

Evaluation of Incident Detection Algorithms

Physical Research Report No. 85



Illinois Department of Transportation
Bureau of Materials and Physical Research

1. Report No. FHWA/IL/PR-085		2. Government Accession No.		3. Recipient's Catalog No.	
4. Title and Subtitle Evaluation of Incident Detection Algorithms				5. Report Date December 1979	
				6. Performing Organization Code	
7. Author(s) Moshe Levin Gerianne M. Krause				8. Performing Organization Report No. Physical Research No. 85	
9. Performing Organization Name and Address Illinois Department of Transportation Bureaus of Materials & Physical Research 126 East Ash Street Springfield, Illinois 62706				10. Work Unit No.	
				11. Contract or Grant No. IHR-005	
12. Sponsoring Agency Name and Address Illinois Department of Transportation Bureau of Materials & Physical Research 126 East Ash Street Springfield, Illinois 62706				13. Type of Report and Period Covered Final Report	
				14. Sponsoring Agency Code	
15. Supplementary Notes Study was conducted in cooperation with the U. S. Department of Transportation Federal Highway Administration					
16. Abstract Off-Line and On-Line evaluations were conducted. Six algorithms were evaluated using incident and incident-free data collected on Chicago's expressways under various traffic and environmental conditions. Four of the algorithms - pattern recognition in nature - were developed by Technology Services Corporation (TSC). The other two - a pattern recognition algorithm and a probabilistic algorithm - were developed by the Research Group. Algorithm efficiency was evaluated in terms of Detection Rate, False-Alarm Rate, and Mean-Time-To-Detect. The evaluation included a comparative analysis of algorithm efficiency; effect of lateral detectorization on algorithm performance; hierarchical analysis of threshold effectiveness and the effect of incident severity on algorithm performance. In the Off-Line evaluation the algorithms did not differ statistically in their Mean-Time-To-Detect, rendering this parameter ineffective in algorithm selection. The relationship between Detection Rate and False-Alarm Rate was found to be the critical criterion in algorithm selection. Thresholds developed for accidents occurring on the detector lane proved to be effective in detecting accidents and non-accident incidents on the detector and non-detector lane. In the On-Line evaluation, statistical analysis showed no difference in Detection Rate, False-Alarm Rate, and Mean-Time-To-Detect among the three TSC algorithms at any of the evaluated detection levels. The apparent best of TSC algorithms was then compared with the two local algorithms and showed overall superiority.					
17. Key Words Incidents; Detection Algorithms; Control System; Thresholds; Detection Rate; False-Alarm Rate; Mean-Time-To-Detect; Detectorization Level.			18. Distribution Statement No restrictions. This document is available to the public through the National Technical Information Service, Springfield, Virginia 22161		
19. Security Classif. (of this report) Unclassified		20. Security Classif. (of this page) Unclassified		21. No. of Pages 121	22. Price

State of Illinois
DEPARTMENT OF TRANSPORTATION
Bureau of Materials and Physical Research

EVALUATION OF INCIDENT DETECTION ALGORITHMS

by

Moshe Levin

and

Gerianne M. Krause

Final Report

IHR-005 - Testing and Evaluating Incident Detection Algorithms

A Research Project Conducted by
Illinois Department of Transportation
in cooperation with
U. S. Department of Transportation
Federal Highway Administration

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December 1979

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SUMMARY OF CODES AND INITIALS

Incident Category Codes

R	=	Rush
NR	=	Non-Rush
RW	=	Rush Wet
NRW	=	Non-Rush Wet
RD	=	Rush Dry
NRD	=	Non-Rush Dry
RD-0 (NRD-0)	=	Incident occurring on non-detector lanes during Rush Dry period (Non-Rush Dry)
RD-1 (NRD-1)	=	Incident occurring on detector lane during Rush Dry period (Non-Rush Dry)
RD-50-1 (NRD-50-1)	=	Accident occurring on detector lane during Rush Dry period (Non-Rush Dry)
RD-50-0 (NRD-50-0)	=	Accident occurring on non-detector lanes during Rush Dry period (Non-Rush Dry)
RD-46-1 (NRD-46-1)	=	Non-Accident incident occurring on detector lane during Rush Dry period (Non-Rush Dry)
RD-46-0 (NRD-46-0)	=	Non-Accident incident occurring on non-detec- tor lanes during Rush Dry period (Non-Rush Dry)
RD-50 (NRD-50)	=	Accident occurring during Rush Dry period (Non-Rush Dry)
RD-46 (NRD-46)	=	Non-Accident incident occurring during Rush Dry period (Non-Rush Dry)
10-50	=	Accident (Police Code)
10-46	=	Non-Accident Incident (Police Code)

Algorithm Features

OCC(t)	=	Minute average occupancy measured at upstream detector at time t
DOCC(t)	=	Minute average occupancy measured at downstream detector at time t
OCCDF(t)	=	$OCC(t) - DOCC(t)$
OCCRDF(t)	=	$OCCDF(t)/OCC(t)$
SPEED(t)	=	Minute average speed calculated at upstream detector at time t
SPDTDF(t)	=	$(SPEED(t-2) - SPEED(t))/SPEED(t-2)$
DOCCTD(t)	=	$(DOCC(t-2) - DOCC(t))/DOCC(t-2)$
OCCRDF(t-1)	=	$(OCC(t-1) - DOCC(t-1))/OCC(t-1)$
UPDF(t)	=	$OCC(t-1) - OCC(t-2)$
UPRDF(t)	=	$UPDF(t)/OCC(t-1)$
DNDF(t)	=	$DOCC(t-2) - DOCC(t-1)$
DNRDF(t)	=	$DNDF(t)/DOCC(t-2)$
UPDNDF(t)	=	$UPDF(t) - DNDF(t)$
UPDNR1(t)	=	$UPDNDF(t)/OCC(t-1)$
UPDNR2(t)	=	$UPDNDF(t)/(OCC(t-1) - DOCC(t-1))$
RDF(t)	=	$OCCDF(t)/(OCC(t-1) - DOCC(t-1))$

Algorithm Measures of Effectiveness

DR	=	Detection Rate
FAR	=	False-Alarm Rate,
MTTD	=	Mean-Time-To-Detect,

CALB Parameters

CALB	=	Threshold Optimization Program
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X	=	the initial threshold vector
XMIN	=	vector of minimum threshold values
XMAX	=	vector of maximum threshold values
DX	=	vector of weighting factors
DXFCTR	=	factor by which DX is reduced after NTRY successive failures
NTRY	=	number of successive failures after which DX is reduced
ITMAX	=	maximum number of iterations

Expressway Codes

Ken	=	Kennedy Expressway
Eis	=	Eisenhower Expressway
Ede	=	Edens Expressway

Other Codes & Abbreviations

CCTV	=	Closed-Circuit Television
CAESP	=	Chicago Expressway Surveillance Project
TSC	=	Technology Services Corporation
L.O.S.	=	Level of Significance

I. INTRODUCTION

Capacity-reducing incidents are one of the causes of breakdown in urban freeway operation. It has been estimated that nearly 750 million vehicle-hours of delay and a loss of approximately 400 million gallons of fuel are experienced on the nation's freeways every year.

Freeway incident management systems offering various levels of service to the motoring public have been in operation for quite some time. In essence, each such system provides 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.
4. Early removal of an incident and return to normal flow conditions.

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

Detection of traffic flow abnormalities on a freeway is carried out by a surveillance system, usually through its electronic detector subsystem. The availability of such a subsystem allows for a continuous quantification of traffic flow characteristics, definition of an incident, and application of an appropriate control strategy.

The process of identifying traffic flow abnormalities as incidents is a key element in such a management system since a positive identification will normally activate the control, driver communication, and incident handling subsystems. Obviously, a missed incident or a false alarm will affect the efficiency of the management system and its credibility.

The incident identification process utilizes an incident detection algorithm which relates certain 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 were:

1. Pattern recognition - comparing current flow patterns to expected ones based on historical data or traffic flow theoretic considerations and identifying consistent deviations as incidents (1,2,6).
2. Statistical forecasting of traffic behavior - comparing current traffic characteristics with forecasted ones based on time series analysis and identifying calibrated deviations as incidents (3,4,5).

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

Detection Rate - Percent of detected incidents out of all capacity-reducing incidents that occur during a specified time period.

False Alarm Rate - Percent of false-incident messages out of total incident messages during a specified time period (on-line definition).

Another definition used in the literature (6) for off-line situation is: percent of incident messages (1's) out of all messages (1's & 0's) where messages are produced at specific intervals (i.e. every 1 minute) out of representative incident-free data.

Mean-Time-To-Detect - The mean delay between the apparent occurrence of the incident and its detection for all detected incidents during a certain period of time, in minutes.

The inherent positive correlation that exists between the detection and false alarm rates could be detrimental to the effectiveness of the incident management system since the desired low false alarm rate is coupled with a low detection rate. The implication of such a detrimental effect could best be illustrated by applying the detection characteristics of an existing algorithm taken from reference (1), which is considered an efficient one, to the incident situation on Chicago expressways. It is estimated that the Eisenhower Expressway in Chicago experiences four capacity-reducing incidents per day during the PM rush period. By applying an algorithm optimally calibrated to have .01 percent false-alarm rate coupled with a 34 percent detection rate, it can be shown that only 1 incident will be detected, but two false alarms will be reported. In reality, the false-alarm rate as viewed by the incident management decision maker would be close to .67 percent. With such a high probability of making the wrong decision, no decision would be made unless more information as to the reliability of the incident message is provided.

High message reliability could be achieved by a sophisticated incident verification system (CCTV, CB radio) which would offset the weakness of a detection algorithm. However, for large freeway systems this type of verification is probably not feasible at this point in time.

The FHWA, recognizing the need for developing improved incident detection algorithms, contracted Technology Services Corporation (TSC) to evaluate existing algorithms comprising the state-of-the-art (2), and develop improved ones (1).

The Illinois Department of Transportation, through its Traffic Research Group, has assumed the task of the off-line and on-line evaluations of selected promising incident detection algorithms developed by TSC, utilizing the facilities of The Traffic Systems Center of I.D.O.T., formerly the Chicago Area Expressway Surveillance Project (CAESP). In addition, the efficiency of the TSC algorithms was compared to that of those developed by the Traffic Research Group.

The specific objectives of the research reported herein were:

1. To determine the efficiency of the selected TSC algorithms in detecting incidents on Chicago expressway system for various traffic and environmental conditions.
2. To develop algorithm thresholds compatible with the traffic characteristics of the expressway system and various environmental conditions.
3. To determine the effects of the existing level of detectorization on the operation of the algorithms.
4. To determine the effects of the severity of incidents on the operation of the algorithms.
5. To compare the efficiency of TSC algorithms with a pattern-recognition algorithm and a probabilistic algorithm developed locally.
6. To determine the on-line efficiency of algorithms proven to be effective in an off-line evaluation.
7. To correlate algorithm efficiency parameters derived from the on-line evaluation with those derived from the off-line evaluation.
8. To evaluate combinations of thresholds with respect to geometric conditions on the freeway.

Chapter two of this report describes the pattern-recognition algorithms evaluated in this research. It then presents the collection of the off-line data base used in calibration of these algorithms, and closes with an evaluation of CALB, a program developed by TSC to calibrate pattern-recognition algorithms in binary decision-tree form.

Chapter three presents the theoretical development of the Bayesian algorithm, a locally developed algorithm based on a conditional probabilistic approach to incident detection, and concludes with the calibration of this algorithm.

The fourth chapter presents a comparative off-line evaluation of the pattern-recognition algorithms, including an evaluation of the effect of incident severity and level of detectorization on algorithm performance. This is followed by an off-line comparison of the Bayesian algorithm with selected TSC algorithms.

Finally, the on-line evaluation of three TSC algorithms, the locally developed pattern-recognition algorithm and the Bayesian algorithm is covered in Chapter five.

II. PATTERN-RECOGNITION ALGORITHMS

A. ALGORITHM DESCRIPTION

Consider an n-lane freeway section of length L between two fully detectorized stations. At each detector station a set of flow characteristics consisting of occupancy, volume, and speed is measured at specific time intervals.

Suppose that at time t_0 an incident occurs at a certain point on one of the lanes within section L. A shock wave will develop and travel upstream of the incident, with intensity depending on the severity and lateral location of the incident, environmental and geometric conditions. At time $t_0 + dt$ an incident detection algorithm, by continuously measuring and comparing relationship of flow characteristics upstream and downstream (features) of the incident with predetermined thresholds, will detect the incident.

This section describes the structure of the five pattern-recognition incident detection algorithms evaluated in this research, four of which were developed by Technology Services Corporation (TSC) (1) and the fifth one, developed locally in the course of this research.

The research effort of TSC included the development of 10 incident detection algorithms which could be grouped into three categories.

The first, consisting of algorithms 1 to 7, is composed of variations on the classic California algorithm. The second consists of algorithms 8 and 9 which are characterized by suppression of incident detection following detection of a compression wave. Finally, algorithm 10 represents an attempt to detect those incidents occurring in light-to-moderate traffic which do not lower capacity below the volume of oncoming traffic. It uses a feature which measures a temporal change in speed.

Out of these ten algorithms, four were selected for evaluation - algorithms 7, 8, 9, & 10.

Preliminary investigation by TSC indicated algorithm 7 to be a superior form of the California algorithm (2).

Algorithm 8 is identical to algorithm 9 except for an added persistence check. According to TSC's preliminary investigation, algorithm 8 has a slightly lower false rate, but a longer mean-time-to-detect than algorithm 9.

Although algorithm 10 did not perform especially well in TSC's evaluation, it was included in the off-line evaluation because it represents a first attempt to solve the problem of detecting incidents which do not produce marked traffic flow discontinuities.

The TSC algorithms are in binary decision tree form; at each node of the decision tree a feature value is compared with a user-specified threshold value to determine whether an incident is to be signalled. Clearly the effectiveness of the algorithm depends upon the thresholds chosen.

TSC developed a program for optimizing threshold selection. This program, called CALB, uses a random number generator which produces increments to be added to the current optimal threshold vector to produce a new threshold vector for evaluation. After a pre-determined number of iterations, the threshold vector which has the lowest false-alarm rate given a certain level of detection is termed the optimal threshold vector at that level of detection. A detailed discussion of CALB is presented in the next chapter.

Finally, the above four TSC algorithms were compared with algorithm 16-14, a pattern recognition algorithm developed in the course of this research.

The following is a detailed description of the above algorithms. The meaning of the features involved in each algorithm is given in Table 1.

Algorithm 7 - differs from the classic California algorithm in the following three ways - whereas the California algorithm produces an incident signal whenever OCCDF, OCCRDF and DOCCTD are greater than associated thresholds, algorithm 7 replaces DOCCTD by DOCC, it suppresses incident signals after the

TABLE 1
DEFINITION OF FEATURES

Feature Name	Definition
OCC(t)	= Minute average occupancy measured at upstream detector at time t
DOCC(t)	= Minute average occupancy measured at downstream detector at time t
OCCDF(t)	= OCC(t) - DOCC(t)
OCCRDF(t)	= OCCDF(t)/OCC(t)
SPEED(t)	= Minute average speed calculated at upstream detector at time t
DOCCTD(t)	= (DOCC(t-2) - DOCC(t))/DOCC(t-2)
OCCRDF(t-1)	= (OCC(t-1) - DOCC(t-1))/OCC(t-1)
UPDF(t)	= OCC(t-1) - OCC(t-2)
UPRDF(t)	= UPDF(t)/OCC(t-1)
DNDF(t)	= DOCC(t-2) - DOCC(t-1)
DNRDF(t)	= DNDF(t)/DOCC(t-2)
UPDNDF(t)	= UPDF(t) - DNDF(t)
UPDNR1(t)	= UPDNDF(t)/OCC(t-1)
UPDNR2(t)	= UPDNDF(t)/(OCC(t-1) - DOCC(t-1))
RDF(t)	= OCCDF(t)/(OCC(t-1) - DOCC(t-1))

initial detection and it contains a persistence requirement that OCCRDF be greater than the threshold for two consecutive minutes. The tree structure of this algorithm is shown in Figure 1.

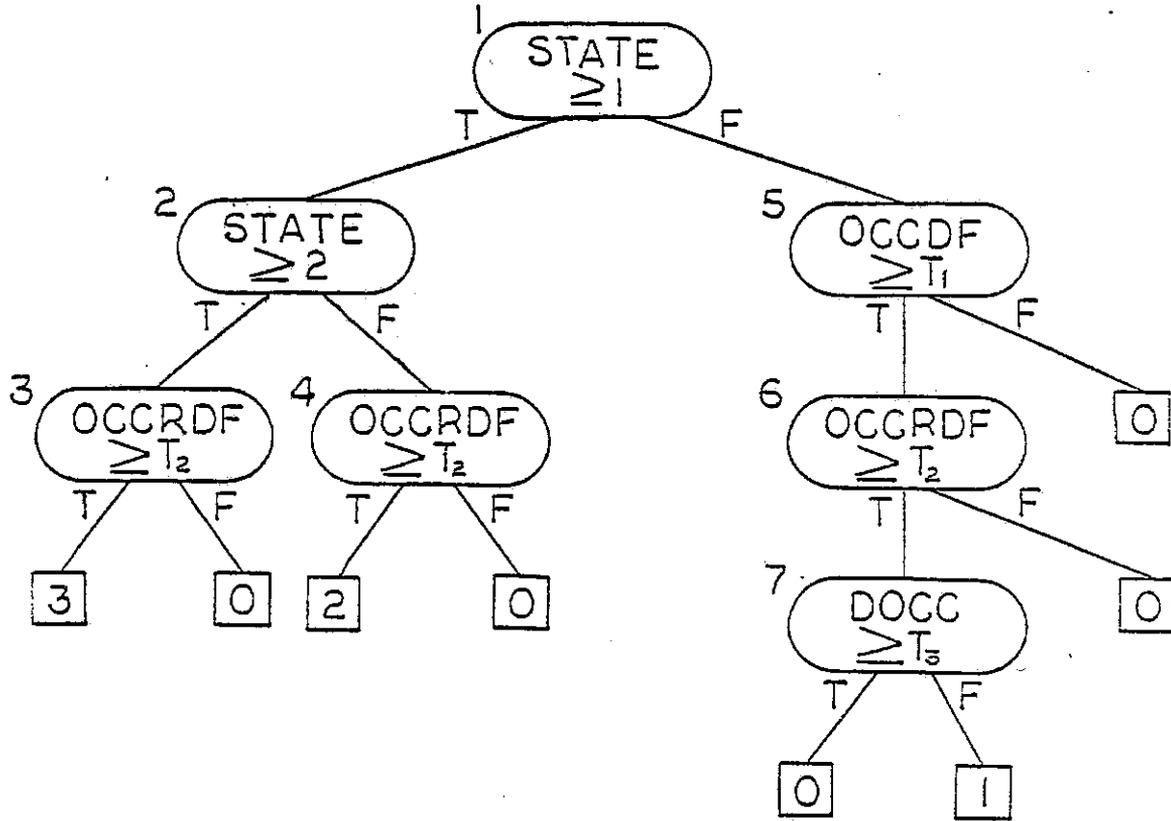
Algorithm 9 - consists of algorithm 4 (a variant of the California algorithm) coupled with a compression wave check, using features DOCC and DOCCID. It works as follows. First, a compression wave check is made. If successful, then algorithm 4 is not applied until five consecutive minutes have passed without a compression wave. If it fails, then algorithm 4 is immediately applied.

Algorithm 8 - is algorithm 9 with an OCCRDF - persistence requirement added. It can also be thought of as algorithm 7 incorporated with the 5-minute compression wave check. The tree structure of this algorithm is shown in Figure 2.

Algorithm 10 - separates traffic data into light, moderate & heavy traffic using the feature OCC. No incident check is applied to light-traffic data. Algorithm 7 is used under heavy-traffic conditions, and under moderate conditions OCCRDF and SPD'DF, a temporal speed-change feature, are applied. The tree structure of this algorithm is shown in Figure 3.

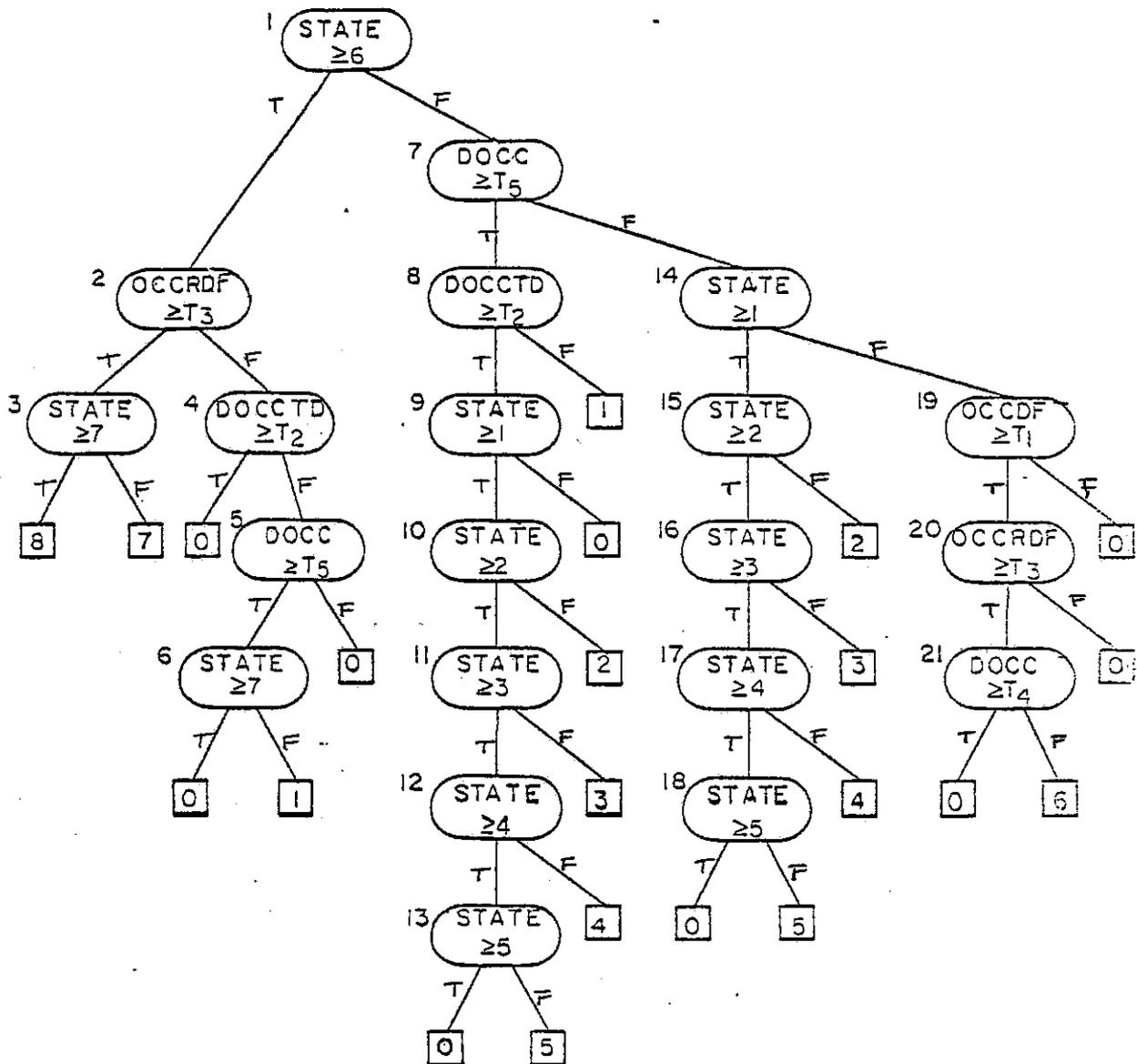
Algorithm 16-14 - is a complex pattern-recognition algorithm developed locally utilizing occupancy-based features reflecting variabilities in traffic flow, which were obtained empirically through observations and studies of traffic behavior on different parts of the Chicago area expressway system. It signals an incident when there is a large relative temporal change in upstream or in downstream occupancy, or when the overall change in upstream and downstream occupancy relative to upstream occupancy is sufficiently large (8). The tree structure of this algorithm is shown in Figure 4.

