance was the average performance of each pair. The exponential station occupancy and volume algorithms detected significantly more incidents than all but five other algorithms including the LAAFSCP algorithm and all the TTI algorithms except station discontinuity. The TTI station discontinuity algorithm, in turn, detected significantly more incidents than the other TTI algorithms and the LAAFSCP algorithm. All nine station algorithms together detected 74.5 percent of the incidents, a significantly better performance than the 10 subsystem algorithms (63.2 percent, $\chi^2 = 23.2$). Similarly, the combined performance of the 13 exponential algorithms (73.4 percent) was significantly better than the TTI and LAAFSCP algorithms together (62.4 percent, $\chi^2 = 12.3$).

Joint application of the exponential volume and occupancy algorithms yielded the detection of 49 of the 50 incidents, while the exponential occupancy and station discontinuity variables together detected all 50 incidents. The disadvantage of the joint application of independent models is that the false-alarm rate will also double with the use of two independent models. Alternatively, it is seen in Figure 8 that joint algorithm performances can be matched by permitting more false alarms in individual algorithms.

In summary, the most effective detection algorithms were the exponential algorithms, using either occupancy, volume, or station discontinuity as the variables to be smoothed. Information on the performances of these algorithms and the best TTI algorithm, station discontinuity, at three arbitrary false-alarm levels is given in Table 1. The corresponding detection thresholds are given in Tables 2 and 3. The low false-alarm range allows a few false alarms rather than none, and these would be tolerable in many operational detection systems. There was a significant improvement in the number of incidents detected by each algorithm from the low to the medium false-alarm level but no significant improvement in detection from the medium to the high level.

Time Lags to Detection

The most effective algorithms for detection tended to have the shortest mean time lags, eliminating the need to consider a trade-off between total detections and time lag. The relationship between the false-alarm rate and mean time lag is shown in Table 4 for the four algorithms of Table 1. Time lags generally decreased as false alarms increased, as expected, the difference being statistically significant for the combined algorithms between the medium and high false-alarm levels.

Effect of Detector Station Spacing

No significant difference was found between the station and subsystem algorithms in subsystems 2 and 3, but the station algorithms were significantly better in subsystem 1 ($\chi^2 = 22.7$). The LAAFSCP algorithm had particular difficulties in subsystem 1. Inasmuch as subsystems 1 and 3 were similar in length, length was apparently not the explanation for the differences in performance. A possibly significant factor may have been the effect of a geometric discontinuity (a reduction from 4 lanes to 3 in subsystem 1) on upstream and downstream flow states in the subsystem algorithms. In subsystem 1, only 15 of the 26 incidents displayed a flow response similar to the LAAFSCP assumptions, i.e., increases in occupancy upstream and occupancy decreases downstream in a short period of time. This pattern was observed in 22 of the 24 incidents in the other subsystems.

In subsystem 3 those incidents taking place within 1,000 to 1,500 ft (300 to 450 m) of a detector station were no easier to detect than those located midway in the subsystem. This was not the case in subsystem 1, where the subsystem algorithms experienced more difficulties with incidents located near either detector station than the more centrally located incidents. In these long subsystems, the shock waves moving upstream and downstream of an incident located near one end would be less likely to reach both stations in the same minute, but this apparently is not the explanation for the subsystem algorithm difficulties. Difficulties in subsystem 1 were not paralleled in subsystem 3, and simultaneous shock-wave impact at both stations would not appear to be essential for a subsystem algorithm. The lane-drop factor remains, and it was concluded that the range of detector spacings in this study was not a factor in algorithm detection performance. In addition, the lane of occurrence was not a factor in algorithm performance in any subsystem.

An important consideration for any station algorithm is whether the detection signal consistently indicates an incident upstream or downstream of the station. Four incidents resulted in increased occupancy levels downstream that were detected by the exponential station occupancy algorithm. In every case congested operations prevailed before the incidents. Fortunately, the effect of this location error on a ramp-metering strategy response to the incident would be to divert vehicles farther downstream than necessary, a less costly outcome than allowing vehicles to enter upstream of the incident if the location error had been in the other direction. Ambiguous detections were also observed with the station discontinuity variable, where three incidents were detected downstream only because of disproportionately few vehicles in the blocked lane at the downstream station. Many incidents were detected both upstream and downstream with this variable.