<u>State</u>	<u>Designates</u>
0	Incident-free conditions
1	Tentative incident
2	Incident confirmed
3	Incident continuing



DECISION TREE FOR ALGORITHM 7

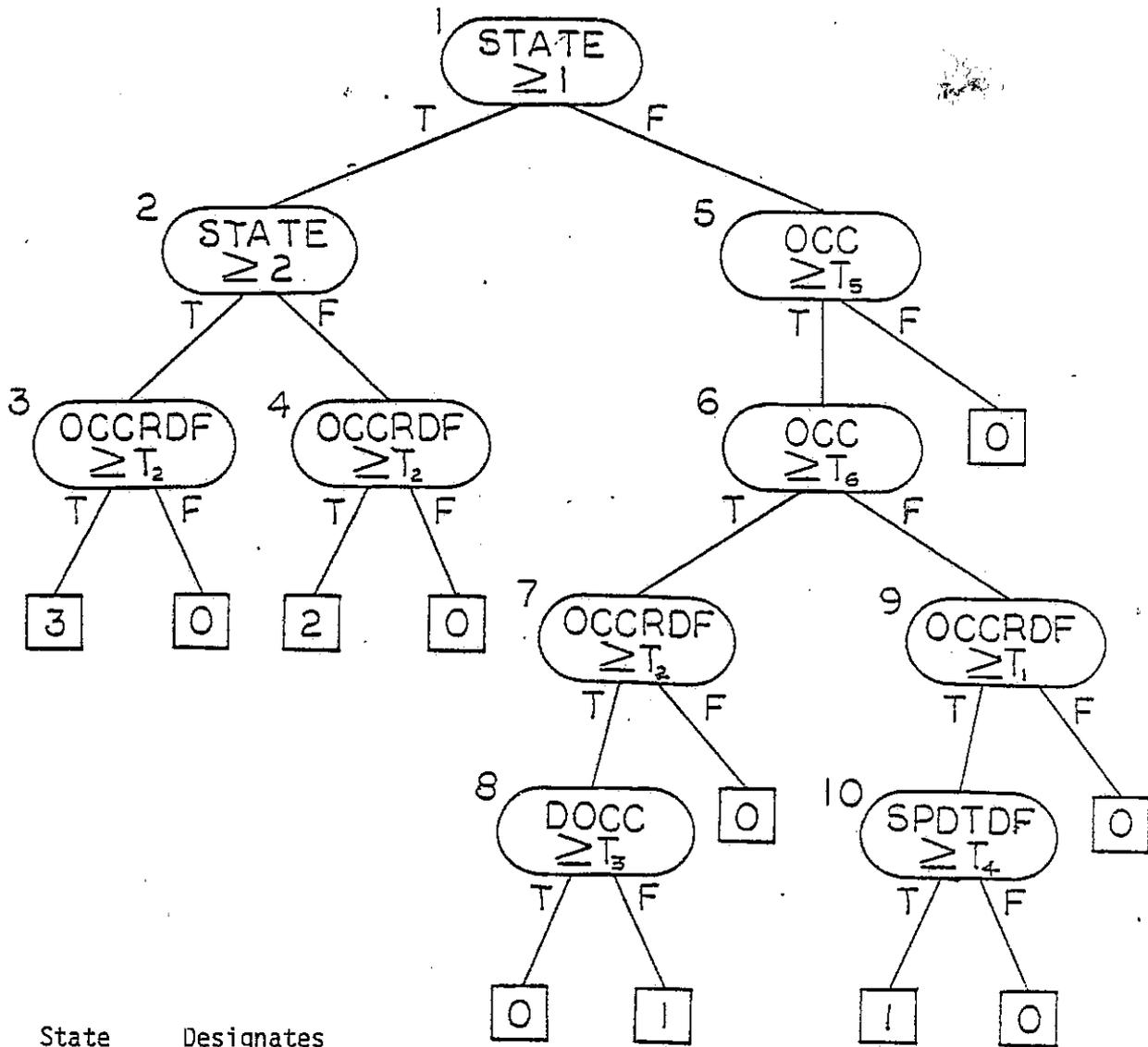
FIGURE 1



State	Designates
0	Incident-free conditions
1	Compression wave downstream in this minute
2	Compression wave downstream 2 minutes ago
3	Compression wave downstream 3 minutes ago
4	Compression wave downstream 4 minutes ago
5	Compression wave downstream 5 minutes ago
6	Tentative incident
7	Incident confirmed
8	Incident continuing

DECISION TREE FOR ALGORITHM 8

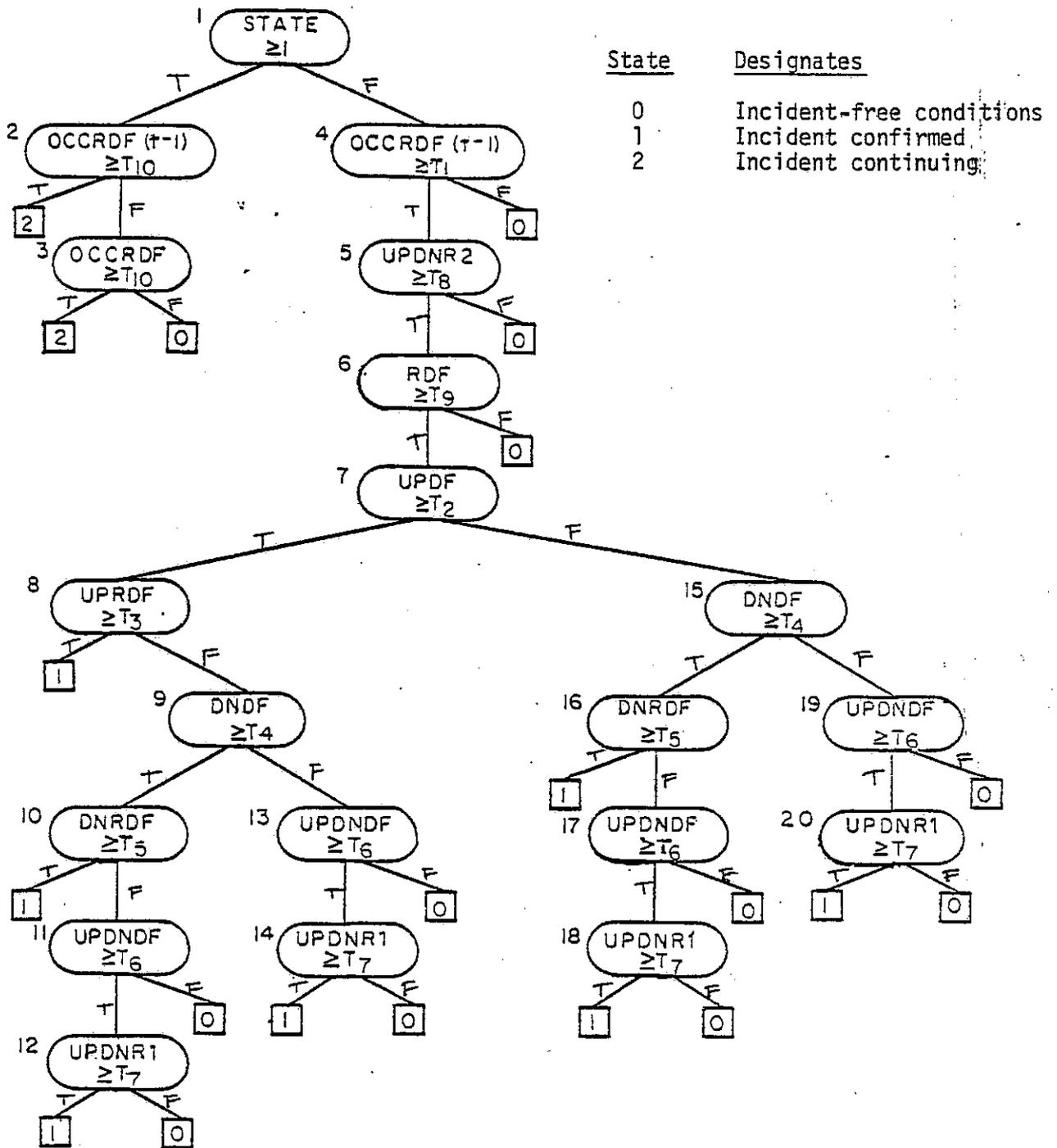
FIGURE 2



<u>State</u>	<u>Designates</u>
0	Incident-free conditions
1	Tentative incident
2	Incident confirmed
3	Incident continuing

DECISION TREE FOR ALGORITHM 10

FIGURE 3



DECISION TREE FOR ALGORITHM 16-14

FIGURE 4

B. CALIBRATION METHODOLOGY

Development of Data Base

While on-line testing of candidate detection algorithms is an indispensable aspect of selecting and implementing an operative one, off-line testing is necessitated by two major factors. The first is the need to test competing algorithms on the same data to provide a basis for comparative evaluation. The second is the need to make several runs of a promising algorithm on the same data in order to optimize the thresholds employed. This section discusses the contents of the off-line data base and summarizes the methodology employed to obtain it.

The data base is divided into two parts: incident data and incident-free data. The former consist of sets of surveillance data, each of which reflect the traffic operations surrounding the site of a specific incident. These are used to compute an algorithm's detection rate and mean-time-to-detect. The latter consist of sets of surveillance data from expressway segments confirmed to be incident-free during the period of data collection. From these an algorithm's false-alarm rate can be calculated.

The data base includes a total of 100 incident and fourteen incident-free data sets, taken from various portions of the Chicago expressway system. The incident data sets are described in Table A-1 by p-time (discussed below), longitudinal location, lateral location and incident type.

The surveillance data which make up each set consist of 20-second occupancies and volumes from each mainline detector on the relevant directional expressway.

Each of the fourteen incident-free data sets has location boundaries which consist of the first and last detector stations of the section of the expressway confirmed as incident-free. The time boundaries of the incident-free data sets are the time limits within which no incident occurred (the maximum period possible, given the data-collection program, was two and a half hours).

For the incident data sets the location boundaries are determined by the incident's location and the type of algorithm employed: a simple algorithm may require data only from the upstream or downstream station or both; more complex algorithms may employ data from several upstream or downstream stations.

The time boundaries are given by two time coordinates established by a data analyst. These are p-time, or probable time of incident occurrence, and t-time, or termination time. P-time is simply the time when the first trace of an incident is noticeable in the data, either as a rise in the upstream or a drop in the downstream occupancies. T-time is an estimate of the time of the incident's removal or the time the resulting congestion clears; it is determined using the following convention, based on congestion formation at the incident site.

After an incident's p-time has been determined, c-time (congestion time) is determined as the first time period in which

1. the upstream station's occupancy exceeds 29% (30% is the usual CAESP guideline for congested conditions) and
2. the ratio of upstream occupancy to downstream occupancy is two or greater for three consecutive 20-second readings.

Thereafter, a time is noted as a possible termination time if

1. either the upstream occupancy drops below 30% or the downstream occupancy rises above 20% (CAESP guideline for transition flow) and

2. the upstream to downstream occupancy ratio is less than two in three consecutive 20-second readings.

If congestion resulting from the incident's presence does not set in again (i.e. another c-time doesn't follow) this time is taken as t-time. Otherwise, the process is continued until no further congestion formation is attributable to the incident.

Each incident-free data set covers approximately two to two and a half hours of data. Each incident data set starts at least fifteen minutes prior to the incident's occurrence (p-time) and runs continuously to at least ten minutes after the incident is cleared (t-time).

While the term "incident" may refer to any unusual event having an adverse effect on traffic operations, in the collection of incident data sets it was limited to mean unplanned physical obstructions of the travelled lanes. Hence, included in the incident data base are crashes, disabled vehicles and spilled loads (occurring on the travelled lanes); excluded are geometric deficiencies, entrance ramp merging overloads, lane closures for maintenance, adverse environmental conditions and gaper blocks.

In collecting the incident-free data, obviously, anything which qualified as an incident in the above-limited sense would have been edited out. Further, of the non-incident situations listed above, lane closures and gaper blocks would also have been edited out; a detection produced by either of these causes couldn't realistically be termed a false alarm.

The incident data were collected by monitors at the I.D.O.T.'s Traffic Systems Center. Indications of a potential incident came in two ways. In the most common case, the data collector would spot a disturbance in the traffic stream variables by monitoring the expressway system map panel, occupancy maps

on the CRT display or typer output of the surveillance system. In these cases, the monitor would activate a program for saving the surveillance data from the affected directional expressway (the data-collection program kept a thirty-minute historical file of surveillance data, enabling the requisite 15 minutes of pre-incident data to be saved, if an incident was detected by the monitor within 15 minutes of its occurrence). He then requested the Communication Center of I.D.O.T. to dispatch an Emergency Patrol Vehicle (EPV) to the area for confirmation and identification. In other cases, an incident would be reported by a field unit before signs of it appeared in the surveillance data. When traffic stream measurements began to manifest signs of the incident's effect on traffic operations, data saving was initiated.

Data sets collected as above would be stored temporarily on an on-line disc pack until the data collector was assured that minimal documentation information was available and that the data set contained the requisite pre- and post-incident data. Then the data set was edited and transferred to an off-line disc pack for permanent storage.

The bulk of the incident data sets are from June - August and December of 1975. During these periods, full-time data collecting was carried on, each week-day being broken into two (0700-1200 and 1200-1700) or three (0600-1030, 1030-1430 and 1430-1900) shifts. Coverage was also attempted for some evening (1900-2300) and nighttime (2300-0700) periods, but proved to be unproductive and was soon dropped.

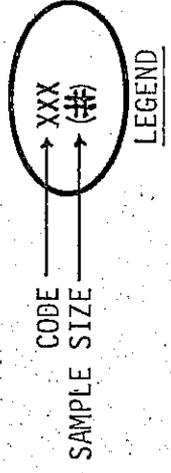
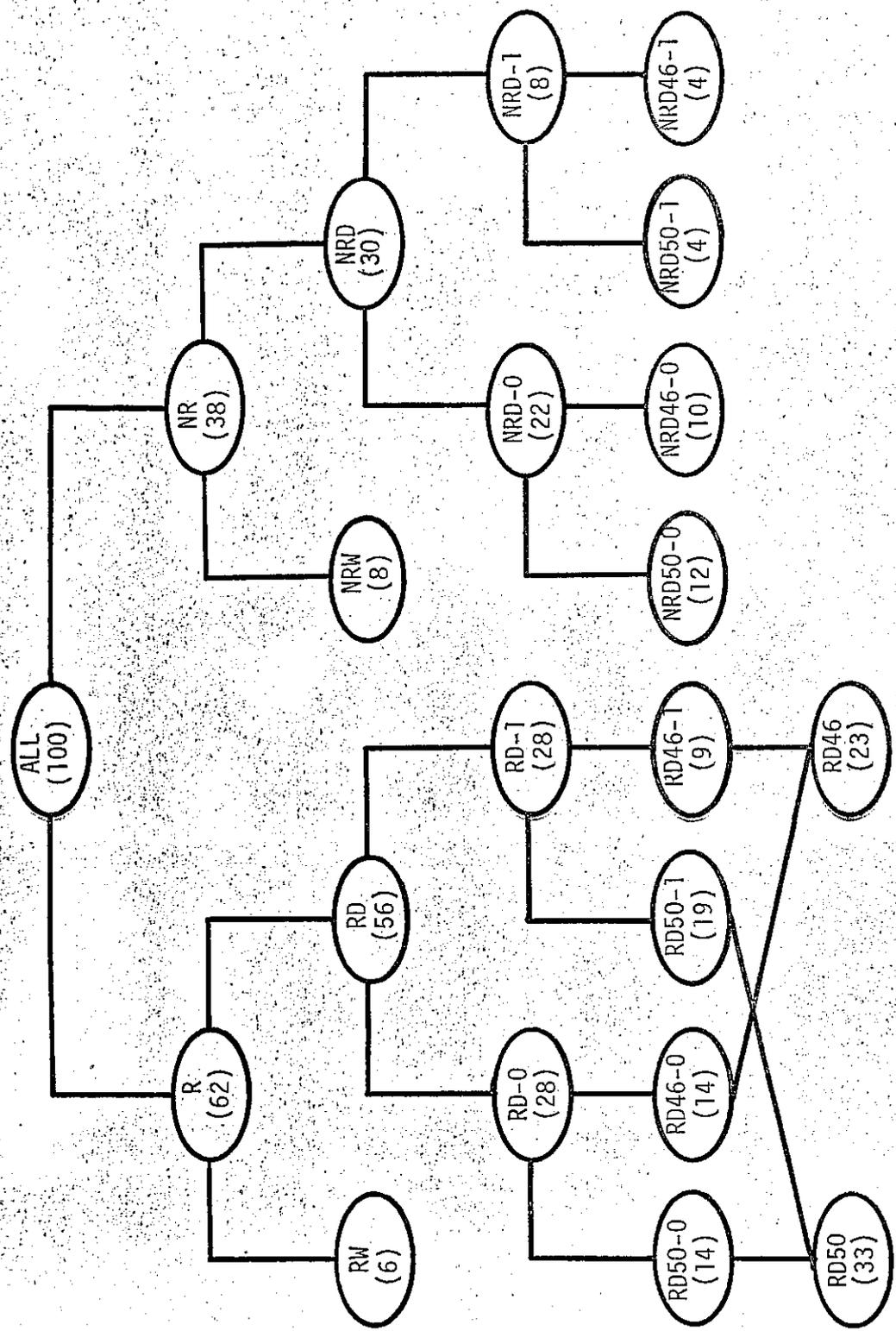
The incident data were collected to represent the following factors:

1. traffic conditions - rush or non-rush
2. pavement conditions - wet or dry
3. incident type - accident (10-50) or non-accident incident (10-46) according to Illinois State Police Code.

4. incident lateral location - detector lane or non-detector lanes.

Figure (5) shows the stratification of the incident data and the code of each stratum. The meaning of the codes is explained in Table 2.

The collection of incident-free data sets involved the use of the same data-saving software as employed in the incident data set collection. Verification of this data as incident-free was carried out with the use of a helicopter. Nearly 30 hours of incident-free data were collected to approximately represent rush, non-rush, wet and dry conditions.



Note: Refer to Table 2 for definitions of codes.

INCIDENT DATA STRATIFICATION

FIGURE 5

TABLE 2

INTERPRETATION OF INCIDENT DATA CODES

Code *		Interpretation
R	=	Rush
RW	=	Rush-Wet
RD	=	Rush-Dry
RD-0	=	Incident occurring on non-detector lanes during Rush Dry period
RD-1	=	Incident occurring on detector lane during Rush Dry period
RD-50-1	=	Accident occurring on detector lane during Rush Dry period
RD-50-0	=	Accident occurring on non-detector lanes during Rush Dry period
RD-46-1	=	Non-Accident incident occurring on detector lane during Rush Dry period
RD-46-0	=	Non-Accident incident occurring on non-detector lanes during Rush Dry period
RD-50	=	Accident occurring during Rush Dry period
RD-46	=	Non-Accident incident occurring during Rush Dry period

* NR, NRW, NRD, NRD-0, NRD-1, NRD50-0, NRD46-0, NRD50-1, and NRD46-1 have the same interpretation as above except for the Non-Rush period.

Evaluation of CALB

The TSC algorithms are in binary decision-tree form; at each node of the decision tree a feature value is compared with a user-specified threshold value to determine whether an incident is to be signalled. Clearly, the effectiveness of the algorithm depends upon the thresholds chosen.

TSC developed a program for optimizing threshold selection. This program, called CALB, uses a random number generator which produces increments to be added to the current optimal threshold vector to produce a new threshold vector for evaluation. After a pre-determined number of iterations, the threshold vector which has the lowest false-alarm rate while maintaining a certain level of detection is termed the optimal threshold vector at that level of detection.

Before using CALB to calibrate the algorithms for the off-line evaluation, a detailed study of CALB was performed to determine how best to set certain user-supplied parameters needed by CALB in the algorithm calibration process, so as to insure selection of optimal threshold vectors for use in the algorithm evaluation.

CALB operates as follows: Maximum and minimum values for the features are set, defining a space of threshold vectors from which vectors can be randomly chosen for evaluation. An initial threshold vector X is chosen. When the algorithm is run using this threshold vector, there is an associated false-alarm rate $\alpha(X)$ and detection rate $p(X)$. Note that the false-alarm rate and detection rate are functions of the threshold vector X .

A Gaussian random number generator produces a vector of random increments which are normalized, yielding a uniformly distributed random unit vector v . Each random increment in the unit vector v is weighted by a user-supplied factor; these factors make up the vector DX . The unit vector v is then modified by the weighting vector DX , and the resulting vector is added to the initial threshold,

vector X , giving a test vector X^* . The associated false-alarm rate $\alpha(X^*)$ and detection rate $p(X^*)$ are determined.

If $p(X^*)$ is less than the minimum desirable detection rate, or if $\alpha(X^*)$ is larger than the current minimum false-alarm rate, then the test vector is a failure, and a new test vector is determined. DX , the vector of weighting factors, is decreased by a certain user-supplied factor ($DXFCTR$) after a specified number of consecutive failures in the optimizing routine.

If $\alpha(X^*)$ is less than the current minimum false-alarm rate, then the test vector is a success, and $\alpha(X^*)$ becomes the new current minimum false-alarm rate.

Each threshold vector tested is an iteration of the optimization routine; there is a user-supplied upper bound ($ITMAX$) to the total number of iterations. The flowchart of CALB operation is given in Figure (6).

Before CALB can be effectively used, it is necessary to determine how to optimize the user-supplied parameters.

The user-supplied parameters are:

X	-	the initial threshold vector
$XMIN$	-	vector of minimum threshold values
$XMAX$	-	vector of maximum threshold values
DX	-	vector of weighting factors
$DXFCTR$	-	factor by which DX is reduced after $NTRY$ successive failures
$NTRY$	-	number of successive failures after which DX is reduced
$ITMAX$	-	maximum number of iterations

Each combination of CALB parameter values results in a different search strategy. DX , the vector of weighting factors, determines a neighborhood

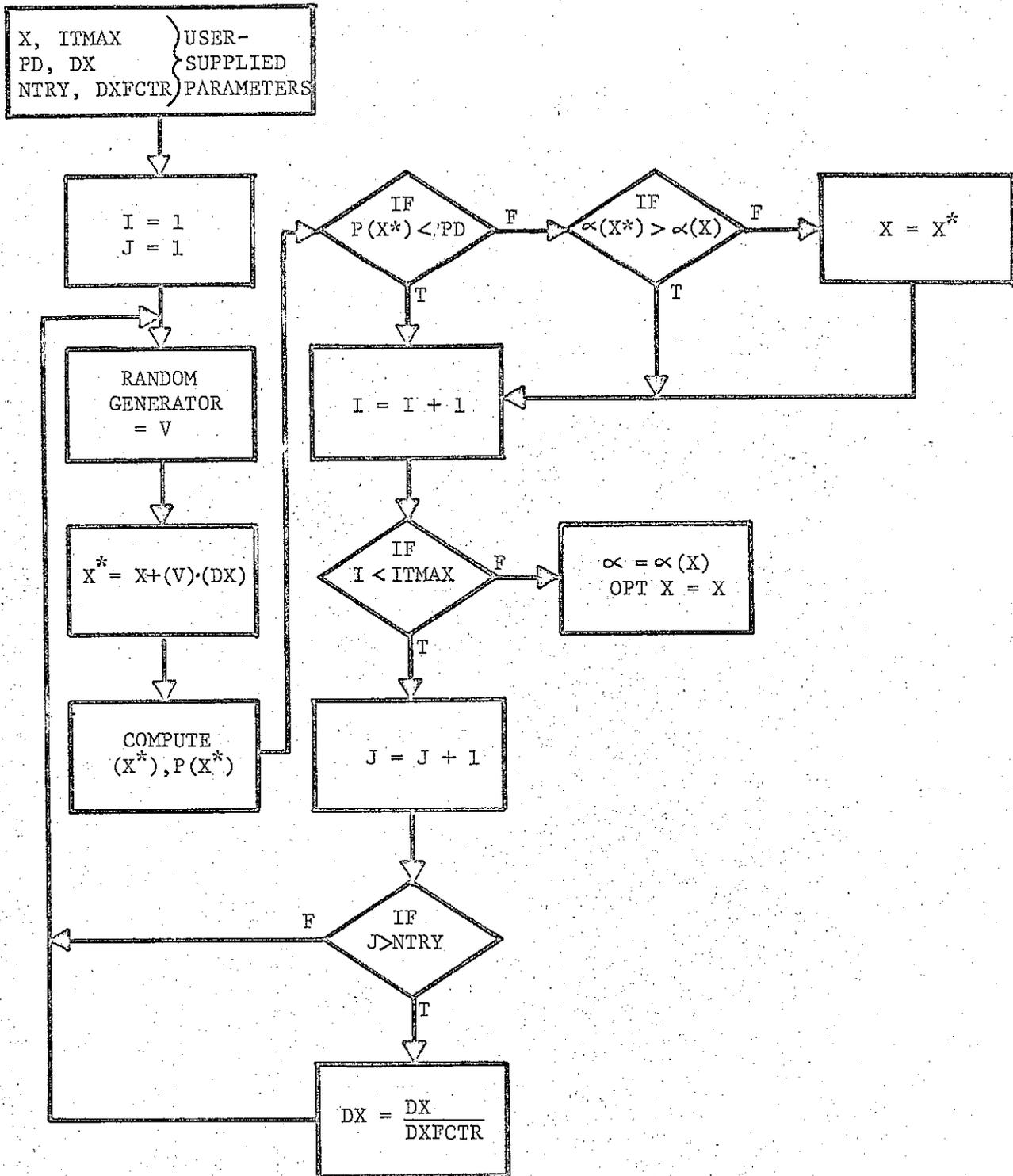


FIGURE 6

FLOWCHART OF CALB OPERATION

around X from which other test vectors can be chosen. The size of DX determines how large a section of the vector space will be scanned by CALB. DXFCTR determines the rate of convergence of the neighborhood around X - how quickly it "shrinks down" to some locally optimal point. NTRY specifies how stringent the requirements are for determining optimality, in that there must be NTRY successive failures in the DX neighborhood around X before X is judged to be locally optimal point, and the neighborhood around X is reduced for DXFCTR. Finally, the choice of X - the initial threshold vector - may result in a local instead of a global optimal point being reached.

Sixteen search strategies were investigated, (Table 3). Each of the four relevant factors - DX, X, DXFCTR & NTRY - was considered at two levels, resulting in sixteen search strategies. XMIN & XMAX were set equal to the minimum & maximum feature values achieved by the incident data. Algorithm 2 (the California algorithm), being a simple algorithm, was used for evaluation purposes; it was calibrated at the 95% detection level.

The factor levels are:

X	-	XMIN: P(XMIN) = 99%
		XMAX: P(XMAX) = 0%
NTRY	-	NTRY small = 5
		NTRY large = 40
DXFCTR	-	DXFCTR small = 1.5
		DXFCTR large = 3.0
DX	-	DX small = 1/20 (XMAX - XMIN)
		DX large = 1/4 (XMAX - XMIN)

For DX small, the initial neighborhood scanned is 1/1000 of the volume of the entire vector space; for DX large, it is 1/8 of the volume of the space.

TABLE 3
CALB OPTIMIZATION STRATEGIES

Strategy	X	DXFCTR	NTRY	DX
1.	XMIN	1.5	5	1/20
2.	XMIN	1.5	40	1/20
3.	XMIN	3.0	5	1/20
4.	XMIN	3.0	40	1/20
5.	XMIN	1.5	5	1/4
6.	XMIN	1.5	40	1/4
7.	XMIN	3.0	5	1/4
8.	XMAX	3.0	40	1/4
9.	XMAX	1.5	5	1/20
10.	XMAX	1.5	40	1/20
11.	XMAX	3.0	5	1/20
12.	XMAX	3.0	40	1/20
13.	XMAX	1.5	5	1/4
14.	XMAX	1.5	40	1/4
15.	XMAX	3.0	5	1/4
16.	XMAX	3.0	40	1/4

Also, to minimize computer time required, ITMAX was investigated. First, each different search strategy is run on algorithm 2 with ITMAX=100. Then, the final stepsize obtained from each run was multiplied by DX, giving a new vector DX of weighting factors. A second set of runs is made again with ITMAX=100, but using the adjusted vector DX. This process is continued until there is no appreciable improvement in false-alarm rate. This was used to discover which search strategy reaches the lowest false-alarm rate in the least number of iterations.

It was found that there was virtually no change in the optimal threshold achieved after three hundred iterations when one hundred more iterations were run, and thus no improvement in false alarm rate. Hence the CALB evaluation was terminated after four hundred iterations (Table 4).

The next stage was to test the facility of the various search strategies in moving from a given detection level to a lower detection level. The general procedure is to use the optimal threshold achieved at one detection level as the initial threshold vector for calibration at a lower detection level.

Consequently, the optimal thresholds achieved by the sixteen search strategies at the 95% level of detection were used as initial thresholds in calibration runs at the 90% level. One hundred iterations were run on each strategy (Table 5).

Inspection of the output immediately eliminates strategy 11 from consideration. This strategy converges very quickly to a small neighborhood around the initial threshold vector X, for which $P(X) = 0\%$. Hence, the desired level of detection cannot be reached.

Strategies 6, 14 and 16 are eliminated because of instability: they do not reach an optimum point within 100 iterations because of extremely slow convergence properties.

TABLE 4
EVALUATION OF STRATEGIES FOR CHOOSING "CALB" PARAMETERS
UTILIZING THE CALIFORNIA ALGORITHM

# OF ITER.	STRATEGY	1		2		3		4		5		6		7		8	
		XMIN	(DX / (XMAX-XMIN))														
100	X	1.5	1/20	1.5	1/20	3.0	1/20	3.0	1/20	1.5	1/4	1.5	1/4	3.0	1/4	3.0	1/4
	DXFCTR	5		40		5		40		5		40		5		40	
	NTRY	1/20		1/20		1/20		1/20		1/4		1/4		1/4		1/4	
	THRESHOLD	0.95		0.96		0.96		0.96		.96		0.97		0.96		0.95	
200	DR	0.00089		0.00092		0.00089		0.00092		.00092		0.0012		0.000892		0.00092	
	FAR	2.82		1.34		1.92		1.34		1.43		1.20		1.86		1.46	
	MTTD (MIN.)	270.6875		273.9297		274.6484		273.9297		294.5549		266.0078		273.1406		292.4648	
	THRESHOLD	0.0367		0.1008		0.0003		0.1008		0.2189		0.1763		0.0169		0.1672	
300	DR	0.0759		-0.0892		0.0060		-0.0392		-0.5549		-0.3566		-0.0197		-0.3630	
	FAR	0.96		0.96		0.96		0.96		.96		.95		.96		.95	
	MTTD	0.00089		0.00092		0.00089		0.00092		.00092		0.0095		0.00089		0.00092	
	THRESHOLD	2.68		1.35		.182		.135		1.43		1.29		1.86		1.41	
400	DR	270.5234		275.2187		275.3242		272.6563		294.7852		289.2891		274.4180		292.2852	
	FAR	0.0226		0.0070		0.0018		0.0457		.1379		.1683		.0088		.1862	
	MTTD	0.0702		-0.0860		.02		-0.0844		-0.5723		-0.3622		-0.0170		-0.5085	
	THRESHOLD	0.95		0.96		0.95		0.96		.95		.95		.95		.95	
500	DR	0.00089		0.00092		0.00089		0.00092		.00092		0.0092		0.00089		0.00092	
	FAR	2.68		1.35		1.82		1.35		1.46		1.35		1.92		1.44	
	MTTD	270.9570		275.2187		274.0		274.7344		295.2461		291.7344		275.9687		293.1875	
	THRESHOLD	0.0145		0.007		0.0034		0.0252		.0973		.1839		.0106		.1116	
600	DR	0.07		-0.086		0.0241		0.0838		-0.5736		-0.492		0.0033		-0.5618	
	FAR	0.95		0.96		0.95		0.96		.96		.96		0.96		0.95	
	MTTD	0.00089		0.00092		0.00089		0.00092		.00092		0.0092		0.000892		0.00092	
	THRESHOLD	2.68		1.78		1.82		2.71		1.19		1.44		1.87		1.44	
700	DR	270.0664		273.2148		275.3125		270.6289		290.6758		293.3633		271.3984		293.4258	
	FAR	0.0059		0.0031		0.005		0.0018		0.0845		0.1943		0.0112		0.0189	
	MTTD	0.0059		-0.0529		0.0193		0.0734		-0.5789		-0.5785		-0.0152		-0.5649	
	THRESHOLD	0.95		0.96		0.95		0.96		.96		.96		0.96		0.95	

* Optimal Thresholds for
OCDF -
OCGRDF -
DOCCTD -

TABLE 4 (Cont'd)
 EVALUATION OF STRATEGIES FOR CHOOSING "CALB" PARAMETERS
 UTILIZING THE CALIFORNIA ALGORITHM

# OF ITER.	STRATEGY	9	10	11	12	13	14	15	16
	X	XMAX							
	DXFCTR	1.5	1.5	3.0	3.0	1.5	1.5	3.0	3.0
	NTRY	5	40	5	40	5	40	5	40
	(DX (XMAX-XMIN))	1/20	1/20	1/20	1/20	1/4	1/4	1/4	1/4
	DR	.95	.95	NOT	.95	.96	.96	.95	.95
	FAR	.000661	.00085	ACHIEVED	.00085	.00072	.00079	.00066	.00069
100	MTTD (MIN)	1.43	1.22	1.45	1.45	1.43	1.47	2.08	2.02
	THRESHOLD	290.8516	290.4023	294.2461	294.2461	274.1875	257.6094	270.1602	296.9766
		.6138	.5193	.5140	.5140	.5669	.6250	.6412	.6403
		-.5081	-.4636	-.0676	-.0676	-.0607	-.3162	-.02385	-.04068
	DR	.95	.95	.95	.95	.95	.96	.95	.96
	FAR	.0006	.00072	.00082	.00082	.00072	.00066	.00066	.00072
200	MTTD	1.74	1.51	1.38	1.38	1.41	1.73	2.08	1.56
	THRESHOLD	296.3477	792.4609	291.6445	291.6445	271.7148	268.6797	2.704844	247.1445
		.6294	.5821	.5249	.5249	.5673	.6261	.6402	.6104
		-.5745	-.5584	-.4810	-.4810	-.0926	-.1170	-.2488	-.1062
	DR	.96	.95	.95	.95	.95	.95	.95	.95
	FAR	.00066	.00069	.00082	.00082	.00072	.00056	.00066	.00052
300	MTTD	1.72	1.50	1.22	1.22	1.44	2.26	2.09	2.94
	THRESHOLD	292.4492	294.3359	290.0977	290.0977	274.8789	272.7578	270.6719	262.3555
		.6277	.5775	.525	.525	.5687	.6254	.6406	.6284
		-.5795	-.5358	-.4813	-.4813	-.0747	.0151	-.24	.0732
	DR	.96	.95	.95	.95	.95	.95	.95	.95
	FAR	.000661	.00069	.000826	.000826	.00072	.00056	.00066	.00052
400	MTTD	1.50	1.50	1.24	1.24	1.44	2.18	2.09	2.81
	THRESHOLD	290.7422	292.0234	290.0977	290.0977	273.543	243.6602	269.3008	257.7695
		.6225	.5685	.5253	.5253	.5699	.6231	.641	.6288
		-.5782	-.5471	-.4381	-.4381	-.0616	.043	-.2351	.0489

TABLE 5

EVALUATION OF STRATEGY EFFICIENCY IN MOVING
TO LOWER DETECTION LEVEL

<u>STRATEGY</u>	<u>RESULTS AFTER 400 ITERATIONS AT 0.95 DETECTION LEVEL</u>	<u>RESULTS AFTER 100 ITERATIONS AT 0.90 DETECTION LEVEL*</u>
1. DR= FAR= MTTD (MIN.)= OPTIMAL THRESHOLD=	0.95 0.00089 2.68 (270.07, 0.01, 0.07)	0.90 0.00076 3.51 (277.91, 0.00, 0.11)
2. DR= FAR= MTTD (MIN.)= OPTIMAL THRESHOLD=	0.96 0.00092 1.78 (273.21, 0.00, -0.05)	0.92 0.00082 1.56 (303.37, 0.02, -0.16)
3. DR= FAR= MTTD (MIN.)= OPTIMAL THRESHOLD=	0.95 0.00089 1.82 (275.31, 0.01, 0.02)	0.91 0.00076 2.28 (306.57, 0.00, 0.02)
4. DR= FAR= MTTD (MIN.)= OPTIMAL THRESHOLD=	0.95 0.00089 2.71 (270.63, 0.00, 0.07)	0.90 0.00076 2.15 (300.63, 0.07, 0.03)
5. DR= FAR= MTTD (MIN.)= OPTIMAL THRESHOLD=	0.96 0.00092 1.19 (290.68, 0.08, -0.58)	0.90 0.00076 2.13 (327.27, 0.12, 0.57)
6. DR= FAR= MTTD (MIN.)= OPTIMAL THRESHOLD=	0.96 0.00092 1.44 (293.36, 0.19, -0.58)	0.96 0.00092 1.44 (293.36, 0.19, -0.58)
7. DR= FAR= MTTD (MIN.)= OPTIMAL THRESHOLD=	0.96 0.00089 1.87 (271.40, 0.01, -0.02)	0.90 0.00082 1.66 (308.22, 0.02, 0.07)
8. DR= FAR= MTTD (MIN.)= OPTIMAL THRESHOLD=	0.95 0.00092 1.44 (293.43, 0.02, -0.56)	0.90 0.00089 1.46 (310.04, 0.04, 0.56)

*INITIAL THRESHOLD VECTOR = OPTIMAL THRESHOLD VECTOR AT 0.95 DETECTION LEVEL

TABLE 5 (Cont'd)

EVALUATION OF STRATEGY EFFICIENCY IN MOVING
TO LOWER DETECTION LEVEL

<u>STRATEGY</u>	<u>RESULTS AFTER 400 ITERATIONS AT 0.95 DETECTION LEVEL</u>	<u>RESULTS AFTER 100 ITERATIONS AT 0.90 DETECTION LEVEL*</u>
9. DR= FAR= MTTD (MIN.)= OPTIMAL THRESHOLD=	0.96 0.00066 1.50 (290.74, 0.62, -0.58)	0.95 0.00066 1.65 (292.14, 0.61, 0.54)
10. DR= FAR= MTTD (MIN.)= OPTIMAL THRESHOLD=	0.95 0.00069 1.50 (292.02, 0.57, -0.55)	0.91 0.00069 2.41 (306.26, 0.65, -0.45)
11. DR= FAR= MTTD (MIN.)= OPTIMAL THRESHOLD=	NOT ACHIEVED	NOT ACHIEVED
12. DR= FAR= MTTD (MIN.)= OPTIMAL THRESHOLD=	0.96 0.00083 1.24 (290.10, 0.52, -0.44)	0.93 0.00069 1.55 (301.35, 0.59, -0.49)
13. DR= FAR= MTTD (MIN.)= OPTIMAL THRESHOLD=	0.95 0.00072 1.44 (273.54, 0.57, -0.06)	0.90 0.00039 4.64 (248.32, 0.63, 0.18)
14. DR= FAR= MTTD (MIN.)= OPTIMAL THRESHOLD=	0.95 0.00056 2.18 243.66, 0.62, 0.04)	0.95 0.00056 2.19 (243.66, 0.62, 0.04)
15. DR= FAR= MTTD (MIN.)= OPTIMAL THRESHOLD=	0.95 0.00066 2.09 (269.30, 0.64, -0.24)	0.91 0.00056 1.92 (306.50, 0.62, 0.10)
16. DR= FAR= MTTD (MIN.)= OPTIMAL THRESHOLD=	0.95 0.00052 2.81 (257.77, 0.63, 0.05)	0.91 0.00046 4.48 (262.71, 0.61, 0.15)

*INITIAL THRESHOLD VECTOR = OPTIMAL THRESHOLD VECTOR AT 0.95 DETECTION LEVEL

Strategies 2, 6, 9, 12 and 14 are unacceptable because of inability to move from a 95% detection level to a 90% detection level within 100 iterations.

Strategies 1, 3, 4, 5, 7 and 8 reach optimal thresholds with relatively high false-alarm rates, and so are unacceptable.

This leaves strategies 10, 13, and 15 as possible candidates for our calibration strategy. Our final criterion for deciding among these strategies is that of independence with respect to the initial threshold vector; that is, that an optimal threshold be reached regardless of the choice of initial threshold vector. This criterion immediately eliminates strategy 10, since strategy 2 (identical to strategy 10 except for the initial threshold vector) does not move from the 95% level to the 90% level of detection.

Finally, out of a choice of strategies 13 and 15, the latter was chosen, as it reached the lowest false-alarm rate. Table 6 summarizes the reasons for eliminating the various strategies.

TABLE 6
SUMMARY OF REASONS FOR STRATEGY ELIMINATION

Strategy	Reason For Elimination
1.	High false-alarm rate.
2.	Does not move to next detection level; high false alarm rate.
3.	High false-alarm rate.
4.	High false-alarm rate.
5.	High false-alarm rate.
6.	Slow optimization; does not move to next detection level; High false-alarm rate.
7.	High false-alarm rate.
8.	High false-alarm rate.
9.	Does not move to next detection level.
10.	Unacceptability of strategy 2 (related strategy).
11.	Does not reach desired detection level.
12.	Does not move to next detection level.
13.	(Acceptable strategy).
14.	Slow optimization; does not move to next detection level.
15.	(Optimal strategy).
16.	Slow optimization.

III. THE BAYESIAN ALGORITHM

A. THEORETICAL CONSIDERATIONS

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

Based on the history of capacity-reducing incidents on the above freeway section, the probability of an incident occurring on the section, under certain environmental and traffic conditions, could be derived and denoted by $P(U_1)$. Likewise, the probability of not having any capacity-reducing incidents will be denoted by $P(U_0)$. It holds that:

$$(1) \quad P(U_0) = 1 - P(U_1)$$

and

$$(2) \quad P(U_0) \int_{a_0}^{b_0} f(Z/U_0) dZ + P(U_1) \int_{a_1}^{b_1} f(Z/U_1) dZ = 1$$

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 our algorithm feature Z choose a threshold Z_1 . If $Z > Z_1$, a possible incident state is signalled; if $Z < Z_1$, an incident-free state is signalled. "1" shall signify an incident-state signal, "0" shall signify an incident-free state signal. It can be shown that the probability of getting an incident signal, $P(1)$, could be expressed as follows:

$$P(1) = P(U_0) \int_{Z_1}^{b_0} f(Z/U_0) dZ + P(U_1) \int_{Z_1}^{b_1} f(Z/U_1) dZ$$

Similarly, the probability of getting a non-incident signal, $P(0)$, is:

$$P(0) = P(U_0) \int_{a_0}^{Z_1} f(Z/U_0) dZ + P(U_1) \int_{a_1}^{Z_1} f(Z/U_1) dZ$$

Applying Bayesian considerations one can develop an expression for the probability of having an incident given that an incident signal "1" was output.

This expression is:

$$P(\text{incident}/1) = \frac{P(U_1) \int_{z_1}^{b_1} f(Z/U_1) dZ}{P(U_0) \int_{z_1}^{b_0} F(Z/U_0) dZ + P(U_1) \int_{z_1}^{b_1} f(Z/U_1) dZ}$$

The probability of no incident when a non-incident signal "0" is output could be expressed as:

$$P(\text{no incident}/0) = \frac{P(U_0) \int_{a_0}^{z_1} f(Z/U_1) dZ}{P(U_0) \int_{a_0}^{z_1} f(Z/U_0) + P(U_1) \int_{a_1}^{z_1} f(Z/U_1) dZ}$$

The optimal threshold Z_1 could be obtained by maximizing the expression:

$$P(\text{incident}/1) + P(\text{no-incident}/0)$$

Theoretically, the above optimization procedure for Z_1 could be repeated for all $f_i (A/U_1)$ yielding a set of optimal thresholds Z_i where i represents consecutive determined time intervals after detecting an incident. However, by selecting a feature with no statistically significant differences between $f_i(Z/U_1)$ and $f_{i+1}(Z/U_1)$ only one threshold value could be utilized in the detection process. The utilization of such a feature is important in view of the fact that delay is encountered between the occurrence of an incident and its detection. In such cases, the calculated Z_1, Z_2 , etc. will not represent consecutive time intervals immediately after the occurrence of the incident. Thus, by selecting one appropriate threshold the threshold synchronization problem is eliminated.

The Bayesian concepts applied to incident considerations yielding probabilities of having an incident given one signal "1" or "0" could be extended to the case of strings of signals. That is, the algorithm could be applied over n successive time intervals generating an n-signal string. Though forcing the decision maker to wait n time intervals before making an incident management decision, it would provide more reliable information. Obviously, for practical reasons, n could be limited to three, and signal strings of interest would be 10, 11, 100, 101, 110, and 111. The string 110, for example, would indicate that during the first two time intervals incident signals (11) were output and a no-incident signal (0) was output in the third time interval. The nature of the probabilities of having an incident given that any of the above signal strings have occurred could be shown to be such that:

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

and

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

The above relationships are necessary conditions for the Bayesian approach to be valid.

The probabilities of having an incident or no-incident given that the n-signal strings shown above have occurred, were developed and are shown below:

$$P(\text{inc.}/1) = \frac{P(1/\text{inc.}) P(\text{inc.})}{P(1/\text{inc.}) P(\text{inc.}) + P(1/\text{no-inc.}) P(\text{no-inc.})}$$

$$P(\text{inc.}/0) = \frac{P(0/\text{inc.}) P(\text{inc.})}{P(0/\text{inc.}) P(\text{inc.}) + P(0/\text{no-inc.}) P(\text{no-inc.})}$$

$$P(\text{no-inc.}/1) = \frac{P(1/\text{no-inc.}) P(\text{no-inc.})}{P(1/\text{inc.}) P(\text{inc.}) + P(1/\text{no-inc.}) P(\text{no-inc.})}$$

$$P(\text{no-inc.}/0) = \frac{P(0/\text{no-inc.}) P(\text{no-inc.})}{P(0/\text{inc.}) P(\text{inc.}) + P(0/\text{no-inc.}) P(\text{no-inc.})}$$

$$P(\text{inc./10}) = \frac{P(0/\text{inc.}) P(\text{inc./1})}{P(0/\text{inc.}) p(\text{inc./1}) + P(0/\text{no-inc.}) P(\text{no-inc./1})}$$

$$P(\text{inc./11}) = \frac{P(1/\text{inc.}) P(\text{inc./1})}{P(1/\text{inc.}) P(\text{inc./1}) + P(1/\text{no-inc.}) P(\text{no-inc./1})}$$

$$P(\text{inc./100}) = \frac{P(0/\text{inc.}) P(\text{inc./10})}{P(0/\text{inc.}) P(\text{inc./10}) + P(0/\text{no-inc.}) P(\text{no-inc./10})}$$

$$P(\text{inc./101}) = \frac{P(1/\text{inc.}) P(\text{inc./10})}{P(1/\text{inc.}) P(\text{inc./10}) + P(1/\text{no-inc.}) P(\text{no-inc./10})}$$

$$P(\text{inc./110}) = \frac{P(0/\text{inc.}) P(\text{inc./11})}{P(0/\text{inc.}) P(\text{inc./11}) + P(0/\text{no-inc.}) P(\text{no-inc./11})}$$

$$P(\text{inc./111}) = \frac{P(1/\text{inc.}) P(\text{inc./11})}{P(1/\text{inc.}) P(\text{inc./11}) + P(1/\text{no-inc.}) P(\text{no-inc./11})}$$

The above probabilities could be computed for any particular freeway section and specific traffic and environmental conditions, utilizing the history of capacity-reducing incidents.

For appropriate freeway sections and environmental and traffic conditions the theoretical probabilities of having an incident given a certain signal string could be correlated with actual string probabilities derived from on-line implementation of the Bayesian algorithm. Once the calibration is complete, a certain criterion value could be selected for making an incident management decision.

B. ALGORITHM DEVELOPMENT

The process of quantifying the theoretical considerations presented previously required three data bases:

1. Incident data base,
2. Incident-free data base, and
3. Emergency Patrol Vehicle assists data base.

The first two data bases were used in developing $f(Z/U_1)$ and $f(Z/U_0)$, respectively, while the third one was utilized in developing historical probabilities of capacity-reducing incidents.

The historical data base for the capacity-reducing incidents was developed utilizing emergency patrol vehicles assistance-rendered reports for the years 1973, 1974 and 1975. These reports provide information as to the type of incident (accident, stalled vehicle, etc.), its location, estimated occurrence time, environmental conditions, and other related information.

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 development of historical probabilities of capacity-reducing incidents, and the selection of the appropriate traffic flow feature to be incorporated in the Bayesian model.

Study Site Selection

The selection of the study site was confined to iso-operational sections for which large enough samples of incident-free and incident data from the above data bases were available.

Investigations into the matter led to the study site selection of the Outbound Kennedy between the Chicago loop and its junction with the Edens Expressway. This section of the Kennedy is basically four lanes wide with two

reversible lanes operating outbound in the PM rush period, and experiencing an ADT of approximately 115,000 vehicles. In 1975, the number of weekdays EPV assists (capacity-reducing incidents and others) was nearly 1500 on that section of the Kennedy averaging approximately one capacity-reducing incident during the PM rush.

Feature Selection

In the feature-selection process, seven traffic features were considered. These features, taken from the TSC incident detection algorithms, are given below:

Feature Name

OCC(t)	=	Minute average occupancy measured at upstream detector time t
DOCC(t)	=	Minute average occupancy measured at downstream detector at time t
OCCDF(t)	=	$OCC(t) - DOCC(t)$
OCCRDF(t)	=	$OCCDF(t)/OCC(t)$
SPEED(t)	=	Minute average speed measured at upstream detector at time t
DOCCTD(t)	=	$(DOCC(t-2) - DOCC(t))/DOCC(t-2)$
SPDTDF(t)	=	$(SPEED(t-2) - SPEED(t))/SPEED(t-2)$

The criteria for selecting a feature were:

1. Considerable differences between the feature values before and during the incident.
2. Stability of the above difference during the incident.

High stability would allow the usage of a single threshold throughout the detection process with benefits as described earlier.

Feature analysis was conducted and the features OCCRDF(t) were selected for the Bayesian model. However, since theoretically $-\infty \leq \text{OCCRDF}(t) \leq 1$, it was decided, for the purpose of mathematical convenience, to introduce the feature $Z = 1 - \text{OCCRDF}(t)$, where $0 \leq Z \leq +\infty$.

The next step was to develop a mathematical expression for $f(Z/U_0)$ and $f(Z/U_1)$. These functions were developed for data collection on the study site for the afternoon rush of dry-weather weekdays. Statistical analysis, using the Kolmogorov-Smirnov test at the 5% level of significance, confirmed the following truncated shifted Gamma distributions.

$$f(Z/U_1) = \frac{21.6 [21.6(Z+0.4)]^{16.1} e^{-21.6(Z+0.4)}}{.993 (17.1)}$$

$$f(Z/U_0) = \frac{1.082 [1.082(Z-0.821)]^{-0.711} e^{-1.082(Z-0.821)}}{.991 (0.289)}$$

Probabilities of Capacity-Reducing Incidents

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

The probability of an incident occurring at a given detector at a specified minute during a certain time period is given by the ratio $A/B*C$, where A is the average number of incidents occurring on the study section within the total time period, B is the total number of detectors in the study section, and C is the number of minutes in the time period. For $A = 1.04$, $B = 15$, and $C = 240$; $P(\text{inc})$ is found to be 0.00027 and $P(\text{no-inc}) = 1 - 0.00027 = 0.99973$.

Derivation of the Optimal Threshold

Having derived mathematical expressions for $P(U_0)$, $P(U_1)$, $f(Z/U_0)$, and $f(Z/U_1)$ it was possible, through simple numerical analysis, to obtain values for $P(\text{incident}/1) + P(\text{no-incident}/0)$ for different values of Z . The values of $P(\text{incident}/1) + P(\text{no-incident}/0)$ were plotted against the corresponding Z values, and the optimal threshold Z_1 was the one that maximized $P(\text{incident}/1) + P(\text{no-incident}/0)$. The value of Z_1 was found to be 0.57 to yield $\text{OCCRDF}(t) = 1 - Z_1 = 0.43$.

IV. OFF-LINE EVALUATION OF ALGORITHM PERFORMANCE

A. COMPARISON OF PATTERN-RECOGNITION ALGORITHMS

The ultimate goal of the off-line evaluation was to obtain for the tested algorithms optimal sets of thresholds related to various traffic and environmental conditions to be implemented in an operational on-line incident-response system. In the process to achieve that goal, the off-line evaluation was divided into four major tasks:

1. Comparative analysis of algorithms' efficiency.
2. Evaluation of the effect of lateral detectorization on algorithms' performance.
3. Evaluation of the effect of incident severity on algorithms' performance.
4. Hierarchy analysis of thresholds' effectiveness.