Detection of Incident Termination

An algorithm was considered successful in detecting the end of an incident if it either ceased generating detection signals or produced a distinct termination signal within ±3 minutes of the end of noticeable congestion at nearby detector stations. The LAAFSCP termination logic, the restoration of occupancy to the preincident level downstream, was successful for every incident, which suggests that it should be employed with the exponential and TTI algorithms as well.

SUMMARY AND CONCLUSIONS

It has been determined that accidents and other capacity-reducing incidents that are typical occurrences on urban freeways can be detected by the flow perturbations they generate in traffic data at nearby detector stations. The following conclusions on detection algorithm effectiveness apply to prevailing volumes of 1,200 to 2,000 vph per lane and occupancies of 9 to 45 percent. Algorithms were evaluated in terms of probability of detection, probability of false alarm, time lag to detection, impact of detector station spacing on algorithm effectiveness, and detection of the end of the incident.

The technique of exponential smoothing of traffic data to better detect flow disruptions was found to be most effective, and superior to algorithms developed by TTI and LAAFSCP. The most effective traffic variables were volume (vehicles per minute), occupancy (percent, compiled over 1-minute intervals), and station discontinuity (the variable that measures the uniformity of lane kinetic energies at a detector station), for data recorded at individual detector stations. The exponential station occupancy algorithm detected 46 of 50 representative incidents at a false-alarm rate of 1.87 percent and a mean time lag of 0.74 minute after the onset of congestion. Of these incidents, 42 percent would be detected if thresholds for detection were made sufficiently stringent to eliminate most false alarms.

Algorithm effectiveness was not adversely affected by weather conditions, the given range of volumes and occupancies, the particular lane in which the incident took place, or detector spacings up to 4,815 ft (1468 m). Algorithms that used traffic data at two adjacent detector stations were less effective than those that used data from just one station and were adversely affected by a geometric discontinuity in the form of a lane drop between two of the stations. Termination of the incident was most effectively determined using the LAAFSCP termination logic, the restoration of occupancy to the preincident level downstream.

Incorporation of a detection logic in a freeway surveillance system should foster a more flexible and effective response in diverting vehicles away from congested areas. Inasmuch as the magnitude of the capacity reduction is recorded directly, this can serve as a means for determining priorities in the dispatch of aid units. The incidents studied did not permit the evaluation of the feasibility of determining type of incident from traffic-stream characteristics alone. False alarms will likely be an important operational problem, and the research demonstrated that neither the variables used nor the sudden change in variable values over time were exclusive to incident situations as opposed to incident-free operations. However, the algorithms should prove to be useful in alerting surveillance personnel to potential incident situations and perhaps eliminate the need, for example, for continuous television surveillance of all sections of a freeway.

ACKNOWLEDGMENT

This research was in part sponsored by the American Association of State Highway Officials in conjunction with the National Cooperative Highway Research Program. The authors express their appreciation for the cooperation and aid of various officials of the Detroit Department of Streets and Traffic, the Michigan Department of State Highways, and the University of Michigan Highway Safety Research Institute.

REFERENCES

1. Goolsby, M. E. Influence of Incidents on Freeway Quality of Service. Highway Research Record 349, 1971, pp. 41-46.
2. Lighthill, M. J., and Whitham, G. B. Hydrodynamic Approaches, Part II: On Kinematic Waves—II. A Theory of Traffic Flow on Long Crowded Roads. Proceedings of the Royal Society, Vol. 229, Series A, May 10, 1955, pp. 317-345.
3. West, J. T. California Makes Its Move. Traffic Engineering, Vol. 41, No. 4, Jan. 1971, pp. 12-18.
4. Courage, K. G., and Levin, M. A Freeway Corridor Surveillance, Information, and Control System. Texas Transportation Institute, Texas A&M Univ., College Station, Res. Rept. 488-8, Dec. 1968, 349 pp.
5. Cook, A. R., and Cleveland, D. E. The Detection of Freeway Capacity Reducing Incidents by Traffic Stream Measurements. HSRI Rept. TrS-1, Univ. of Michigan, Ann Arbor, 1970, 300 pp.
6. Whitson, R. H., Burr, J. H., Drew, D. R., and McCasland, W. R. Real-Time Evaluation of Freeway Quality of Traffic Service. Highway Research Record 289, 1969, pp. 38-50.
7. Brown, R. G. Smoothing, Forecasting and Prediction of Discrete Time Series. Prentice-Hall, Englewood Cliffs, N. J., 1963.