Comparative Analysis of Algorithms Efficiency

The comparative analysis of the tested algorithms was performed by running each of the five algorithms: 7, 8, 9, 10 and 16-14 through the various incident and incident-free data strata, utilizing TSC's CALB Program which had been modified for the Traffic Systems Center's GE 4020 computer. The CALB evaluation of these algorithms was performed for nominal detection rates of 75%, 80%, 85%, 90%, 95% and 99%, and for the following incident data categories: "ALL", "RD" and "NRD". The strata of "RW" and "NRW" included only 6 and 8 incident cases, respectively, and were excluded from the detailed analysis.

A comparison of the Detection Rate-False-Alarm Rate (DR-FAR) relationships of Algorithms 9 and 16-14 with those of Algorithm 7, 8, and 10 indicated that algorithms 9 and 16-14 experience relatively high FAR across

the whole DR spectrum. At the same time, however, their Detection Rate-Mean-Time-To-Detect (DR-MTTD) relationships seemed to be more favorable than those for the other algorithms. However, since in many cases the differences in MTTD for the various algorithms were not found to be statistically significant, the relatively poor DR-FAR relationships between algorithms 9 and 16-14 suggested the elimination of these algorithms from further analysis even though favorable results were indicated for algorithm 9 in Reference (1). However, for the sake of representative analysis and future on-line evaluation, it was decided to eliminate only algorithm 9.

Figures (7) and (8) present the optimal relationships between the DR and FAR and between the DR and MTTD, respectively, as obtained by the CALB program, for algorithms 7, 8, 10 and 16-14.

Overall, the three algorithms (7, 8, 10) produced better DR-FAR relationships for the "Non-Rush Dry" (NRD) category than for the "Rush-Dry" (RD) category. Over the investigated range of the DR, the FAR for the "Non-Rush Dry" category ranged from .00% to .01%, while the range for the "Rush Dry" category was from .02% to .11%.

Within the "Rush Dry" category no single algorithm displaying invariably better FARs over the DR spectrum could be found. However, for the higher DRs (.95 and above) algorithm 7 was the most efficient. Also, the same algorithm was found to yield the least FARs over the whole DR spectrum for the "Non-Rush Dry" category.

The Time-To-Detect analysis utilized the optimal sets of thresholds developed for the DR-FAR relationships. As shown in Figure (8), the MTTD for the "Rush Dry" and "Non-Rush Dry" categories ranges from 1.3 min. to 4.4 min. and from 3.3 min. to 6.5 min., respectively. The results for the "All" category (2.2 min. to 4.7 min.) represent, to a large extent, the combinations of the "Rush Dry" and "Non-Rush Dry" results.

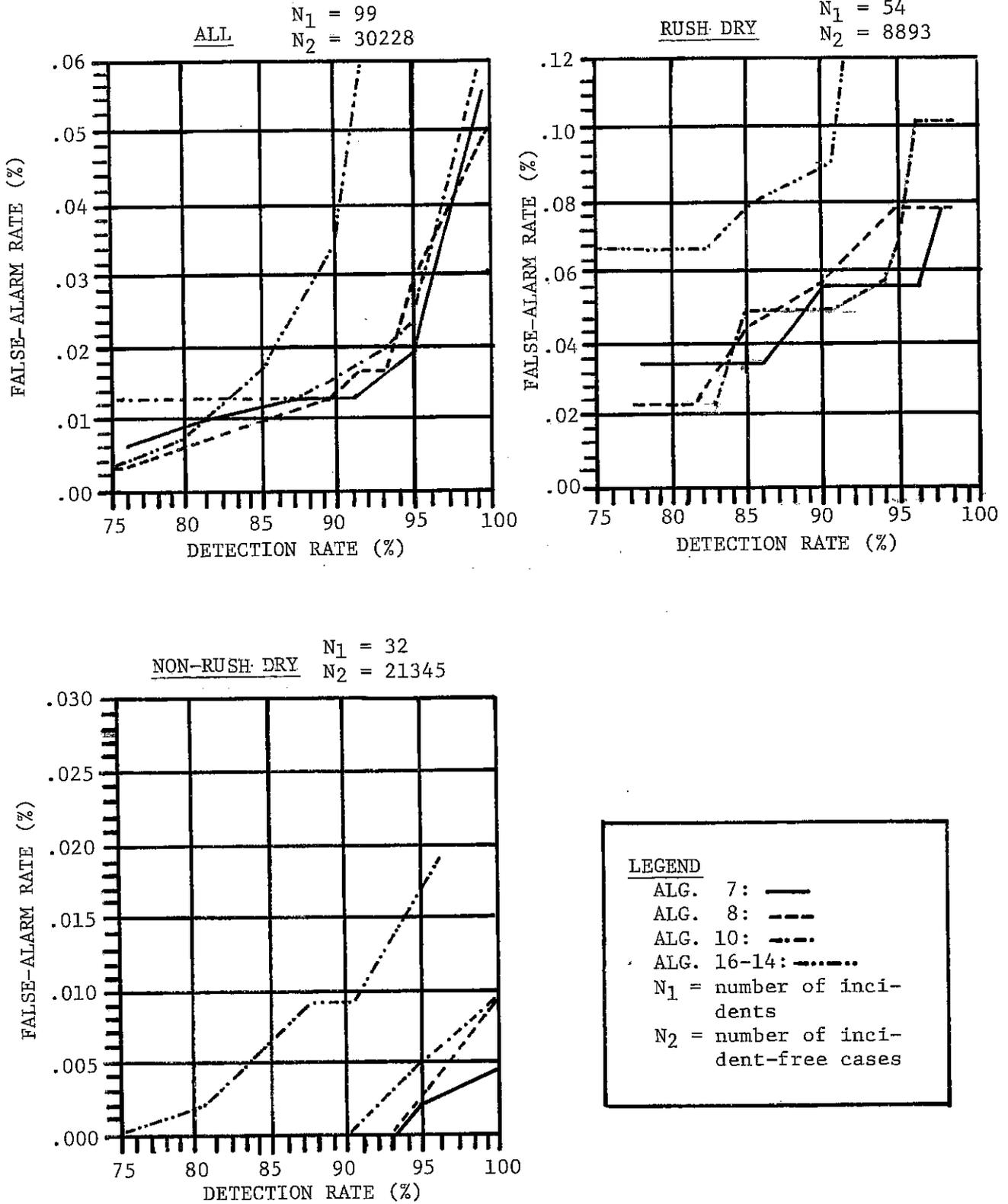


FIGURE 7
 RELATIONSHIP BETWEEN DETECTION RATE AND
 FALSE ALARM RATE FOR ALL, RUSH DRY, AND
 NON-RUSH DRY INCIDENT DATA CATEGORIES

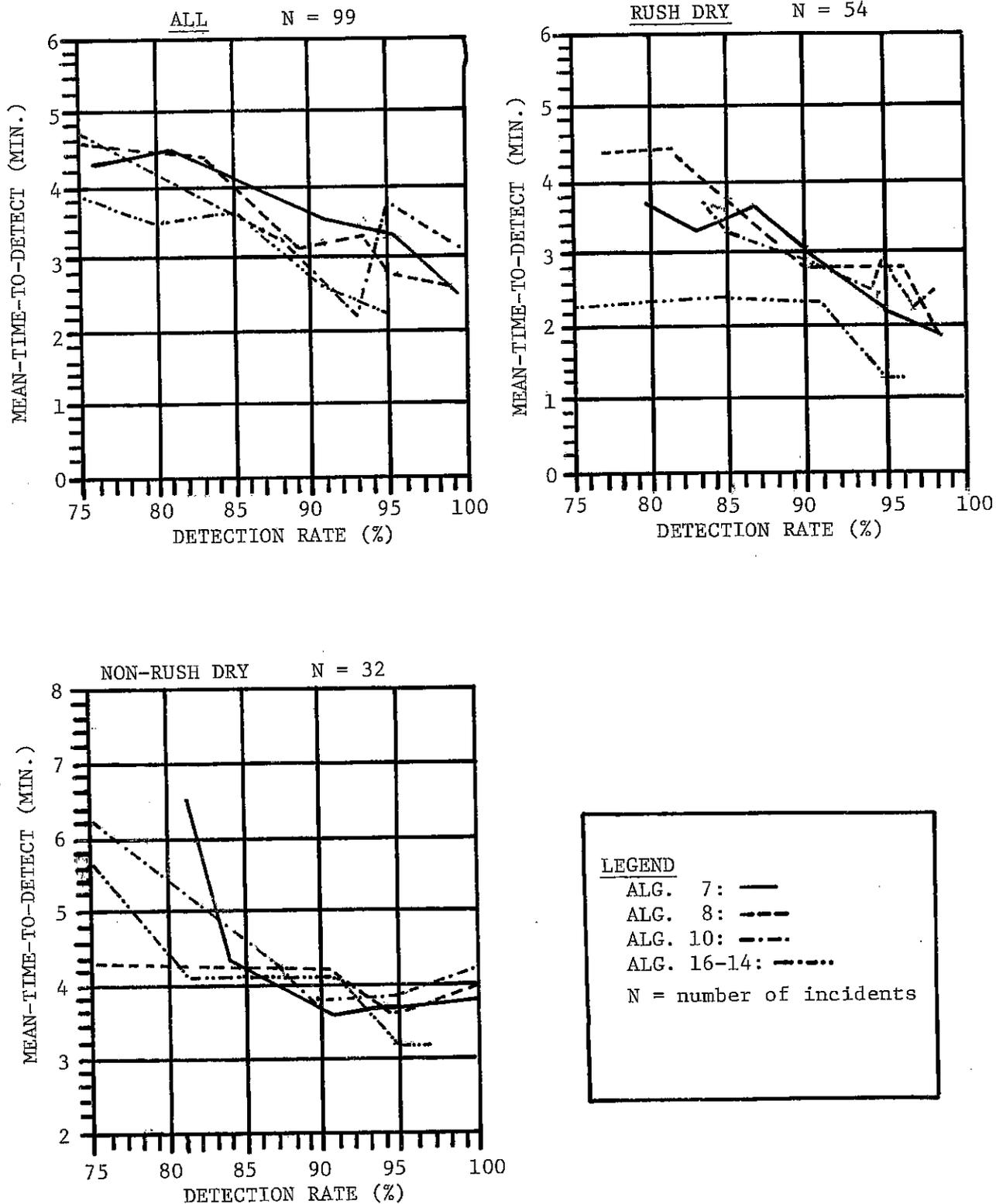


FIGURE 8
RELATIONSHIP BETWEEN DETECTION RATE AND
MEAN-TIME-TO-DETECT FOR ALL, RUSH DRY, AND
NON-RUSH DRY INCIDENT DATA CATEGORIES

Within the "Rush Dry" category, Algorithm 16-14 displayed the lowest MTTD for all detection rates. The same algorithm displayed the lowest MTTD at the 95% detection rate within the "Non-Rush Dry" category. For lowest detection rates no single algorithm displayed invariably lower MTTD within that category.

Further insight as to the differences in MTTD between algorithms for the various incident data categories was obtained utilizing the Kolmogorov-Smirnov and the Mann-Whitney U tests (8) for thresholds representing the 95% detection level. This level was selected for its assumed applicability to an operational on-line system. The results of the statistical analyses for Algorithms 7, 8, 10, and 16-14 are presented in Table 7. From this table it can be seen that as far as the MTTD is concerned, no statistically significant difference (5% level of significance) was found between the algorithms at the 95% detection level for all the incident categories.

It seems, then, that the DR-FAR relationship is more representative of the difference among algorithms than the DR-MTTD relationship, and should be the major criterion for selecting algorithms.

Based on the results in Table 7 for the false-alarm rate, Algorithm 7 was the apparent best for the "All", "Rush Dry", "Non-Rush Dry", and "Non-Rush Wet" categories at the 95% detection level while Algorithm 8 was the apparent best for the "Rush Wet" category, at the same detection level. The apparent best algorithms for other detection levels could easily be obtained from Figure 7.

Evaluation of the Effect of Lateral Detectorization on Algorithms Performance

In the design process of a freeway surveillance and control system there is always the question of a trade-off between the level of detectorization (longitudinal and lateral) and the gains in terms of control and incident detection effectiveness. The analysis presented in this section compares the

TABLE 7

COMPARISON OF ALGORITHMS' PERFORMANCE
AT 95% DETECTION RATE
FOR VARIOUS INCIDENT DATA CATEGORIES

Category	Sample Size	Alg. 7	Alg. 8	Alg. 10	Alg. 16-14	Apparent Best Alg. (For α , or μ)	Statistically Best Alg. (for MTTD)
All	99	α = 0.019 μ = 3.39 σ = 3.25	0.0297 2.85 3.01	0.0231 3.68 3.42	0.11 2.28 3.05	7 (α) 16-14 (μ)	None ^a
Rush-Dry (RD)	54	α = 0.056 μ = 2.23 σ = 1.60	0.0786 2.75 2.15	0.067 2.88 2.65	0.26 1.26 1.83	7 (α) 16-14 (μ)	None ^a
Rush-Wet (RW)	6	α = 0.0336 μ = 2.83 σ = 0.69	0.0 3.99 2.89	0.045 2.50 5.02	0.045 2.33 3.03	8 (α) 16-14 (μ)	None ^{a, b}
Non-Rush-Dry (NRD)	32	α = 0.002 μ = 3.73 σ = 3.75	0.002 3.56 3.77	0.005 3.87 3.81	0.018 3.22 4.72	7 (α) 16-14 (μ)	None ^a
Non-Rush-Wet (NRW)	8	α = 0.005 μ = 2.71 σ = 2.31	0.005 2.63 1.99	0.005 2.50 2.24	0.009 1.88 2.15	7, 8, 10 (α) 16-14 (μ)	None ^{a, b}

α = False-Alarm Rate (%)
 μ = Mean-Time-To-Detect (min)
 σ = Standard Deviation (min)
^a = Kolmogorov-Smirnov Test (5% los)
^b = Mann-Whitney U Test (5% los)

performance of algorithms 7, 8, 10, and 16-14 as related to incidents occurring on the detector lane versus those occurring on the non-detector lanes. The Chicago area expressway system under surveillance utilizes full detector stations every three miles and single detector stations, usually on lane 2 (lane 1 being the inner lane), every half mile.

The relationships between DR and FAR and between DR and MTTD for algorithms 7, 8, 10, and 16-14 for incidents occurring on the detector lane and non-detector lanes, and falling within the "Rush Dry" category (RD-1, RD-0) and the "Non-Rush Dry" category (NRD-1, NRD-0), are presented in Figures (9) and (10), respectively.

The presented relationship between the DR and FAR suggests that for both categories ("Rush Dry" and "Non-Rush Dry"), the optimal thresholds obtained for incidents occurring on the detector lane are less sensitive to discontinuities in traffic flow, as expressed in lower FAR than those obtained for incidents occurring on the non-detector lanes. This is explained by the fact that, generally, incidents occurring on the detector lane have higher feature values requiring less sensitive thresholds which lower FARs. Incidents occurring on non-detector lanes have a somewhat attenuated impact when measured off another lane, thus requiring more sensitive thresholds (lower value) risking a high FAR.

It is observed in Figure (10) that for the "Rush Dry" category, the relationship between the DR and MTTD is more favorable for incidents occurring on the non-detector lane than for those occurring on the detector lane. This trend could be explained by the fact that the FAR increases with DR, while the MTTD decreases with DR, yielding a decrease in MTTD with an increase in FAR. Thus, for a certain DR, the FAR on the detector lane is higher than the one experienced on the non-detector lanes,

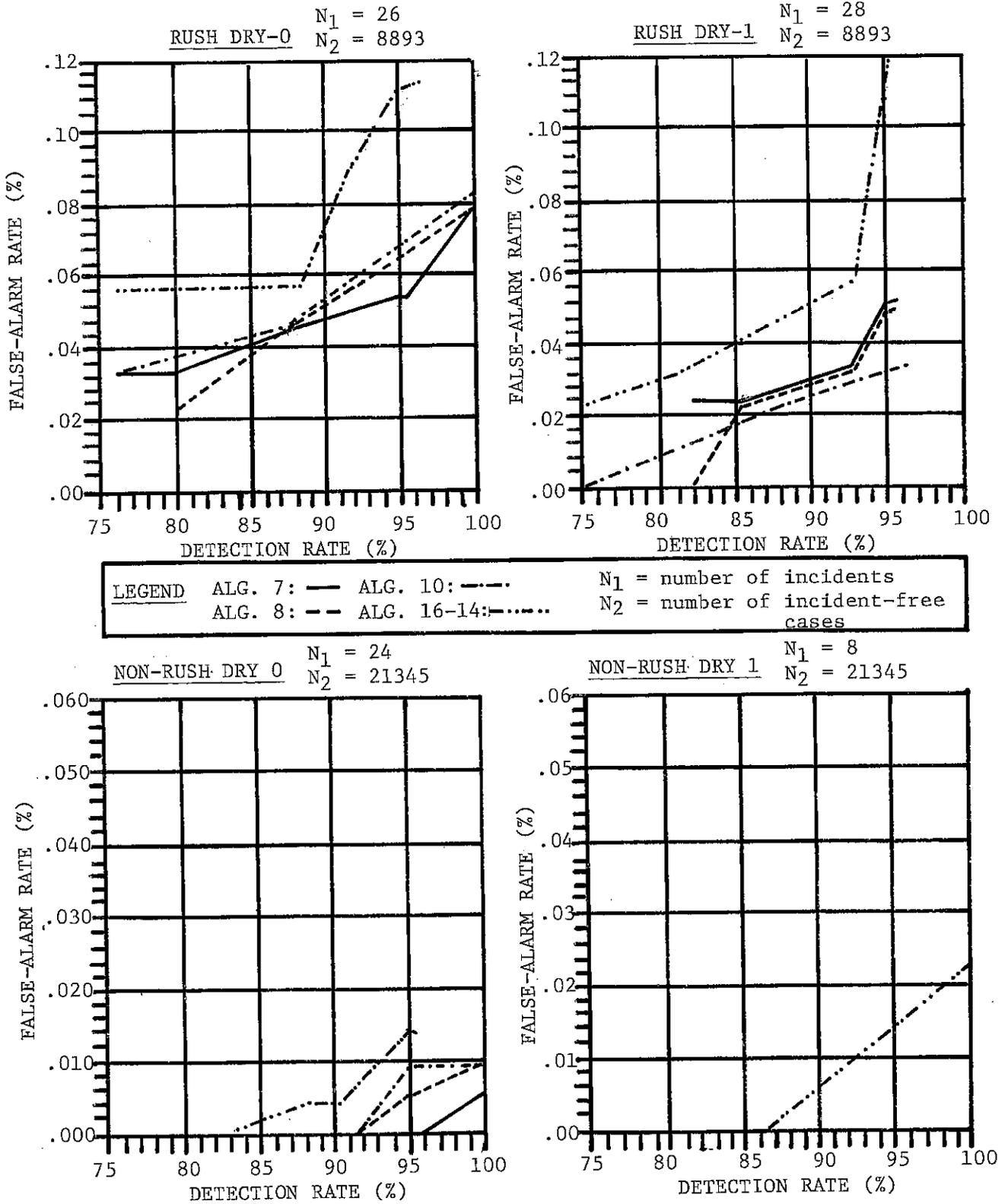
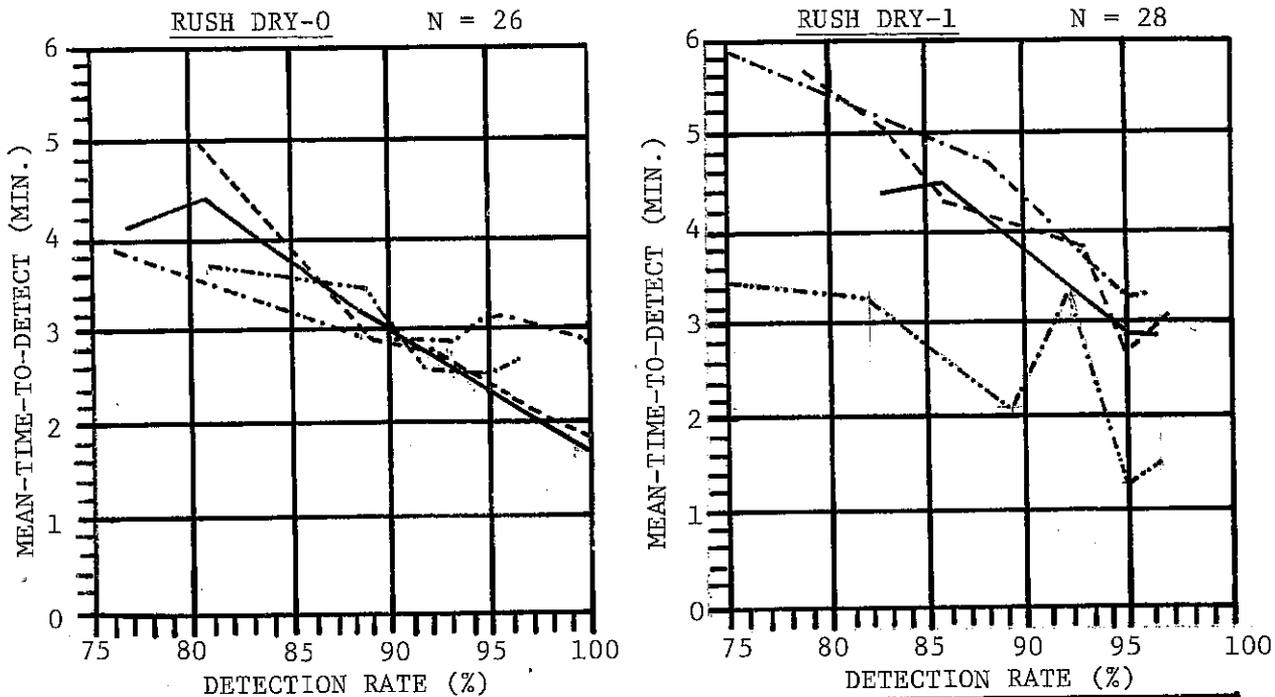


FIGURE 9
RELATIONSHIP BETWEEN DETECTION RATE AND
FALSE-ALARM RATE FOR RUSH DRY AND NON-RUSH DRY INCIDENT DATA
ON DETECTOR LANE (1) AND NON-DETECTOR LANE (0)



LEGEND ALG. 7 ——— ALG. 10 ····· N = number of incidents
 ALG. 8 - - - ALG. 16-14 ·····

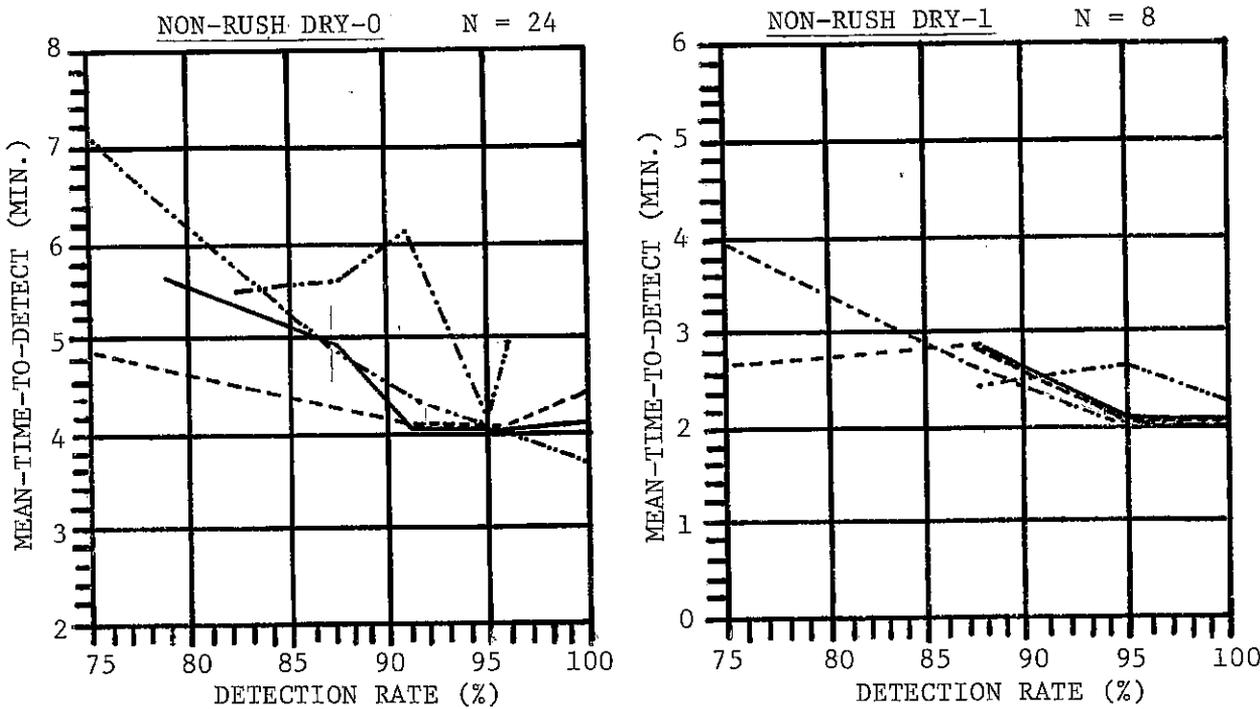


FIGURE 10
 RELATIONSHIP BETWEEN DETECTION RATE AND
 MEAN-TIME-TO-DETECT FOR RUSH DRY AND NON-RUSH DRY INCIDENT DATA
 ON DETECTOR LANE (1) AND NON-DETECTOR LANE (0)

yielding a higher MTTD. This, however, is not the case for the "Non-Rush Dry" category. The reason could be the small sample of (8) incidents occurring on the detector lane in the "Non-Rush" category.

In order to find out whether there was a statistically significant difference between the MTTD for incidents on the detector lane and for those on the non-detector lanes, for both the "Rush Dry" and "Non-Rush Dry" categories, the Kolmogorov-Smirnov test was conducted. The test was conducted at the 95 percent detection level. For the "Rush Dry" and "Non-Rush Dry" categories tests were made for Algorithm 7, and Algorithm 10, respectively, both being the most efficient algorithms at the detection level. According to the Kolmogorov-Smirnov test, no significant differences between the MTTD were found for both the "Rush Dry" and "Non-Rush Dry" categories at the 10% level of significance.

The above analyses suggest that the relationship between DR and FAR is more critical than that between the DR and the MTTD.

As to the relative performance of the individual algorithms within the various incident data categories, Table 8 presents, for the 95 percent level of detection, the MTTD, the standard deviation of the detection time, and the FAR for algorithms 7, 8, 10 and 16-14, and for the incident data categories: "RD-1", "RD-0", "NRD-0" and "NRD-1". The Kolmogorov-Smirnov and Mann-Whitney U tests were conducted for significant differences in the MTTD. The results of these tests are also presented in the following table in terms of the statistically best algorithm as compared with the apparent best. According to these tests, no single algorithm proved to be superior to others with respect to the MTTD for the "RD-0", "NRD-1", and "NRD-0" categories. Algorithm 16-14, however, proved to be the best for the "RD-1" category. Considering the FAR, algorithm 10 seemed to be the best for the "RD-1" category, while algorithm 7

TABLE 8
 COMPARISON OF ALGORITHMS PERFORMANCE
 AT 95% DETECTION RATE
 DURING RUSH DRY AND NON-RUSH DRY PERIODS

Category	Sample Size	Alg. 7	Alg. 8	Alg. 10	Alg. 16-14	Apparent Best Alg. (For α , or μ)	Statistically Best Alg.(MTTD)
Rush-Dry-1 (RD-1)	28	$\alpha = 0.0449$	0.0449	0.0336	0.112	10 (α)	16-14 ^{a,b}
		$\mu = 2.96$	2.69	3.18	1.26	16-14 (μ)	
		$\sigma = 1.93$	1.93	3.49	1.14		
Rush-Dry-0 (RD-0)	26	$\alpha = 0.0561$	0.0673	0.0673	0.112	7 (α)	None ^{a,b}
		$\mu = 2.28$	2.32	3.07	2.56	7 (μ)	
		$\sigma = 1.84$	1.91	3.09	2.22		
Non-Rush-Dry-1 (NRD-1)	8	$\alpha = 0.0$	0.0	0.0	0.014	None (α)	None ^{a,b}
		$\mu = 2.12$	2.12	2.12	2.75	None (μ)	
		$\sigma = 1.89$	1.89	1.89	2.5		
Non-Rush-Dry-0 (NRD-0)	24	$\alpha = 0.0$	0.0047	0.0094	0.014	7 (α)	None ^{a,b}
		$\mu = 4.08$	4.04	4.08	4.13	None (μ)	
		$\sigma = 4.06$	4.16	2.74	5.69		

- a. α = False-Alarm Rate (%)
- b. μ = Mean-Time-To-Detect (min.)
- c. σ = Standard Deviation (min.)
- d. a = Kolmogorov-Smirnov Test
- e. b = Mann-Whitney U Test

excelled in the "RD-0" and "NRD-0" categories. No apparent best algorithm was found for the "NRD-1" category.

Additional analysis was made of the differences in FAR and MTTD for accidents and non-accident incidents occurring on both the detector lane (coded 50-1 and 46-1, respectively) and non-detector lanes (coded 50-0 and 46-0, respectively) with optimal thresholds obtained for each particular situation. The analysis included tests for significant differences in MTTD among and within the "Rush-Dry" (RD) for algorithms 7, 8, 10, and 16-14 at the 95 percent detection level using the Kolmogorov-Smirnov and Mann-Whitney U test at the 5 percent level of significance. The results of this analysis are presented in Table 9.

From this table it can be seen that as far as the MTTD was concerned, there was no significant difference for accidents and non-accident incidents occurring on either the detector lane or the non-detector lanes for each of the tested algorithms. Also, no significant differences in MTTD were found among algorithms within the categories RD50-1, RD50-0, and RD46-1. Algorithm 7, however, was found to be the best within the RD46-0 category.

As far as the FAR was concerned, thresholds that were developed for accidents and non-accident incidents occurring on the detector lane yielded equal or better results than thresholds developed for accidents and non-accident incidents occurring on the non-detector lane for all the tested algorithms. This is expected since thresholds for detecting incidents on the detector lane could be less sensitive to discontinuities in traffic flow than thresholds for incidents on the non-detector lanes.

With regard to the individual categories, algorithms 7 and 8 performed the best for RD50-1, RD50-0, and RD46-1, whereas algorithm 10 excelled in the RD-46-0 category. The local algorithm 16-14 yielded relatively high FAR for all categories tested.

TABLE 9
 COMPARISON OF ALGORITHMS PERFORMANCE AT 95% DETECTION
 RATE FOR ACCIDENT AND NON-ACCIDENT INCIDENT
 DATA DURING RUSH DRY PERIODS

Category	Sample Size	Alg. 7		Alg. 8		Alg. 10		Alg. 16-14		Signif. Diff. (For μ)
		μ	α	μ	α	μ	α	μ	α	
RD-50-1	18	4.94	0.0225	4.83	0.0225	2.05	0.0562	2.77	0.0337	No
RD-50-0	12	2.92	0.0562	3.83	0.0562	3.08	0.0786	2.41	0.1123	No
Signif. Diff.		No		No		No		No		
RD-46-1	9	2.11	0.0562	2.22	0.0562	2.11	0.0562	1.89	0.1123	No
RD-46-0	14	0.93	0.1123	1.35	0.0786	3.21	0.0562	2.92	0.1235	Yes
Signif. Diff. (For)		No		No		No		No		

μ = MTTD (min.)
 α = False-Alarm Rate (%)

The above results indicate that the MTTD did not prove to be a major criterion, unlike the FAR, in the selection of algorithms.

It seems that, in order to generate a low FAR, thresholds developed for incidents on the detector lanes should be used even though the probability of occurrence of incidents on the non-detector lanes is naturally higher than for those occurring on the detector lane. However, these less-sensitive thresholds would reduce the rate of detection of incidents occurring on the non-detector lanes.

Evaluation of the Effect of Incident Severity on Algorithm Performance

One of the considerations in selecting a particular set of thresholds for the operation of a certain algorithm could be its relative effectiveness in detecting accidents and non-accident incidents, which usually differ in their impact on traffic flow. As shown previously, thresholds for incidents occurring on the detector lane are less sensitive in terms of FAR than those for incidents occurring on the non-detector lanes. However, the effectiveness and efficacy of thresholds developed separately for accidents and non-accident incidents are yet to be evaluated.

Table 10 presents a comparison of MTTD and FAR, at the 95 percent detection level for algorithms 7, 8, 10 and 16-14, between accidents and non-accident incidents occurring either on the detector-lane or the non-detector lanes or on both.

As can be seen from Table 10, as far as the MTTD was concerned the Kolmogorov-Smirnov and Mann-Whitney U test did not show any significant difference, at the 5 percent level of significance.

As far as the FAR was concerned, thresholds that were developed for the accident data performed better than those developed for the non-accident data in all cases. This, of course, is expected, since an accident would have

TABLE 10

EFFECT OF INCIDENT SEVERITY
ON ALGORITHM PERFORMANCE

Category	Sample Size	Alg. 7		Alg. 8		Alg. 10		Alg. 16-14	
		μ	α	μ	α	μ	α	μ	α
RD-46	23	2.31	0.056	2.36	0.078	2.36	0.078	2.27	0.112
RD-50	30	2.17	0.056	2.53	0.078	2.53	0.078	1.59	0.112
Significant Difference in MTTD		No		No		No		No	
RD-46-1	9	3.34	0.045	344	0.045	2.89	0.045	1.89	0.112
RD-50-1	18	4.94	0.022	2.05	0.056	3.22	0.045	2.77	0.033
Significant Difference in MTTD		No		No		No		No	
RD-46-0	14	0.93	0.112	1.35	0.078	3.21	0.056	2.92	0.123
RD-50-0	12	2.92	0.056	3.83	0.056	3.08	0.078	2.41	0.112
Significant Difference in MTTD		No		No		No		No	

μ = MTTD (min.)
 α = False-Alarm Rate, FAR, (%)

a greater disruptive impact on traffic flow than a non-accident incident.

The question that remains to be answered concerns the effectiveness of thresholds developed for accidents in detecting non-accident incidents. Analysis showed that thresholds developed for accident data off the detector lane at the 95 percent detection level detected only 78 percent of the non-accident incidents on that lane for algorithms 7 and 8 (FAR=0.22%) and detected all these non-accident incidents for algorithm 10 (FAR=0.56%). It seems that if FAR is the major criteria, then thresholds developed for accidents (RD50-1) could be used to detect other incidents (RD46-1). This also holds true for RD46-0 and RD50-0, for algorithms 7, 8, and 10.

Hierarchy Analysis of Threshold Effectiveness

The effort involved in developing the input necessary for an optimal on-line incident detection system could be quite enormous. Part of this effort is the development of thresholds appropriate for various environmental, geometric, and traffic conditions. In addition, for freeway systems with low level of detectorization, the question exists as to whether thresholds representing accidents or non-accident incidents on either the detector or non-detector lanes should be used.

This section evaluates the efficiency, in terms of DR, FAR and MTTD, of applying lower level thresholds to higher level incident data categories (i.e. thresholds developed for the "All" category are tested on the "Rush-Dry" category). The objective of such an analysis is to investigate the possibilities of reducing the amount of effort required in developing the optimal sets of thresholds. The thresholds for each lower level incident category were obtained for the 95 percent nominal DR and were applied to a higher level incident category to yield appropriate values for the other measures of effectiveness. The Mann-Whitney U test was applied to establish

the significance of the difference between the MTTDs of each two compared incident categories. Table 11 presents the results of this analysis.

As it can be seen from this table, thresholds developed for "All" could be used during "Rush Dry" (RD) periods by all three algorithms, if lower FARs were sought. There was no advantage, however, in using the "All" thresholds during the "Rush Wet" (RW), "Non-Rush Wet" (NRW), and "Non-Rush Dry" (NRD) periods as far as the False-Alarm Rate (FAR) and MTTD were concerned. However, as far as the Detection Rate (DR) was concerned, the "All" thresholds could be used more effectively in algorithms 7 and 10 during the "Non-Rush Dry" period.

The "Rush Dry" thresholds, when used during the "Non-Rush Dry" period, yielded improved DRs for algorithms 7 and 8 compared to those obtained by the thresholds of the "Non-Rush Dry" period itself. As far as the FAR and MTTD were concerned, no advantage was found using the "Rush Dry" thresholds.

Thresholds developed for the "Rush Dry" category were applied to both the "Rush Dry" incidents detected on the detector lane (coded RD-1) and the "Rush Dry" incidents detected on the non-detector lane (coded RD-0). In both cases these thresholds were found to be inferior to the thresholds representing the two categories. When the "RD-1" thresholds were applied to the "RD-1" category, the FAR improved but the DR decreased for all algorithms.

When the "RD-1" thresholds were applied to the "RD-50-1" category (accident incidents occurring on the detector lane during the "Rush Dry" period), there was no change in the DR and no significant difference in the MTTD.

Other thresholds hierarchy could be easily obtained from the Table 11.

TABLE 11

THRESHOLD HIERARCHY ANALYSIS

Thresholds Compared	ALG. 7				ALG. 8				ALG. 10			
	DR	FAR	MTTD	SIG.* DIF.	DR	FAR	MTTD	SIG.* DIF.	DR	FAR	MTTD	SIG.* DIF.
All on RD vs RD on RD	0.92 0.96	.056 .056	3.40 2.23	No	0.90 0.96	.067 .078	2.52 2.75	No	0.93 0.95	.056 .067	3.25 2.88	No
RW on RD vs RD on RD	0.85 0.96	.034 .056	3.63 2.23	Yes	0.64 0.96	.000 .078	5.43 2.75	Yes	0.81 0.95	.045 .067	4.21 2.88	No
NRD on RD vs RD on RD	0.92 0.96	.056 .056	3.36 2.23	No	0.83 0.96	.045 .078	2.86 2.75	No	0.87 0.95	.056 .067	2.21 2.88	No
NRW on RD vs RD on RD	0.92 0.96	.056 .056	3.40 2.23	No	0.83 0.96	.045 .078	2.86 2.75	No	0.87 0.95	.056 .067	2.21 2.88	No
All on RW vs RW on RW	1.00 1.00	.056 .034	2.33 2.83	No	1.00 1.00	.067 .000	2.33 3.99	No	1.0 1.0	.056 .045	2.50 2.50	No
RD on RW vs RW on RW	1.00 1.00	.056 .034	2.16 2.83	No	1.00 1.00	.078 .000	2.16 3.99	No	1.0 1.0	.067 .045	2.50 2.50	No
NRD on RW vs RW on RW	1.00 1.00	.056 .034	2.21 2.83	No	0.84 1.00	.044 .000	2.80 3.99	No	1.0 1.0	.056 .045	1.99 2.50	No
NRW on RW vs RW on RW	1.00 1.00	.056 .034	2.33 2.83	No	0.84 1.00	.044 .000	2.80 3.99	No	1.0 1.0	.056 .045	1.99 2.50	No
All on NRD vs NRD on NRD	1.00 0.96	.005 .005	3.78 3.93	No	0.96 0.96	.014 .005	3.61 3.67	No	1.0 0.96	.009 .005	4.28 2.87	No
RD on NRD vs NRD on NRD	1.00 0.96	.014 .005	3.46 3.93	No	1.00 0.96	.023 .005	3.46 3.67	No	0.93 0.96	.019 .005	4.23 2.87	No
RW on NRD vs NRD on NRD	0.90 0.96	.009 .005	4.38 3.93	No	0.68 0.96	.009 .005	4.27 3.67	No	0.97 0.96	.005 .005	4.71 2.87	No
NRW on NRD vs NRD on NRD	1.00 0.96	.005 .005	3.78 3.93	No	0.68 0.96	.009 .005	4.27 3.67	No	0.96 0.96	.005 .005	2.87 2.87	No
All on NRW vs NRW on NRW	0.87 0.87	.005 .005	2.71 2.71	No	1.00 1.00	.014 .005	2.62 2.63	No	0.87 1.0	.009 .005	5.14 2.87	No
RD on NRW vs NRW on NRW	1.0 0.87	.014 .005	2.50 2.71	No	1.00 1.00	.023 .005	2.50 2.63	No	1.0 1.0	.019 .005	6.00 2.50	Yes
RW on NRW vs NRW on NRW	0.75 0.87	.009 .005	7.14 2.71	No	0.75 1.00	.009 .005	3.34 2.63	No	0.87 1.0	.009 .005	5.14 2.50	No
NRD on NRW vs NRW on NRW	0.87 0.87	.005 .005	2.85 2.71	No	1.00 1.00	.005 .005	2.63 2.63	No	1.0 1.0	.005 .005	2.50 2.50	No

* for MTTD

TABLE 11

THRESHOLD HIERARCHY ANALYSIS (cont.)

Thresholds Compared		Alg. 7			SIG. DIF.	Alg. 8			SIG. DIF.	Alg. 10			SIG. DIF.
		DR	FAR	MTTD		DR	FAR	MTTD		DR	FAR	MTTD	
RD on RDO	vs	0.96	.056	2.47	No	0.96	.078	2.04	No	0.92	.067	3.04	No
RDO on RDO		0.96	.056	2.28		0.96	.067	2.32		0.96	.067	3.07	
RD1 on RDO	vs	0.77	.045	2.45	No	0.77	.045	3.15	No	0.69	.033	3.72	No
RDO on RDO		0.96	.056	2.28		0.96	.067	2.32		0.96	.067	3.07	
RD on RD1	vs	0.96	.056	1.99	No	0.96	.078	1.81	No	0.96	.067	2.74	No
RD1 on RD1		0.96	.045	2.96		0.96	.045	3.77		0.96	.033	3.18	
RDO on RD1	vs	0.96	.056	1.84	Yes	0.96	.067	1.88	Yes	0.96	.067	2.77	No
RD1 on RD1		0.96	.045	2.96		0.96	.045	3.77		0.96	.033	3.18	
RD on RD46	vs	0.96	.056	2.31	No	0.96	.078	2.05	No	0.96	.067	2.86	No
RD46 on RD46		0.96	.056	2.31		0.96	.078	2.18		0.96	.078	2.36	
RD50 on RD46	vs	0.96	.056	2.31	No	0.87	.067	2.44	No	0.91	.078	2.56	No
RD46 on RD46		0.96	.056	2.31		0.96	.078	2.18		0.96	.078	2.36	
RD on RD50	vs	0.97	.056	2.17	No	0.97	.078	1.83	No	0.93	.067	2.89	No
RD50 on RD50		0.97	.056	2.17		0.97	.067	2.56		0.97	.078	2.53	
RD46 on RD50	vs	0.97	.056	2.17	No	0.97	.078	2.03	No	0.94	.078	2.03	No
RD50 on RD50		0.97	.056	2.17		0.97	.067	2.56		0.97	.078	2.53	
RDO on RD46-0	vs	0.93	.056	1.84	No	0.93	.067	2.00	No	1.0	.067	2.43	No
RD46-0 on RD46-0		0.93	.056	1.84		1.0	.078	1.35		1.0	.056	3.21	
RD46 on RD46-0	vs	1.0	.078	1.35	No	0.93	.078	1.77	No	0.93	.078	2.00	No
RD46-0 on RD46-0		0.93	.056	1.84		1.0	.078	1.35		1.0	.056	3.21	
RD1 on RD46-1	vs	1.0	.045	3.34	No	1.0	.045	3.44	No	1.0	.045	2.89	No
RD46-1 on RD46-1		1.0	.045	3.34		1.0	.045	3.44		1.0	.045	2.89	
RD46 on RD46-1	vs	1.0	.056	2.11	Yes	1.0	.078	2.78	No	1.0	.078	2.89	No
RD46-1 on RD46-1		1.0	.045	3.34		1.0	.045	3.44		1.0	.045	2.89	
RDO on RD50-0	vs	1.0	.056	2.65	No	1.0	.067	2.67	No	0.92	.067	3.30	No
RD50-0 on RD50-0		1.0	.056	2.92		1.0	.056	3.83		1.0	.078	3.08	
RD50 on RD50-0	vs	1.0	.078	2.58	No	1.0	.067	3.42	No	1.0	.078	3.08	No
RD50-0 on RD50-0		1.0	.056	2.92		1.0	.056	3.83		1.0	.078	3.08	
RD1 on RD50-1	vs	0.95	.045	2.76	No	0.95	.045	2.85	No	0.95	.045	3.22	No
RD50-1 on RD50-1		0.95	.022	4.94		0.95	.022	4.83		0.95	.045	3.22	
RD50 on RD50-1	vs	0.95	.078	1.49	Yes	0.95	.067	1.77	No	0.95	.078	2.11	Yes
RD50-1 on RD50-1		0.95	.022	4.94		0.95	.022	4.83		0.95	.045	3.22	

DR = Detection Rate
 FAR = False Alarm Rate (%)
 MTTD = Mean-Time-To-Detect (min.)

B. EVALUATION OF THE BAYESIAN ALGORITHM

The effectiveness of the Bayesian 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 to 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 was not exceeded. The first "1" signal was considered an indication of a tentative incident for both the incident and 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 on dry-weather weekdays and two hours of incident-free data taken at fifteen subsystems, were analyzed. The detection rate (percent detected among incidents), false-alarm rate (percent of "1111" signal strings in incident-free data) and mean-time-to-detect were as follows:

Detection Rate	- 100%
False-Alarm Rate	- 0.0%
Mean-Time-To-Detect	- 3.9 min.

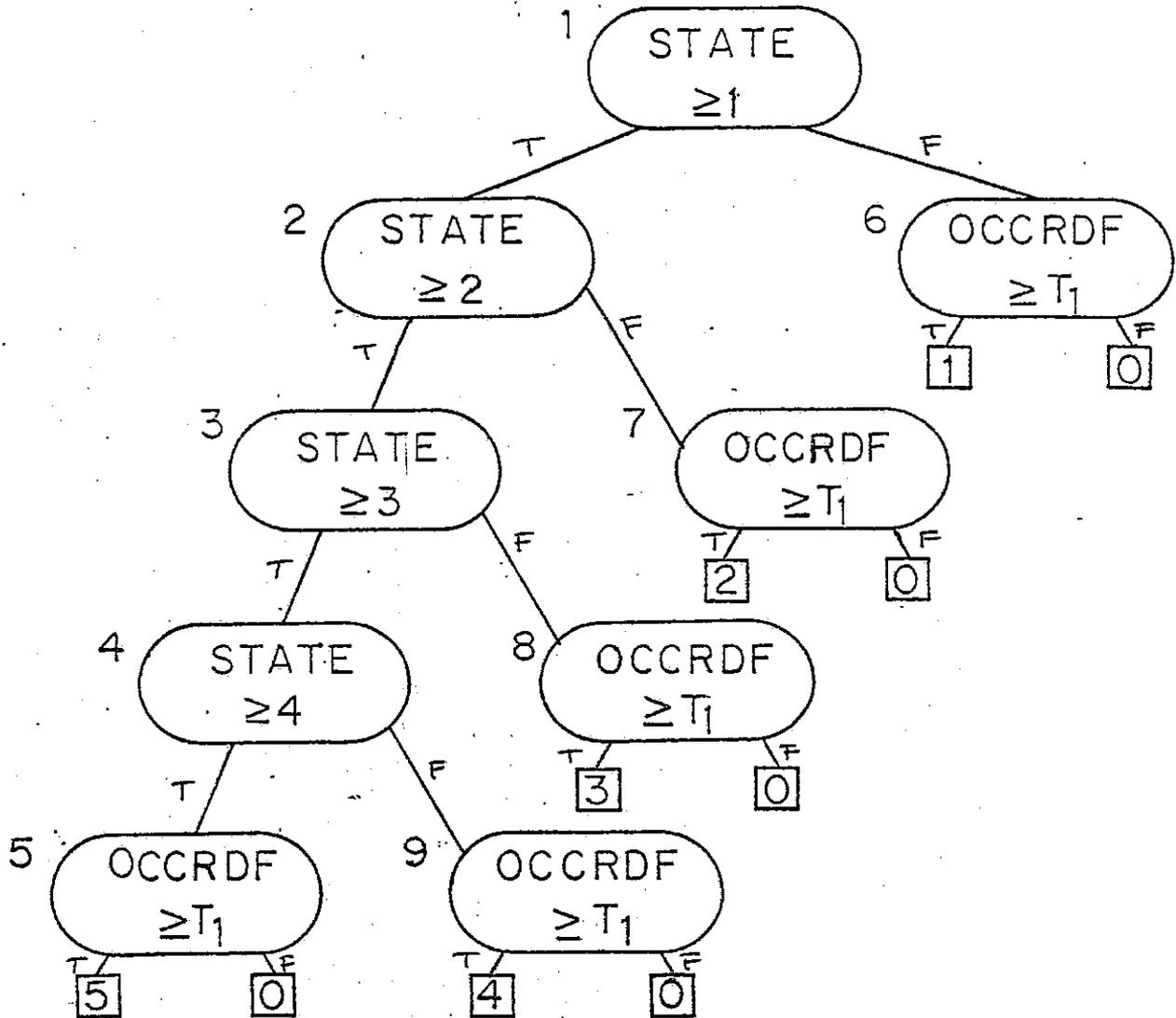
Note that the structure of the algorithm requires that the mean-time-to-detect be at least four minutes. Thus, the mean-time-to-detect actually achieved is as good as can be expected from this algorithm. (The slight discrepancy between 3.9 min. and 4 min. is due to inaccuracies in determining the apparent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

The Bayesian algorithm was compared with the California algorithm (TSC-2) and TSC's algorithms 7 and 8. The structure of the Bayesian algorithm is shown in Figure 10. A comparison among the four algorithms using the incident and incident-free data obtained from the study site is given in Table 12. The Mann-Whitney U Test was conducted to determine the significance of the difference in MTTD between the Bayesian algorithm and each one of the others. At the 5 percent level of significance such difference was found.

From the above results it can be seen that, for the 17 incidents on the Outbound Kennedy, the Bayesian algorithm compared favorably with the other tested algorithms. In some cases a difference of 2-2.5 minutes in detecting an incident might not be extremely significant. This could be in cases where the variability in response time of the incident handling subsystem is quite considerable, or in cases where traffic messages by commercial radio are given every 5-10 minutes or so during the rush period. Also, such a delay in implementing ramp control strategies for incident situations should not be detrimental, especially for a dynamic control system which is responsive to flow changes.

Probabilities of Incidents Given Various Signal Strings

As discussed previously, theoretical probabilities for incidents given certain signal strings could be developed once $f(Z/U_0)$, $f(Z/U_1)$, $P(U_0)$ were defined quantitatively. Moreover, such values could be computed considering the number of capacity-reducing incidents that occurred during the particular time slice (i.e. PM rush) prior to the incident under consideration. Table 13 presents probability values for the occurrence of an incident given various signal strings.



State	Designates
0	Incident-free conditions
1	Tentative incident
2	Tentative incident
3	Tentative incident
4	Incident confirmed
5	Incident continuing

DECISION TREE FOR BAYESIAN ALGORITHM
FIG. 11

TABLE 12
COMPARISON OF ALGORITHM'S EFFICIENCY

Algorithm	Detection Rate	False-Alarm Rate	Mean-Time-To-Detect (min.)
Bayesian	100%	0.0%	3.9
California	100%	0.11%	1.5
TSC Algorithm 7	100%	0.0%	1.5
TSC Algorithm 8	100%	0.0%	1.5

TABLE 13
PROBABILITY OF INCIDENT OCCURRENCE
FOR VARIOUS SIGNAL STRINGS

Signal String * P(inc/abcd)	Probability of Incident
P(inc/1)	.00305
P(inc/11)	.03351
P(inc/10)	.00104
P(inc/111)	.28209
P(inc/110)	.01166
P(inc/101)	.01166
P(inc/100)	.00035
P(inc/1111)	.81662

* 1 - incident state signalled by algorithm
 0 - non-incident state signalled by algorithm
 abcd (where a, b, c, d = 0 or 1) - states signalled by algorithm at times
 t, t+1, t+2, t+3.

From the above table it can be seen that once a signal "1" is output, the probability that an incident has occurred is .00305 and the probability of making a wrong incident management decision being close to 100 percent. The probabilities of the occurrence of an incident do not improve significantly for two or three consecutive signals. For a string of four "1" this probability increases to .817, obviously the longer the string of "1" the higher is the probability of occurrence of an incident. However, the decision on what string size to operate should come after an on-line evaluation.

V. ON-LINE EVALUATION OF INCIDENT DETECTION ALGORITHMS

In the on-line evaluation, five incident detection algorithms are evaluated and compared -- the three TSC algorithms (algorithms 7, 8 and 10), the locally developed pattern-recognition algorithm (algorithm 16-14) and the Bayesian algorithm.

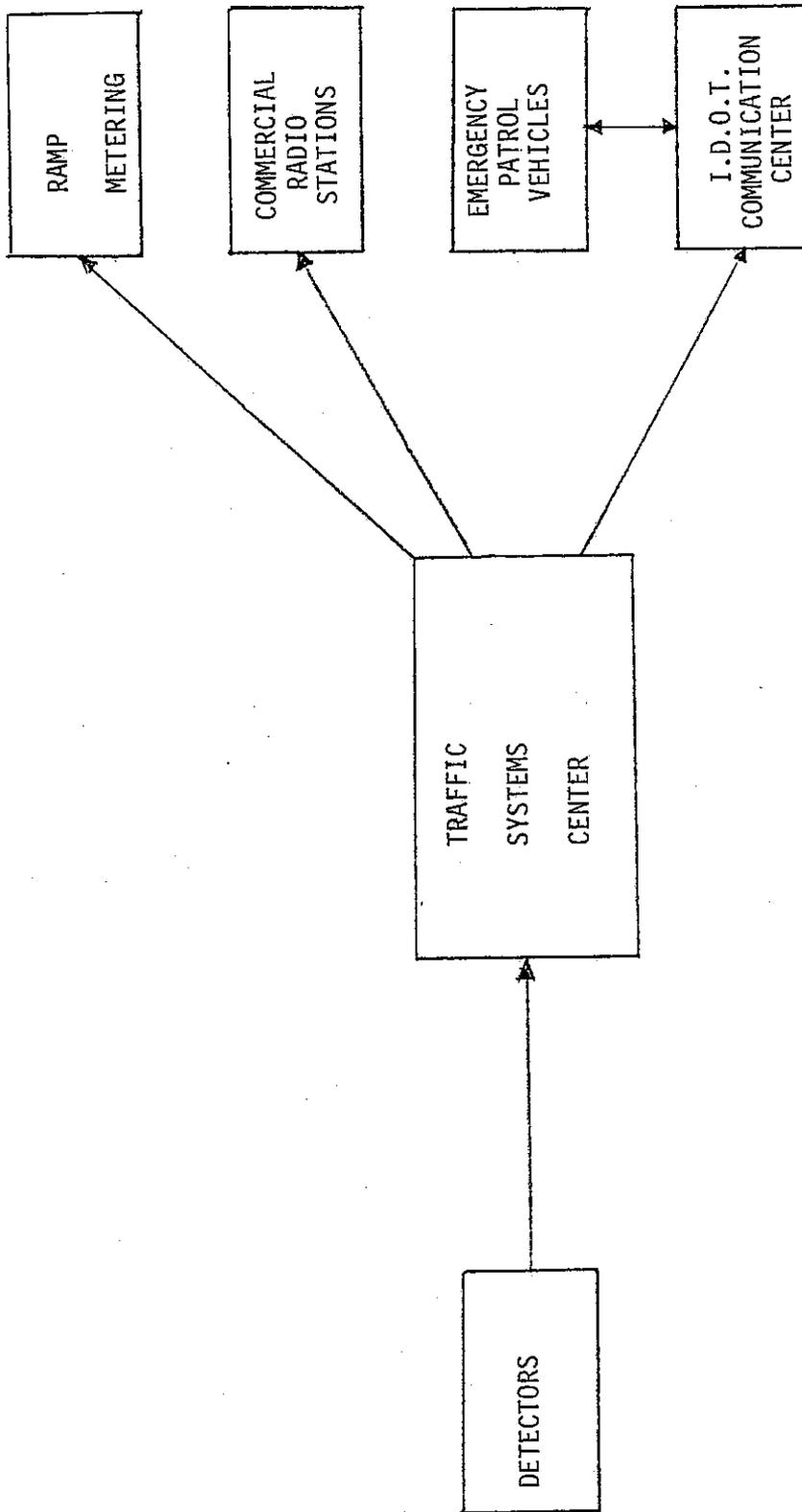
The specific goals of the on-line evaluation were:

1. To determine the on-line efficiency of algorithms proven to be effective in an off-line evaluation.
2. To correlate algorithm efficiency parameters derived from the on-line evaluation with those derived from the off-line evaluation.
3. To evaluate combinations of thresholds with respect to geometric conditions on the freeway.

A. THE ON-LINE INCIDENT DETECTION SYSTEM

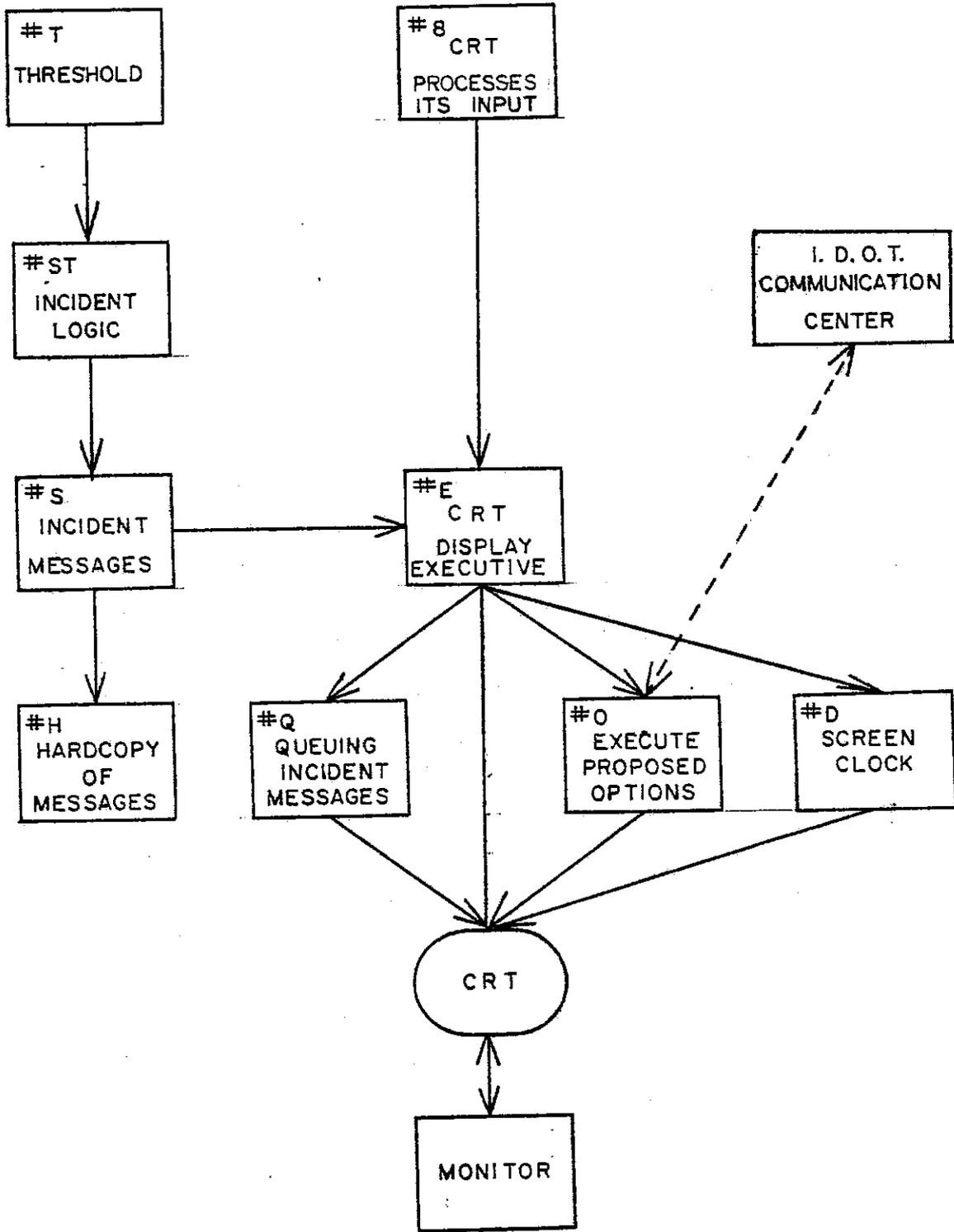
The Traffic Systems Center controls 224 directional miles of expressways through its Freeway Traffic Management System, the flow-chart of which is shown in Figure 12. The backbone of the management system is the detector subsystem which utilizes full- and single-detector stations every three miles and half miles, respectively.

The major function of the on-line incident detection system is to detect a capacity-reducing incident through its incident detection logic, which utilizes three algorithms simultaneously, then delivers a message to the monitor. Another function is to provide for continuous evaluation of the performance of algorithms, refinement of thresholds and evaluation of response to incidents. Figure 13 presents the basic flow-chart of the on-line incident detection system.



I.D.O.T. Traffic Systems Center
Freeway Traffic Management System

Figure 12



On-Line Incident Detection System Software

Fig.13

The basic programs for both functions of the on-line system are the incident determination logic program (#ST) and the incident message program (#S). The incident detection logic program, utilizing appropriate thresholds obtained from previous analyses, determines the incident status of each of the main line detectors. For recording the status, a status matrix is used. The status matrix is updated every minute. At the end of the update, the incident message program (#S) scans the matrix for detected incidents and generates an appropriate message. The generated messages include information on detector subsection, upstream occupancy, downstream occupancy, time of incident, day, and date, and are maintained in a disk-based file.

Once the incident message is produced it becomes possible to monitor the incident file through the CRT display as part of the incident message management phase. The CRT display executive program (#E) is the director of this phase. Appropriate parameters are passed into programs #Q and #O for operation. Program #Q controls the queuing and the displaying of the incident messages. Queue manipulation enables the operator to inspect the incident file and delete old messages since new messages are ignored when the queue is full. These messages consist of six elements, three of which describe the location. They are the expressway name, the direction (IB or OB) and the detector station. The remaining elements are the vector number, incident file number and earliest detection time.

Program #O can handle various options initiated by the operator. These options could include in the future, for instance, CRT communication between the Traffic Systems Center in Oak Park and IDOT Communication Center in Schaumburg.

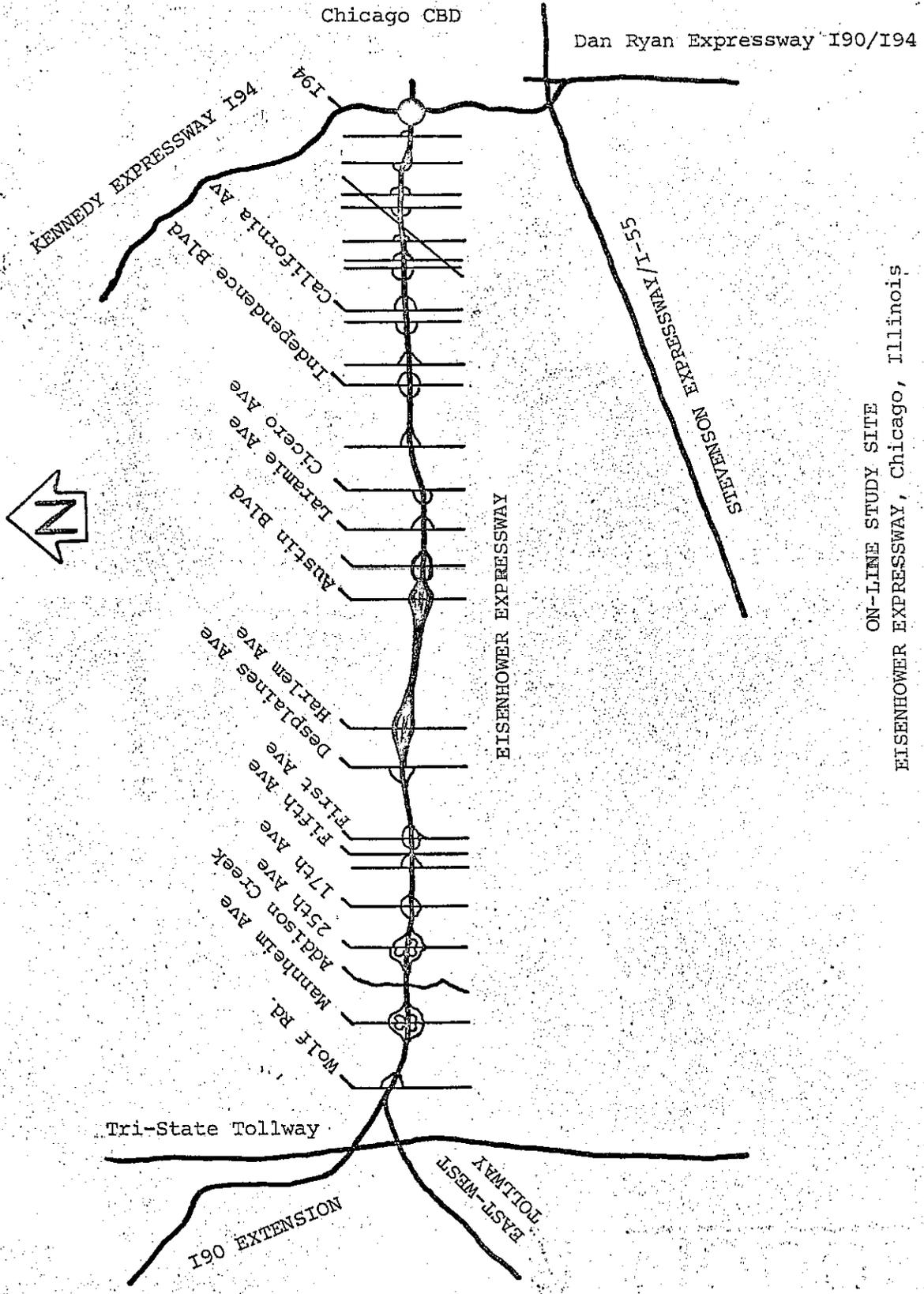
Other related programs in the on-line software are: program #H, which produces a hard copy of the incident file; program #D which records the operator's time of response to the message and also displays the clock-time on the CRT screen; and program #8 which is an existing program extended to include the CRT input required by the CRT display Executive program (#E).

B. DEVELOPMENT OF DATA BASE

The major site chosen for the study was the Eisenhower Expressway (I-90) between I-94 and Wolf Road (Figure 14). This expressway contains various characteristics along its thirteen-mile length. Looking at the geometrics, the expressway is four lanes wide between I-94 and Austin Boulevard and then drops to three lanes from Austin to Wolf Road. This lane drop is the major bottleneck area for westbound traffic. As for eastbound traffic, First Avenue is the major problem area. Here the degree of curvature, change in grade, and volumes of traffic are the main causes of congestion. Both these sections are quite a challenge for the on-line incident detection algorithms, especially during peak hours. For comparison purposes, another expressway (the Dan Ryan between 65th and 95th Streets) was chosen for study. This section of expressway is a straight pipe section four lanes wide with no major bottlenecks between its terminal points.

The time period picked for the survey was Monday thru Friday between the hours of 3:00 and 5:00 PM. During this two-hour period, four capacity-reducing incidents are expected on the Eisenhower Expressway.

Aerial survey of the study section utilizing the State helicopter was carried out to collect the incident data. The information obtained for each stopped vehicle observed was as follows.



ON-LINE STUDY SITE
EISENHOWER EXPRESSWAY, Chicago, Illinois

Figure 14

1. Time of spotting,
2. Longitudinal location (i.e. inbound or outbound),
3. Lateral location (i.e. cross street),
4. Lane,
5. Vehicle description,
6. Reason for stopping, if ascertainable,
7. Type of aid present, if any, and
8. Comments to describe or explain traffic operations.

The helicopter was able to maintain an average speed of 180 KM/H (110 MPH) which allowed one trip along the entire length of expressway to be made in about 7.5 minutes. This meant that the terminal points of the study site would be flown over every 7.5 minutes. In reality, however, each point was viewed nearly every five minutes because of the visibility from the helicopter flying at about 200 to 250 meters (700 to 800 feet) above the expressway.

With the completion of each day of data collection, the aerial survey data were correlated with the incident information produced by the on-line operating algorithms. This recorded information included:

1. Longitudinal location,
2. Lateral location,
3. Lane,
4. Detection time of each individual algorithm being tested,
5. Termination time,
6. Duration time, both computer and actual,
7. Actual time of occurrence, detection and termination,
8. Type of incident, or congestion-causing situation, and
9. Comments.

After completing this correlation of computer-recorded incident messages and actual recorded incidents, various statistics were determined. These were detection rate, false-alarm rate, missed incidents, etc. which were calculated for each day for each individual algorithm.

A total of 29 days of data on the Eisenhower Expressway and 4 days on the Day Ryan Expressway were collected.

C. ALGORITHM EVALUATION

Based on the off-line evaluation of the algorithms it was decided to conduct the on-line evaluation using optimal thresholds developed for the 80 and 90 percent Detection Rates, as obtained in the off-line evaluation. In the first phase, algorithms 7, 8, and 10 were evaluated on the Eisenhower Expressway during the PM rush. Preliminary analysis of the data suggested that problem areas (bottlenecks, curves) were producing a considerable number of false alarms, and it was decided to run an evaluation after having introduced less-sensitive thresholds into the problem areas. These new thresholds represented the off-line 50 percent Detection Rate. Then, an evaluation of the algorithms on the Dan Ryan study section was conducted with thresholds representing the off-line 90 percent Detection Rate.

In the second phase, the apparent best algorithm among the three above was selected to operate simultaneously with algorithm 16-14 and the Bayesian algorithm on the Eisenhower Expressway. Table 14 summarizes the evaluation process. Each of the study cases referred to in Table 14 was analyzed for differences in Detection Rate, False-Alarm Rate, and Mean-Time-to-Detect among the algorithms. Algorithm efficiency at the 80 percent detection level was compared with that at the 90 percent level, and the efficiency at that level was compared with algorithm efficiency at the 90-50 percent detection level. The 90-50 percent detection level was represented by a

TABLE 14
SUMMARY OF ON-LINE EVALUATION PROCESS

Study Case	Facility	Detection Rate (Off-Line)	Algorithms Evaluated	# of Data Days
1	Eisenhower	80%	7, 8, 10	11
2	Eisenhower	90%	7, 8, 10	10
3	Eisenhower	90% - 50%	7, 8, 10	4
4	Ryan	90%	7, 8, 10	4
5	Eisenhower	90% - 50%	7, 16-14, Bayesian	9

set of thresholds derived for the 90 percent and 50 percent detection levels at non-problem and problem sections, respectively.

The most promising algorithms at the detection levels of 90 percent and 90-50 percent were selected for further analysis. In this analysis the cumulative distributions of the message duration of false alarms and real incidents were compared in order to have an indication as to the change with time in the probability of an incident message being true. Also, the distribution of false alarms with respect to time during the rush period was investigated to yield an indication as to the need for threshold refinement.

As to the relationship between the number of false alarms and geometric features of the problem section, analysis was conducted at the 90 and 90-50 percent levels of detection. In this analysis the number of false alarms for each problem section for one detection level was compared with same for the other detection level. This was done for each of the three algorithms 7, 8, and 10. Table 15 presents the type of problems on the various sections of inbound and outbound Eisenhower. These problems, which had the tendency to produce a high number of false alarms, included vertical curves, horizontal curves, "sun effect", bridge effect", "close bridges", up-grades, down-grades, a merge from a double-lane entrance ramp, and a lane drop. The sections that were operating with thresholds related to the 50 percent detection level during the 90-50 percent detection level evaluation period are also indicated in the above table. No attempt was made to find the relationship between the Detection Rate and the geometric features of each section because of the relatively low number of incidents (16) during the 90-50 percent detection level evaluation period.

Comparative Analysis of Algorithm Efficiency

Tables 16, 17, and 18 present the Detection Rate, False-Alarm Rate,

TABLE 15

RELATIONSHIP BETWEEN FALSE ALARMS & GEOMETRIC FEATURES - EISENHOWER EXPRESSWAY (INBOUND)

IB Eisenhower Section	Problem Description	Alg.	90% Threshold (Rush Dry)		90%-50% Threshold (Rush Dry)		Alg.
			Alg.	Alg.	Alg.	Alg.	
		7	8	10	7	8	10
Wolf	Horizontal Curve (Downgrade)	1	--	--	--	--	--
Mannheim	-----	---	--	2	--	--	--
Addison Cr.	Bridge Effect * (Upgrade)	4	--	3	--	--	--
25th Street	Horizontal Curve	--	--	--	--	--	--
17th Street	-----	1	--	1	1	1	1
5th Ave	Double Merge	1	--	1	--	--	2
1st Ave	Horizontal Curve	--	--	--	--	--	--
Desplaines	-----	--	--	--	1	2	2
Harlem	Upgrade *	2	1	2	1	1	1
Austin	Vertical Curve	--	--	--	--	--	--
Laramie	-----	--	--	--	--	--	--
Cicero							

TABLE 15 (Cont'd)

RELATIONSHIP BETWEEN FALSE ALARMS & GEOMETRIC FEATURES - EISENHOWER EXPRESSWAY (INBOUND)

IB Eisenhower Section	Problem Description	90% Threshold (Rush Dry)		90%-50% Threshold (Rush Dry)	
		Alg. 7	Alg. 8	Alg. 7	Alg. 8
Cicero	Horizontal Curve	--	--	--	--
Independence	Close Bridges Effect	2	2	1	1
California	-----	--	--	--	--
	Total	11	3	4	5

* Threshold for 50% Detection Rate used.

TABLE 15 (Cont'd)

RELATIONSHIP BETWEEN FALSE ALARMS & GEOMETRIC FEATURES - EISENHOWER EXPRESSWAY (OUTBOUND)

OB Eisenhower Section	Problem Description	90% Threshold (Rush Dry)		90%-50% Threshold (Rush Dry)			
		Alg. 7	Alg. 8	Alg. 10	Alg. 7	Alg. 8	Alg. 10
25th St	Bridge Effect * (Downgrade)	2	1	1	1	3	2
Addison Creek	-----	---	---	---	---	---	---
Mannheim	Horizontal Curve (Upgrade)	---	---	---	---	---	---
Wolf							
	Total	11	7	9	8	6	10

* Threshold for 50% Detection Rate used.

TABLE 16
ON-LINE EFFICIENCY OF ALGORITHM 7, 8, AND 10 FOR OFF-LINE 80% DETECTION LEVEL
FOR RUSH DRY CONDITIONS ON THE EISENHOWER

Measure of Effectiveness	Alg. 7	Alg. 8	Alg. 10	Apparent Best	Statistically Best (5% I.O.S.)
Detection Rate	.28	.25	.26	8	None
False-Alarm Rate	.87	.70	.82	8	None
Mean-Time-To-Detect (min.)	8.8	9.3	9.0	7	None

TABLE 17

ON-LINE EFFICIENCY OF ALGORITHMS 7, 8, AND 10 FOR OFF-LINE 90% DETECTION LEVEL
FOR RUSH DRY CONDITIONS ON THE EISENHOWER

Measure of Effectiveness	Alg. 7	Alg. 8	Alg. 10	Apparent Best	Statistically Best (5% I.O.S.)
Detection Rate	.37	.36	.34	7	None
False-Alarm Rate	.86	.73	.86	8	None
Mean-Time-To-Detect (min.)	8.9	6.3	2.7	10	None

TABLE 18
ON-LINE EFFICIENCY OF ALGORITHMS 7, 8, AND 10 FOR OFF-LINE 90% - 50% DETECTION LEVEL
FOR RUSH-DRY CONDITIONS ON THE EISENHOWER

Measure of Effectiveness	Alg. 7	Alg. 8	Alg. 10	Apparent Best	Statistically Best (5% L.O.S.)
Detection Rate	.56	.41	.56	7, 10	None
False-Alarm Rate	.63	.74	.73	7	None
Mean-Time-To-Detect (min.)	7.5	5.3	6.2	8	None

and Mean-Time-to-Detect for algorithms 7, 8, and 10, for the off-line detection levels of 80%, 90% and 90%-50%, respectively.

As can be seen from these tables, the on-line Detection Rates are lower than the off-line ones. However, the positive correlation between the Detection Rate and False-Alarm Rate, which was found in the off-line analysis, seems to exist also in the on-line analysis, as shown for the Off-line 80% and 90% detection levels in Tables 16 and 17, respectively.

The statistical t-tests conducted for each off-line detection level for difference in the measures of effectiveness among the algorithms did not indicate any significant differences for any of the measures of effectiveness for any of the detection levels, at the 5 percent level of significance. Differences in MTTD values between the off-line and on-line evaluations were also noted. The on-line evaluation yielded MTTD values ranging between 5.3 to 7.5 minutes for thresholds representing the 90%-50% detection level. The off-line evaluation yielded MTTD values ranging from 2 to 4 minutes. The large MTTD values obtained in the on-line evaluation could be attributed to some inherent inaccuracies in determining the exact time of occurrence of an incident because of the obvious limitations of the aerial survey. Taking this into consideration, one could presume that as far as the MTTD was concerned, both the on-line and the off-line evaluations gave the same results.

Statistical analysis, comparing algorithm efficiency using the 90% detection level thresholds with that using the 90%-50% detection level thresholds, was carried out at the 5% level of significance. It was found that introduction of 50% detection level thresholds into problem areas improved algorithm 7's performance in terms of Detection Rate and False Alarm Rate, but not MTTD. For algorithm 8, the introduction of the problem

section related thresholds did not statistically improve any of the measures of effectiveness. In the case of algorithm 10, such analysis indicated significant differences for Detection Rate and MTTD but not for the False-Alarm Rate.

Comparing the efficiency of each of the above three algorithms at the 80% detection level with that at the 90% detection level showed no significant differences for any of the measures of effectiveness for algorithms 7 and 8. For algorithm 10, however, there were no significant differences in Detection Rate and MTTD but there was one in False-Alarm Rate.

The results of the limited algorithm evaluation on the Dan Ryan Expressway at the 90% detection level are presented in Table 19. Statistical analysis at the 5% level of significance for differences among algorithms 7, 8, and 10 indicated no significant differences for any of the measures of effectiveness.

During the second phase of the study algorithm 7, which was found to be the apparent best for the 90%-50% detection level, was compared with algorithm 16-14 and the Bayesian algorithm. Table 20 presents the results of this evaluation. Statistical analysis at the 5% level of significance indicated that, as far as the Detection Rate was concerned, no best algorithm could be found. Algorithm 7 and the Bayesian algorithm were superior to algorithm 16-14 with respect to the False-Alarm Rate while algorithms 7 and 16-14 were superior as far as the MTTD was concerned.

Duration of Incident Messages

To increase decision credibility regarding an incident message, one could require the message to have a certain duration, assuming that a false message will terminate after a short while. Thus, if the distributions of durations of true and false messages are determined, it should be feasible to relate message duration to the probability of a message being true.

TABLE 19
 ON-LINE EFFICIENCY OF ALGORITHMS 7, 8, AND 10 FOR OFF-LINE 90% DETECTION LEVEL
 FOR RUSH DRY CONDITIONS ON THE DAN RYAN

Measure of Effectiveness	Alg. 7	Alg. 8	Alg. 10	Apparent Best	Statistically Best
Detection Rate	.75	.75	.75	All	All
False-Alarm Rate	.58	.25	.50	8	None
Mean-Time-To-Detect (min.)	10.0	11.0	13.5	7	None

TABLE 20
 ON-LINE EFFICIENCY OF ALGORITHMS 7, 16-14, AND THE BAYESIAN FOR OFF-LINE 90% - 50% DETECTION LEVEL
 FOR RUSH DRY CONDITIONS ON THE EISENHOWER

Measure of Effectiveness	Alg. 7	Bayesian Alg.	Alg. 16-14	Apparent Best	Statistically Best
Detection Rate	.60	.53	.71	16-14	None
False-Alarm Rate	.71	.77	.88	7	7, Bayesian
Mean-Time-To-Detect (min.)	8.02	12.14	6.08	16-14	7, 16-14

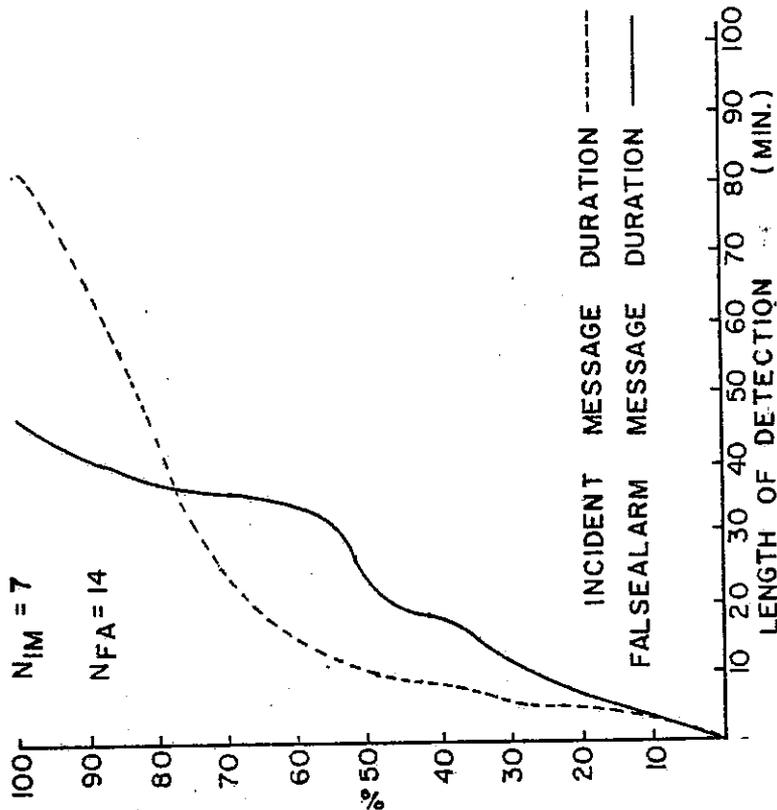
Cumulative distributions of duration of false alarms and incident messages for algorithm 7 are shown in Figure 15 at the 90% and 90%-50% detection levels. From these figures it can be seen that the distribution of duration of false-alarm messages is such that for both levels of detection, nearly 50% of the messages endure 30 minutes or more. This, of course, indicates a weakness in the algorithm which experienced between .60 and .70 False-Alarm Rates.

The distribution of false alarms with time (by 30-minute intervals) during the daily study period (3-5 PM) was found to be uniform. This suggests that no change in thresholds with time was necessary for any particular location.

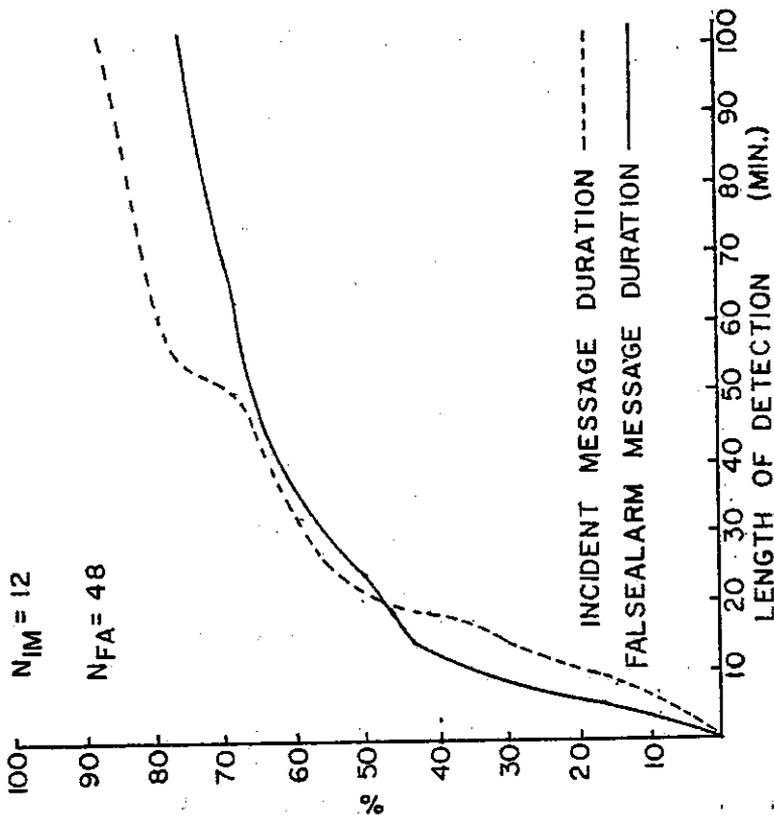
Relationship Between False-Alarm Rate and Geometric Features

The introduction of problem section related thresholds representing the 50% detection level led to some improvement in the efficiency of the algorithms. The relationship between the number of false alarms and geometric features, resulting from the operation of algorithms 7, 8, and 10, is presented in Table 15 for the 90% and 90%-50% detection levels for both directions of the Eisenhower.

Table 15 indicates that algorithm 7 showed the most improvement in terms of reduction of false alarms due to the incorporation of "individualized" thresholds. The other algorithms did not show consistent improvement. For example, the introduction of thresholds representing the 50% Detection Rate at the lane drop at Austin (Figure 14) did not change the False-Alarm Rate of algorithm 8 but increased this rate (not necessarily significantly) for algorithms 7 and 10. This lane drop causes the most severe shock waves on the facility for most of the PM rush period. The long duration of false alarms in this section is a major cause of the



CUMULATIVE DISTRIBUTIONS OF THE DURATION
OF INCIDENTS AND FALSE ALARMS FOR ALGORITHM 7
AT THE 90%-50% DETECTION LEVELS



CUMULATIVE DISTRIBUTIONS OF THE DURATION
OF INCIDENTS AND FALSE ALARMS FOR ALGORITHM 7
AT THE 90% DETECTION LEVEL

Figure 15

Duration Of Incidents And False Alarms For Various Detection Levels

cumulative distribution of incident message duration having a high percentage of messages of long duration (Figure 15). When shockwaves are less severe, as in the case of the sun effect on traffic on the outbound near Des Plaines Avenue, the "individualized" thresholds (related to the 50% detection level) seemed to improve the false alarms situation considerably for all algorithms. Another problem section inducing false alarms and rendering the "individualized" set of thresholds there ineffective was the bridge near Addison Creek between 25th Avenue and Mannheim Road. Only algorithm 8 showed an improved operation there. The effect of other problem sections inducing non-incident shock waves resulting in false alarms can also be determined from Table 15.

VI. FINDINGS, OBSERVATIONS, AND RECOMMENDATIONS

Based on the data collected and the various analyses, the following are the major findings of the off-line evaluation:

1. Algorithm 9, which was found to yield favorable results in previous studies (1), displayed poor DR-FAR relationship relative to algorithms 7, 8, and 10.
2. For the "Rush Dry" period and for detection levels lower than 95 percent, no best algorithm with respect to FAR could be found.
3. For detection levels of 95 percent and above, algorithm 7 was found to have the least FAR for the "Rush Dry" period.
4. The single-feature Bayesian algorithm was found to compare favorably with the leading multi-feature algorithms with respect to Detection Rate and False-Alarm Rate.
5. No significant differences between the MTTD among algorithms were found at the 95 percent detection level at the 5 percent level of significance.
6. In order to be detected, incidents occurring on the detector lane require "less sensitive" thresholds than those occurring on the non-detector lane.
7. For incidents occurring on the detector lane and non-detector lanes during the "Rush Dry" period, algorithms 10 and 7, respectively, were found to be the most efficient, as far as the FAR was concerned, at the 95 percent detection level.
8. No significant differences in MTTD among algorithms were found to exist for incident data categories: RD-50-1, RD-50-0, and RD-46-1. For RD-46-0 algorithm 7 displayed the lowest MTTD.

9. No significant differences in MTTD within algorithms were found to exist when accident data were compared to non-accident incident data on either the detector or non-detector lane, or when accident data and non-accident incident data on the detector lane were compared to the respective data on the non-detector lane.
10. At the 95 percent detection level, thresholds developed for accidents and non-accident incidents occurring on the detector lane are less sensitive to false alarms than those developed for the above incident data on the non-detector lane, for all algorithms during the "Rush Dry" period.
11. Thresholds developed at the 95 percent detection level for accidents occurring on the detector lane detected only 78 percent of the non-accidents on that lane, for algorithm 7 and 8, and all such incidents for algorithm 10.

Based on the major findings at the off-line evaluation the following observations could be made:

1. The MTTD should not be a critical criterion in selecting an operational algorithm since no significant differences in this parameter were found among the tested algorithms for desired detection levels.
2. The DR-FAR relationship should be a critical criterion in the selection process of incident detection algorithms.
3. On the whole, algorithm 7 seemed to yield the most favorable results of all the algorithms tested in this study.
4. The level of lateral detectorization is not a critical issue as far as detection time for incidents on various lanes is concerned.
5. If a high level of lateral detectorization (fully detectorized lanes) exists, algorithms should be applied to each lane in the detection process to yield a low FAR and a high DR.

6. The simplicity of the Bayesian algorithm allows estimation of the likelihood of an incident signal being an actual incident, and hence could be applied during the occurrence of simultaneous signals to determine allocation of limited resources to handle these incidents.
7. Complicated algorithms are not necessarily the best ones.

Based on analyses of the data collected in the on-line evaluation, the following are the major findings and observations:

1. No statistically significant differences at the 5% level of significance in Detection Rate, False-Alarm Rate, and MTTD were found among algorithms 7, 8, and 10 for the 80%, 90% and 90%-50% detection levels, when operated on the Eisenhower Expressway.
2. The introduction of "individualized" thresholds at problem sections did not affect algorithm 8, while improving the Detection Rate and False-Alarm Rate of algorithm 7, and improving the Detection Rate and MTTD for algorithm 10.
3. As far as the MTTD was concerned, no apparent differences between the on-line and off-line evaluations were observed.
4. The efficiency of each of the two algorithms 7 and 8 remained statistically the same for the 90% and 90%-50% detection levels.
5. When compared with the locally developed algorithms (16-14 and Bayesian) at the 90%-50% detection level, algorithm 7 showed overall superiority.
6. Nearly 50% of all incident and false-alarm messages lasted longer than 30 minutes.
7. The introduction of "individualized" thresholds at problem section could reduce the number of false alarms generated in these sections.
8. The Detection Rates obtained by algorithms in the off-line evalua-

tion are considerably higher than those obtained in the on-line evaluation.

9. The shockwave suppressor mechanism of algorithm 8 seemed to be quite effective, requiring less effort in preparing thresholds than for any other algorithm.
10. The False-Alarm rates are quite high and reducing them poses the biggest challenge in refining present algorithms or developing new ones.
11. The distribution of false alarms with time seemed to be uniform for the 90% and 90%-50% detection levels, indicating that no changes in thresholds at any particular section with time during the rush hour were necessary.
12. Algorithms 7 and 8 seem to operate quite similarly, with algorithm 7 being apparently better.

The following recommendations for further action are made:

1. Conduct a discriminant analysis of traffic features to find the best combination of features to be used in an algorithm.
2. Develop algorithms based on speed related features.
3. Since there exist some differences between the results of this study and TSC's, considerations should be given to evaluate other non-pattern recognition algorithms with the above data.
4. Investigate the behavior of traffic features at bottlenecks during incidents to be able to distinguish between incident and non-incident related shockwaves.
5. An improved non-incident shockwave suppressor mechanism needs to be developed and incorporated into the efficient pattern-recognition algorithms.

6. Develop an effective and inexpensive supportive incident verification system (CB radio?) to minimize the False-Alarm Rate.

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APPENDIX A

DESCRIPTION OF INCIDENT DATA BASE

Table A-1
INCIDENT DATA BASE DESCRIPTION
(RD-46)

Location	Lane	Date Mo/Day/Yr.	Day	Actual Time Hr./Min./Sec.	Termination Time Hr./Min./Sec.
Ken - OB Fullerton	3	072974	M	165140	171100
Ken - OB Argyle	1	100374	Th	154740	160620
Ede - IB Devon	1	111474	Th	071840	072320
Ken - IB Foster	3	121874	W	172320	173200
Ede - OB Wilson	2	121974	Th	184200	190720
Ken - IB Pulaski	2	070275	W	093120	093640
Ken - IB Argyle	2	070375	Th	070740	071820
Ken - IB Chicago	2	070375	Th	075600	081400
Ede - IB N. Peterson	2	071875	F	073620	081900
Ken - OB Addison	3	071875	F	160700	162240
Ken - OB Belmont	1	071875	F	162040	163200
Ken - IB Addison	2	071875	F	080020	080340
Ken - IB Western	3	072475	Th	080300	081920
Ken - IB North	1	081275	T	083440	090020
Ken - OB Division	2	082875	Th	175600	180300
Ken - OB Ogden	2	121575	M	162420	164420
Ken - OB Ogden	4	121675	T	074600	075600
Ken - IB Sacramento	1	121675	T	174900	180240
Ken - IB Sacramento	4	121875	Th	074800	080440
Ken - IB Diversey	1	121875	Th	082200	082600
Ken - IB Division	1	121875	Th	084340	084920
Ken - IB Kimball	1	121975	F	081920	082500
Ken - OB Addison	3	122375	T	172640	175800

Table A-1
INCIDENT DATA BASE DESCRIPTION
(RD-50)

Location	Lane	Date Mo./Day/Yr.	Day	Actual Time Hr./Min./Sec.	Termination Time Hr./Min./Sec.
Eis - IB Damen	1	091974	Th	171000	173040
Ken - IB W. Mannheim	2	092774	F	151000	155320
Ken - IB W. Mannheim	2	100174	T	174900	175940
Ken - OB Addison	1,2	100474	F	082700	084740
Ken - OB Cicero	3	100874	T	152540	162040
Eis - OB Kostner	1	100874	T	165620	174340
Eis - IB E. Harlem	1	101774	Th	074500	085640
Eis - IB 9th	3	101774	Th	170740	173320
Ken - IB W. Harlem	3	120474	W	153740	160820
Ken - OB Damen	1	121074	T	150200	150800
Ken - OB Harlem	1	121074	T	150300	170140
Eis - IB Homan	2	050875	Th	092140	095100
Ede - IB Cicero	1	062775	F	151920	160800
Eis - IB Laramie	1	070175	T	082420	083040
Ken - IB Kimball	1	072475	Th	080000	081240
Eis - OB Kostner	1	072575	F	164220	173640
Eis - IB Addison	3	080175	F	072820	074420
Eis - IB 1st	3	080875	F	151940	153800
Ken - IB Pulaski	2	081175	M	080700	084720
Ken - IB Sayre	1	081975	T	155940	163800
Eis - OB DesPlaines	1	091575	M	172400	180920
Ken - OB Division	2	121175	Th	150900	153720
Ken - OB Keeler	2	121175	Th	154040	160040
Ken - IB North	2	121175	Th	162340	164700

Table A-1 (Cont'd)
INCIDENT DATA BASE DESCRIPTION
(RD-50)

Location	Lane	Date Mo./Day/Yr.	Day	Actual Time Hr./Min./Sec.	Termination Time Hr./Min./Sec.
Ken - OB E. Cumberland	1	121675	T	071240	073520
Ken - OB North	2	121775	W	150640	161720
Ken - IB Argyle	1,2	121775	W	170920	172320
Ken - IB Sayre	1	121875	Th	073240	080140
Ken - IB Division	4	121975	F	071720	072540
Ken - OB Belmont	1,2	122375	T	153800	164220
Eis - IB 1st	1	122375	T	152740	164240
Eis - IB W. Racine	1,2	122475	W	081640	090000
Ede - IB Pratt	1	123175	W	154020	164020

Table A-1
INCIDENT DATA BASE DESCRIPTION
(NRD-46)

Location	Lane	Date Mo./Day/Yr.	Day	Actual Time Hr./Min./Sec.	Termination Time Hr./Min./Sec.
Ken - OB North	4	072974	M	132740	134820
Ken - OB Damen	2	082274	Th	143200	145820
Eis - IB E. Mannheim	3	092374	M	143800	144640
Ken - OB Argyle	1	101774	Th	143200	144400
Eis - OB Morgan	2	123074	M	142100	145220
Ede - OB Cicero	3	063075	M	142320	145720
Eis - OB W. Mannheim	1	071975	Sa	112620	113320
Eis - OB 17th	1	072875	M	133320	134240
Ken - IB Kimball	1	081175	M	121820	122320
Ken - OB Damen	1	081975	T	133200	135540
Ken - OB North	4	081975	T	133800	134920
Ken - IB Montrose	3	121875	Th	065440	074440
Ken - OB Division	1	122375	T	135320	141900
Ken - IB Montrose	2,3	122975	M	123040	125320

Table A-1
INCIDENT DATA BASE DESCRIPTION
(NRD-50)

Location	Lane	Date Mo./Day/Yr.	Day	Actual	Termination
				Time Hr./Min./Sec.	Time Hr./Min./Sec.
Ken - IB E. Harlem	1	082974	Th	183120	190000
Ede - IB Oakton	3	092674	Th	145720	151920
Ken - IB Pulaski	1	100174	T	101740	104600
Ken - OB Sayre	1	062775	F	130340	131140
Ken - OB Nagle	3	062775	F	131840	134140
Ken - IB Keeler	1	070275	W	103740	105840
Eis - IB Ashland	3	070375	Th	121220	130600
Ken - IB Montrose	4	072875	M	062400	071120
Eis - OB 25th	3	072875	M	130440	135920
Ken - IB Keeler	4	081475	Th	114440	122940
Eis - OB Homan	1	082075	W	184140	192920
Ken - OB Damen	1	090575	F	192940	195740
Ede - OB Elston	1	121975	F	191900	193440
Ken - OB Keeler	6	122275	M	180120	182900
Ken - OB O'Hare	2	122375	T	134520	140920
Ede - IB Cicero	1	122475	W	122120	125100

Table A-1
INCIDENT DATA BASE DESCRIPTION
(RW)

Location	Lane	46 or 50	Date Mo./Day/Yr.	Day	Actual Time Hr./Min./Sec.	Termination Time Hr./Min./Sec.
Eis - IB Central	1	50	062475	T	155300	164020
Ede - OB Wilson	1	50	091274	Th	150220	150620
Ken - IB Argyle	1	50	091274	Th	164920	170540
Ken - IB Montrose	3	46	122975	M	155020	161320
Ken - IB Kimball	1,2	46	122975	M	162540	164040
Ken - IB Montrose	3	46	122975	M	165020	165320

INCIDENT DATA BASE DESCRIPTION
(NRW)

Location	Lane	46 or 50	Date Mo./Day/Yr.	Day	Actual Time Hr./Min./Sec.	Termination Time Hr./Min./Sec.
Ede - OB N. Foster	3	50	080575	T	064020	065900
Eis - OB Paulina	3,4	40	082875	Th	215440	222220
Eis - OB Kostur	1	50	082075	W	101820	103640
Eis - OB Des Plaines Ave	3	50	082075	W	102920	103920
Ken - IB North	1	46	121575	M	104620	104840
Ede - IB Wilson	2	46	122975	M	130720	132100
Ken - IB Nagle	3	50	122975	M	182640	183740
Ken - IB Kimball	2	46	122475	W	145040	145540

APPENDIX B

ON-LINE INCIDENT DETECTION SAMPLE OUTPUT

The sample output is from June 15, 1978. On that day, three algorithms, 7, 14-16, and the Bayesian, were operating between 2:00 and 7:00 p.m.

For every five minutes, congested freeway sections (occupancy greater than 30%) are indicated. Also, when one of the above algorithms detects an incident, a message is printed out indicating the time of detection and location. Termination messages are printed out when the algorithm decides that the incident has terminated.

06-15-78

OB-KENNEDY O'DFN -> ARHTIC MACLE -> HARLEM
 OB RYAN EXP *TYLOR -> ROOS
 OB RYAN LOC 51ST -> 65TH *
 1441 INCIDENT TERMINATED IB EISENHOWER AT V. AUS (DET. NO. 46)
 1444 INCIDENT TERMINATED IB EISENHOWER AT 1ST AV (DET. NO. 40)

1445
 OB-KENNEDY O'DFN -> NORTH MILWAU -> FOSTER
 OB RYAN EXP *TYLOR -> ROOS 55TH -> 65TH
 OB RYAN LOC 55TH -> 65TH *

1450
 OB-KENNEDY O'DFN -> ARHTIC FOSTER -> MACLE
 OB RYAN EXP *TYLOR -> ROOS 55TH -> 59TH
 OB RYAN LOC 55TH -> 65TH *
 IB RYAN EXP ROOS -> TYLOR *

1455
 OB-KENNEDY O'DFN -> NORTH MILWAU -> FOSTER
 OB RYAN EXP *TYLOR -> ROOS
 1455 INCIDENT INDICATED IB EISENHOWER AT WOLF (DET. NO. 32)

1500
 OB RYAN LOC 55TH -> 65TH *
 IB RYAN EXP ROOS -> TYLOR *
 1500
 OB-KENNEDY O'DFN -> NORTH
 OB RYAN EXP *TYLOR -> ROOS
 OB RYAN LOC 50TH -> 65TH *

1500 *****SPAN-COUNTER-TOTALS:

ALG 1 = 992 1275 0 0 0 0 0 0 0 0
 ALG 2 = 989 1214 0 0 0 0 0 0 0 0
 ALG 3 = 964 1251 0 0 0 0 0 0 0 0
 1502 INCIDENT CONFIRMED OB EISENHOWER AT AUSTIN (DET. NO. 14)

1505
 OB-KENNEDY O'DFN -> NORTH
 OB RYAN EXP *TYLOR -> ROOS
 OB RYAN LOC 59TH -> 65TH *
 1510
 OB-KENNEDY O'DFN -> ARHTIC
 OB RYAN EXP *TYLOR -> ROOS 59TH -> 65TH
 OB RYAN LOC 59TH -> 65TH *

1511 INCIDENT TERMINATED IB EISENHOWER AT WOLF (DET. NO. 32)
 1513 INCIDENT INDICATED OB EISENHOWER AT V. MANN (DET. NO. 3)
 1513 INCIDENT INDICATED OB EISENHOWER AT ADD CK (DET. NO. 5)

1515
 OB-KENNEDY O'DFN -> NORTH
 OB RYAN EXP *TYLOR -> ROOS 55TH -> 59TH
 OB RYAN LOC 59TH -> 65TH *

1517 INCIDENT TERMINATED OB EISENHOWER AT ADD CK (DET. NO. 10)
 1518 INCIDENT INDICATED OB EISENHOWER AT DESP R (DET. NO. 10)

1520
 OB-KENNEDY DIVISN -> ARHTIC
 IB I-90 EXT N. NORT -> S. NORT
 OB RYAN EXP 55TH -> 59TH
 OB RYAN LOC 50TH -> 65TH *
 1525

OB-KENNEDY O'DFN -> NORTH
 IB I-90 EXT B. ROY -> I. N. ST
 OB RYAN EXP 51ST -> 59TH
 OB RYAN LOC 55TH -> 65TH *
 1530

OB-KENNEDY O'DFN -> DIVISN
 IB I-90 EXT N. NORT -> I. N. ST

1525 INCIDENT TERMINATED OB EISENHOWER AT H. MANN (DET. NO. 3)

STOCK NO. 33233

0C-15-78

OB IKE HARLEM ->DESP.A
OB RYAN EXP 55TH -> 59TH
OB RYAN LOC 55TH ->65TH *

1535
OB KENNEDY OGDEN ->DIVISI MILWAU ->FOSTER
IB I-90 EXT N.NORT ->1 N.ST
OB STEVENSON CALIF ->KEDZIE
OB RYAN EXP 51ST -> 59TH
OB RYAN LOC 51ST ->65TH *

1540
OB KENNEDY OGDEN ->NORTH
REVERSIBLES ADDISON ->SACRAH
IB I-90 EXT N.NORT ->1 N.ST
OB STEVENSON CALIF -> ATSF
OB RYAN EXP *TYLOR -> ROOS 51ST -> 59TH
OB RYAN LOC 51ST ->65TH *

1541 INCIDENT INDICATED IB EISENHOWER AT 9TH AV (DET. NO. 39)
1543 INCIDENT INDICATED OB EISENHOWER AT ADD CK (DET. NO. 5)

1545
OB KENNEDY OGDEN ->NORTH
IB KENNEDY CHICGO ->OHIO *
IB I-90 EXT FIROY ->N.ST.C
IB IKE 17TH -> 9TH
OB STEVENSON HOYNE ->4300 W
OB RYAN EXP *TYLOR -> ROOS 55TH -> 65TH
OB RYAN LOC 51ST ->65TH *

1548 INCIDENT COMPLETED OB EISENHOWER AT DESP.R. (DET. NO. 10)
1549 INCIDENT INDICATED OB EISENHOWER AT HARLEM (DET. NO. 12)

1550
OB KENNEDY OGDEN ->NORTH
IB KENNEDY DIVISN ->OHIO *
IB I-90 EXT E.YORK ->1 N.ST
OB IKF AUSTIN ->HARLEM
OB STEVENSON HOYNE -> ATSF
OB RYAN EXP *TYLOR -> ROOS 51ST -> 59TH
OB RYAN LOC 55TH ->65TH *

1551 INCIDENT INDICATED IB EISENHOWER AT E.AUS (DET. NO. 17)

1552 ELECTRIC OUT-8 OUT-OF-SERVICE
1552 4 3 0

1555
OB KENNEDY OGDEN ->NORTH
IB KENNEDY NORTH ->OHIO *
IB I-90 EXT F.YORK ->1 N.ST
OB IKF AUSTIN ->HARLEM
IB IKF ADD CK -> 9TH
OB STEVENSON HOYNE ->KEDZIE
OB RYAN EXP *TYLOR -> ROOS 51ST -> 59TH
OB RYAN LOC 45TH ->65TH *

1556 INCIDENT TERMINATED OB EISENHOWER AT ADD CK (DET. NO. 5)
1559 INCIDENT INDICATED OB EISENHOWER AT W.MANN (DET. NO. 3)
1559 INCIDENT TERMINATED OB EISENHOWER AT DESP R (DET. NO. 10)

1600
OB KENNEDY * OHIO ->ARBITIC C/CFO ->MILWAU HARLF ->HARLF
1000***SCALCOUNTER TOTALS:

ALG 1 = 2317 2814 0 0 0 0 0 0 0
ALG 2 = 2273 2704 0 0 0 0 0 0 0
ALG 3 = 2188 2830 0 0 0 0 0 0 0

IB KENNEDY W.CUMB ->1 HAR NORTH ->OHIO *
IB I-90 EXT E.YORK ->S.NORT

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1B-IKE ADD-OK -> OTTI
OR STEVENSON HOYNE -> ATSF
OR RYAN EXP 51ST -> 65TH
OB RYAN LOC 45TH -> 65TH *

1602 INCIDENT TERMINATED OR EISENHOWER AT HARLEA (DET. NO. 12)

1605
OB KENNEDY ODFM -> NORTH FOSTER -> MACK
IB KENNEDY W. CUMB -> CANFIELD DIVISN -> OHIO *
IR I-90 EXT CHURCH -> I N-ST
IB IKE 25TH -> 17TH
OB STEVENSON HOYNE -> KFOZIF
OB RYAN EXP 51ST -> 50TH
OB RYAN LOC 45TH -> 65TH *

1507 2 3 0
1609 4 2 0

1610
OB KENNEDY ODFM -> ARITIG LAIRFN -> MACK
IB KENNEDY W. CUMB -> CANFIELD DIVISN -> OHIO *

1610 INCIDENT INDICATED OR EISENHOWER AT DESP R (DET. NO. 10)

IB I-90 EXT CHURCH -> I N-ST
OB IKE 9ESP A -> 5TH
IB IKE W. MANN -> 17TH
OB STEVENSON KFOZIF -> ATSF
OB RYAN EXP 51ST -> 65TH
OB RYAN LOC 59TH -> 65TH *

1611 INCIDENT CONFIRMED IB EISENHOWER AT 9TH AV (DET. NO. 39)
1612 INCIDENT INDICATED OR EISENHOWER AT 1ST AV (DET. NO. 0)
1613 INCIDENT TERMINATED OB EISENHOWER AT W. MANN (DET. NO. 3)
1614 INCIDENT INDICATED OR EISENHOWER AT KOSTIN (DET. NO. 18)

1615
OB KENNEDY ODFM -> ARITIG HOYNE -> MACK
IB KENNEDY W. CUMB -> CANFIELD NORTH -> OHIO *
IR I-90 EXT CHURCH -> I N-ST
OB IKE 9ESP A -> 1ST
IB IKE W. MANN -> OTTI
OB STEVENSON HOYNE -> KFOZIF
OB RYAN EXP 51ST -> 59TH
OB RYAN LOC 45TH -> 65TH *

1616 INCIDENT INDICATED IB EISENHOWER AT EAST (DET. NO. 45)
1619 INCIDENT INDICATED OR EISENHOWER AT 17TH (DET. NO. 7)
1619 INCIDENT TERMINATED OB EISENHOWER AT DESP R (DET. NO. 10)

1620
OB KENNEDY ODFM -> NORTH MILWAU -> MACK
IB KENNEDY DIVISN -> OHIO *
IR I-90 EXT CHURCH -> I N-ST
OB IKE AUSTIN -> DESP A
OB STEVENSON HOYNE -> ATSF
OB RYAN EXP 51ST -> 65TH
OB RYAN LOC 45TH -> 65TH *

1621 INCIDENT CONFIRMED IB EISENHOWER AT F. AUS (DET. NO. 47)

1622 3 2 0

1625
OB KENNEDY ODFM -> ARITIG MILWAU -> MACK
IB KENNEDY W. CUMB -> CANFIELD DIVISN -> OHIO *
IB I-90 EXT E. YORK -> S. MORT
OB IKE AUSTIN -> DESP A
IB IKE 17TH -> 1ST

1622 INCIDENT TERMINATED OB EISENHOWER AT 17TH (DET. NO. 7)
1623 INCIDENT TERMINATED IB EISENHOWER AT 9TH AV (DET. NO. 39)
1624 INCIDENT INDICATED IB EISENHOWER AT F. MANN (DET. NO. 35)

06-15-78
OB RYAN EXP 45TH -> 59TH
OB RYAN LOC 45TH -> 65TH *
1626 INCIDENT INDICATED OB EISENHOWER AT 25TH (DET. NO. 6)

1629 LINE PRINTER 10 STALL
I 630
OB KENNEDY DIVISION -> APARTIC LAUREN -> NACLE
IB I-90 EXT E. YORK -> 1 N. ST
IB IKF ADP CK -> 1ST

1630 SELECTRIC OUT - 8 OUT OF SERVICE
1630 LINE PRINTER 10 ACTION, CONTINUE-C, DELAY-D, FAIL-F
OB STEVENSON HOYNE -> KFUZIF
OB RYAN EXP 51ST -> 65TH
OB RYAN LOC 51ST -> 65TH *

1631 SELECTRIC INPUT - 1 OUT OF SERVICE
1631 LINE PRINTER 10 ACTION, CONTINUE-C, DELAY-D, FAIL-F
1631 LINE PRINTER - 10 OUT OF SERVICE
1633 INCIDENT TERMINATED IB EISENHOWER AT E. MANN (DET. NO. 35)

1635
OB KENNEDY DIVISION -> NORTH MONTRF -> CICERO FOSTER -> NACLE
IB KENNEDY W. CUB -> CAMFLD
1635 INCIDENT INDICATED IB EISENHOWER AT E. MANN (DET. NO. 35)

1635 2 2 0
IB I-90 EXT E. YORK -> 1 N. ST
IB IKF E. MANN -> 1ST
OB STEVENSON HOYNE -> ATSE
OB RYAN EXP 51ST -> 71ST
OB RYAN LOC ROOT -> 65TH *

1638 INCIDENT TERMINATED IB EISENHOWER AT E. MANN (DET. NO. 35)
1640
OB KENNEDY DIVISION -> NORTH CICERO -> FOSTER
IB KENNEDY W. CUB -> CAMFLD
REVERSBLS *KFLER -> ANDSON
IB I-90 EXT E. YORK -> 1 N. ST
OB IKE HARLEM -> DFSP A
IB IKE ADP CK -> 1ST
OB STEVENSON HOYNE -> 4300 W
OB RYAN EXP 51ST -> 50TH 71ST -> 75TH
OB RYAN LOC ROOT -> 65TH *

1642 INCIDENT CONFIRMED OB EISENHOWER AT 1ST AV (DET. NO. 9)
1644 INCIDENT CONFIRMED OB EISENHOWER AT KOSTIR (DET. NO. 18)
1645
OB KENNEDY OGDEN -> DIVISION MONTRF -> FOSTER
IB KENNEDY W. CUB -> CAMFLD
IB I-90 EXT E. YORK -> 1 N. ST
OB IKE DESP A -> DFSP R 17TH -> 25TH
IB IKE W. MANN -> 9TH

OB STEVENSON WOOD -> 4300 W
OB RYAN EXP 51ST -> 75TH
OB RYAN LOC 53RD -> 65TH *
OB CALUMET 130TH -> 138TH
1647 INCIDENT CONFIRMED IB EISENHOWER AT EAST (DET. NO. 45)

1649 4 2 0
1650
OB KENNEDY DIVISION -> NORTH HILLWAK -> FOSTER

06-15-78

IB KENNEDY 11:00HR ->CAMFIELD CHICAGO ->MONTRE *
R FEVERSIBLES *KELER<->ARLSON
OB I-90 EXT 141 TRI ->N.Y. ST. C GRAND ->ADD.
IB I-90 EXT HIRBY ->S. PORT
OB IKE HARLEM ->DFSP A 25TH ->MONT CK
IB IKE ADD CK -> 1ST
OB STEVENSON 10RD ->KENZIE
OB RYAN EXP 51ST -> 71ST

1651 INCIDENT TERMINATED OB EISENHOWER AT AUSTIN (DET. NO. 14)

OB RYAN LOC ROOT ->65TH *
1651-1-2-0
OB CALUMET 115TH ->138TH

1653 INCIDENT INDICATED IB EISENHOWER AT 1ST AV (OFF. NO. 4C)

1655
OB KENNEDY DIVISION ->NORTH MONTRE ->MAGLE
IB KENNEDY * LOTC ->M. MANN CHICAGO ->PULASK
OB I-90 EXT GRAND ->ADD.
IB I-90 EXT HIRBY ->N.Y. ST
OB IKE DFSP A ->DFSP R
IB IKE 17TH -> 1ST
OB STEVENSON HOYNE ->KROZIF
OB RYAN EXP 51ST -> 71ST
OB RYAN LOC ROOT ->65TH *
OB CALUMET 111TH ->BRL RR

1656 INCIDENT TERMINATED OB EISENHOWER AT 25TH (DET. NO. 6)

IB CALUMET H. DOLT ->BRL RR
1700
OB KENNEDY DIVISION ->MAGLE CHICAGO ->MAGLE
IB KENNEDY * LOTC ->M. MANN H. CLUMB ->CAMFIELD

1700***SCAN COUNTER TOTALS:

ALG 1 = 3522 4518 0 0 0 0 0 0 0 0
ALG 2 = 3483 4340 0 0 0 0 0 0 0 0
ALG 3 = 3590 4418 0 0 0 0 0 0 0 0

OB I-90 EXT E. YORK ->MAGLE
IB I-90 EXT E. YORK ->N.Y. ST
OB IKE HARLEM -> 5TH
IB IKE 25TH -> 1ST
OB STEVENSON WOOD -> ATSF
OB RYAN EXP 51ST -> 65TH

1701 INCIDENT INDICATED IB EISENHOWER AT 9TH AV (DET. NO. 39)

OB RYAN LOC ROOT -> 59TH
OB CALUMET 111TH ->BRL RR

1704 INCIDENT TERMINATED IB EISENHOWER AT 9TH AV (DET. NO. 39)

1705
IB EDENS WILSON ->MONT *
OB KENNEDY DIVISION ->NORTH
OB I-90 EXT LAUREN ->PULASK
IB I-90 EXT E. YORK ->GRAND
IB IKE ADD CK -> 9TH
1705-3-3-0
OB STEVENSON WOOD ->HOYNE
OB RYAN EXP 51ST -> 65TH
OB RYAN LOC ROOT ->65TH *

1706 MIRA OUTPUT -16 OUT OF SERVICE
OB CALUMET 111TH ->BRL RR
1706-3-3-0

1710
IB EDENS WILSON ->MONT *

06-15-78

OB KENNEDY DIVISION -> NORTH CIGERO -> EOSTIER
 IB KENNEDY FOSTER -> PULASKI
 OB I-90 EXT EMOY -> E. YORK -> MALF -> ADD.
 IB I-90 EXT EMOY -> I H. ST
 OB STEVENSON MOYNE -> ATSE
 OB RYAN EXP *TYLOR -> ROOMS 51ST -> 65TH
 OB RYAN LOC *ROO -> 65TH *
 OB CALUMET LIITH -> BLT RR
 1715
 IB EDENS WILSON -> NORTH *
 OB KENNEDY DIVISION -> NORTH MILUAK -> EOSTIER
 IB KENNEDY FOSTER -> PULASKI
 OB I-90 EXT EMOY -> E. YORK E. 83 -> ADD.
 IB I-90 EXT EMOY -> I H. ST
 IB IKF 9TH -> 1ST
 OB STEVENSON CALIF -> 300 W 51ST -> 75TH
 OB RYAN EXP *TYLOR -> ROOMS
 OB RYAN LOC 51ST -> 65TH *
 OB CALUMET LIITH -> BLT RR
 1716 2 2 0

1717 INCIDENT INDICATED IB EISENHOWER AT F. MANN (DET. NO. 35)

1720

IB EDENS WILSON -> NORTH *
 OB KENNEDY DIVISION -> NORTH MILUAK -> FOSTER
 IB KENNEDY FOSTER -> PULASKI
 OB I-90 EXT GRAND -> ADD.
 IB I-90 EXT EMOY -> I H. ST
 IB IKF 17TH -> 9TH
 OB STEVENSON CALIF -> ATSE
 OB RYAN EXP *TYLOR -> ROOMS 51ST -> 71ST
 OB RYAN LOC 51ST -> 65TH *
 OB CALUMET LIITH -> BLT RR
 IB CALUMET N. SIBL -> BLT RR
 1721 1 3 0
 1722 1 3 0

1720 INCIDENT INDICATED IB EISENHOWER AT 9TH AV (DET. NO. 39)

1723

INCIDENT TERMINATED IB EISENHOWER AT 9TH AV (DET. NO. 39)

1726

INCIDENT CONFIRMED IB EISENHOWER AT 1ST AV (DET. NO. 40)

1724 6 2 0

IB EDENS ELSTON -> NORTH *
 OB KENNEDY DIVISION -> NORTH
 IB KENNEDY MAGLE -> PULASKI
 OB I-90 EXT GRAND -> ADD.
 IB I-90 EXT EMOY -> S. NORTH
 IB IKF 25TH -> 1ST
 OB STEVENSON CALIF -> KENZIE 51ST -> 59TH
 OB RYAN EXP *TYLOR -> ROOMS
 OB RYAN LOC 51ST -> 65TH *
 OB CALUMET LIITH -> BLT RR
 IB CALUMET PULASKI -> STIRLEY
 1728 4 3 0
 1729 4 2 0

1726 INCIDENT TERMINATED IB EISENHOWER AT E. MANN (DET. NO. 35)

1730

IB EDENS ELSTON -> NORTH *
 OB KENNEDY DIVISION -> NORTH
 IB KENNEDY SAYRE -> PULASKI
 OB I-90 EXT E. YORK -> MALF

1730 INCIDENT INDICATED OB EISENHOWER AT 17TH (DET. NO. 7)

06-15-78

IR I-90-EXT EMPLOY ->S. MORT
 IB IKE ADD CK -> 1ST
 OB STEVENSON CALIF -> ATSF
 OB RYAN EXP 51ST -> 71ST
 1731-1-2-0
 OB RYAN LOC 51ST ->65TH *
 OB CALUMET 111TH ->BLT RR
 IB CALUMET PULASK ->STIRLEY
 1732-5-2-0

1733 INCIDENT INDICATED OR EISENHOWER AT ADD CK (DET. NO. 5)
 1733 INCIDENT-TERMINATED-OB-EISENHOWER-AT-17TH (DET. NO. 7)

1735
 IB EDENS WILSON ->PHIT *
 IB KENNEDY CANFLO ->PULASK
 OB I-90-EXT GRAND ->E-83

1735 INCIDENT INDICATED IB EISENHOWER AT 25TH (DET. NO. 37)

IB I-90-EXT EMPLOY ->1 N. ST
 OB STEVENSON PEN RR ->KEDZIF
 OB RYAN-EXP 51ST ->65TH
 OB RYAN LOC 51ST ->65TH *
 OB CALUMET N. STON ->BLT RR
 IB CALUMET PEN RR ->PULASK

1740
 IB EDENS WILSON ->PHIT *
 IB KENNEDY W. HAR ->PULASK
 OB I-90-EXT WDALE ->WELL
 1740 INCIDENT INDICATED-IB-EISENHOWER-AT-E. HANN (DET. NO. 35)

IB I-90-EXT N. MORT ->1 N. ST
 IB IKE E. HANN ->ADD CK
 OB STEVENSON CALIF ->KEDZIF
 OB RYAN-EXP TYLOR ->ROOS 55TH ->65TH
 OB RYAN LOC 55TH ->65TH *
 OB CALUMET 111TH ->BLT RR
 IB CALUMET PEN RR ->PULASK

1741 INCIDENT INDICATED-OB-EISENHOWER AT 5TH AV (DET. NO. 8)
 1742 INCIDENT TERMINATED IB EISENHOWER AT 25TH (DET. NO. 37)
 1744 INCIDENT-TERMINATED-OB-EISENHOWER-AT-ADD-CK (DET. NO. 5)

1745
 IB EDENS WILSON ->PHIT *
 OB KENNEDY NORTH ->ARITTS
 IB KENNEDY W. CURB ->SAYRE FOSTER ->CICERO
 OB I-90-EXT GRAND ->HILL
 IB I-90-EXT N. MORT ->1 N. ST
 OB STEVENSON KEDZIE -> ATSF
 OB RYAN-EXP 51ST ->50TH
 OB RYAN LOC 51ST ->65TH *
 OB CALUMET 111TH ->BLT RR
 IB CALUMET PEN RR ->PULASK S. DOLT ->BLT RR

1750
 IB EDENS WILSON ->PHIT *
 OB KENNEDY NORTH ->ARITTS
 IB KENNEDY W. CURB ->SAYRE FOSTER ->CICERO
 OB I-90-EXT GRAND ->HILL
 IB I-90-EXT N. MORT ->1 N. ST
 OB RYAN-EXP 51ST ->65TH
 OB RYAN LOC 51ST ->65TH *
 OB CALUMET 111TH ->BLT RR
 IB CALUMET N. 150 ->PULASK

1752 INCIDENT-TERMINATED-IB-EISENHOWER-AT-F. HANN (DET. NO. 35)

06-15-78

1755

IR KENNEDY FOSTER ->CICERO
 OR I-90 EXT GRAND ->MALE
 IR I-90 EXT N.MORT ->S.MORT
 OR RYAN EXP 55TH -> 65TH
 OR RYAN LOC 55TH ->65TH *
 OR CALUMET 115TH ->133RD
 IR CALUMET N.159 ->PHE RR N.SIAL ->138TH
 1800

IR KENNEDY W.CUB ->CAIFLD SAYRE ->WACLE
 1800

MULAN ->CICERO
 1800

ALG 1 = 4774 5810
 ALG 2 = 4721 5747
 ALG 3 = 4653 5976

OR I-90 EXT GRAND ->MALE
 IR I-90 EXT N.MORT ->1 N.ST
 OR RYAN EXP 55TH -> 59TH
 OR RYAN LOC 59TH ->65TH *
 OR CALUMET 119TH ->S.130
 IR CALUMET N.159 ->138TH
 1805

IR KENNEDY W.MAP ->SAYRE
 IR I-90 EXT N.MORT ->S.MORT
 OR CALUMET 124TH ->S.130
 IR CALUMET SIBLEY ->138TH
 1810 2 3 0

1810
 OR KENNEDY NORTH ->MATTIG
 IR KENNEDY W.CUB ->CAIFLD
 OR I-90 EXT WMALE ->ADD.
 OR CALUMET 130TH ->S.130
 IR CALUMET S.DOLT ->138TH
 1811 6 2 0

1812 INCIDENT CONFIRMED OR EISENHOWER AT 5TH AV (DET. NO. 8)
 1813 INCIDENT TERMINATED OR EISENHOWER AT 1ST AV (DET. NO. 9)

1815
 IR I-90 EXT N.MORT ->S.MORT
 OR RYAN EXP 65TH -> 71ST
 OR CALUMET S.130 ->133RD
 IR CALUMET N.DOLT ->138TH

1816 INCIDENT INDICATED OR EISENHOWER AT DESP R. (DET. NO. 1D)
 1819 INCIDENT TERMINATED OR EISENHOWER AT 1ST AV (DET. NO. 40)

1820
 OR KENNEDY NORTH ->MATTIG
 IR I-90 EXT N.MORT ->S.MORT
 1825
 OR KENNEDY NORTH ->MATTIG
 IR KENNEDY W.CUB ->CAIFLD
 IR I-90 EXT N.MORT ->S.MORT
 OR RYAN EXP *TYLOR -> ROOS

1830
 OR KENNEDY NORTH ->MATTIG
 OR RYAN EXP *TYLOR -> ROOS
 1835
 OR RYAN EXP *TYLOR -> ROOS
 1840
 OR RYAN EXP *TYLOR -> ROOS
 1845
 OR RYAN EXP *TYLOR -> ROOS

1846 INCIDENT CONFIRMED OR EISENHOWER AT DESP R (DET. NO. 1C)

06-15-78

1850 OB RYAN EXP *TYLOR -> ROOS

1855 OB RYAN EXP *TYLOR -> ROOS

1855 INCIDENT INDICATED IB EISENHOWER AT 1101E (DET. NO. 32)
185R INCIDENT TERMINATED IB EISENHOWER AT 1101F (DET. NO. 32)

1900 OB KENNEDY NORTH -> ARHTIG
OB RYAN EXP *TYLOR -> ROOS

1900**KSCAN COUNTS TOTALS:

ALC 1 = 6889 7321 0 0 0 0 0 0 0 0
ALC 2 = 5972 7249 0 0 0 0 0 0 0 0
ALC 3 = 5923 7560 0 0 0 0 0 0 0 0

1905 OB RYAN EXP *TYLOR -> ROOS

1910 OB RYAN EXP *TYLOR -> ROOS

1912 INCIDENT TERMINATED IB EISENHOWER AT EAST (DET. NO. 45)

1915 OB KENNEDY DIVISN -> NORTH

1920 OB RYAN EXP *TYLOR -> ROOS

1925 OB KENNEDY DIVISN -> ARHTIG

1930 OB RYAN EXP *TYLOR -> ROOS

1935 OB KENNEDY DIVISN -> ARHTIG

1953 INCIDENT INDICATED IB EISENHOWER AT 1101F (DET. NO. 32)
1956 INCIDENT TERMINATED IB EISENHOWER AT 5TH AV (DET. NO. 3)

2000 ILLINOIS DEPARTMENT OF TRANSPORTATION

2100 ILLINOIS DEPARTMENT OF TRANSPORTATION

2200 ILLINOIS DEPARTMENT OF TRANSPORTATION

2225 OB KENNEDY NORTH -> ARHTIG

2230 OB KENNEDY NORTH -> ARHTIG

2235 OB KENNEDY DIVISN -> ARHTIG

2240 OB KENNEDY DIVISN -> ARHTIG

2245 OB RYAN EXP 55TH -> 50TH

2250 OB KENNEDY DIVISN -> ARHTIG

2255 OB KENNEDY DIVISN -> NORTH

2300 OB KENNEDY DIVISN -> NORTH

2305 OB KENNEDY DIVISN -> NORTH

2315 OB KENNEDY NORTH -> ARHTIG

4000 ILLINOIS DEPARTMENT OF TRANSPORTATION

4100 ILLINOIS DEPARTMENT OF TRANSPORTATION

4200 ILLINOIS DEPARTMENT OF TRANSPORTATION

4300 ILLINOIS DEPARTMENT OF TRANSPORTATION

4400 ILLINOIS DEPARTMENT OF TRANSPORTATION

4500 ILLINOIS DEPARTMENT OF TRANSPORTATION