Improved Freeway Incident Detection Using Fuzzy Set Theory

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Freeway incidents often occur unexpectedly and cause undesirable traffic congestion, mobility loss, and environmental pollution even where computerized traffic management systems are installed and in operation. Automatic incident detection, being one of the primary functions of computerized freeway traffic management systems, must be able to detect all freeway incidents as soon as possible with minimum false alarms.

In a study that evaluated the applications of fuzzy set theory to improve existing incident detection algorithms, the potential system performance was compared with that of conventional systems using real-world volume and occupancy data that were collected earlier. The potential benefits and needed improvements in the existing incident detection algorithms to take advantage of the promising fuzzy set methodology are summarized.

Freeway incidents often occur unexpectedly and cause undesirable traffic congestion, mobility loss, and environmental pollution even where computerized traffic management systems are installed and currently in operation. Automatic incident detection (AID) has been used increasingly to improve urban freeway operations and reduce the operational impact of incidents. Being a primary function of computerized freeway traffic management systems (FTMS), the ideal incident detection systems or detection algorithms must be able to detect freeway incidents quickly with minimum false alarms (*1–4*). The operations require the efficient use of available information for reliable incident detection during congested operations and incident conditions.

The commonly used comparative or California-type algorithm requires the continuous evaluation of traffic operational characteristics collected from consecutive detector stations. To develop effective freeway incident management, the algorithms use the principle that an incident will likely increase the occupancy upstream of the incident and decrease occupancy downstream of the incident. Although lane volume and occupancy are the main measures, other algorithms also use measured speeds to distinguish incidents and daily congestion. Most algorithms have been developed to detect freeway incidents through traffic information collected from loop detectors. However, three operational problems often occur when implementing an AID system. These problems include the understanding of the relative operational effectiveness, threshold parameter selection, and better interpretation of the algorithms.

During operations, most conventional incident detection algorithms use a series of decision-making analyses against the predefined thresholds to detect any freeway status changes because these status descriptions often are used with uncertainty measures. Using the "crisp thresholds" cannot reliably distinguish among true and false incidents. In addition, the loss of information also may cause errors, fail to detect incidents, or generate false alarms. Fuzzy logic, which provides approximate reasoning instead of exact reasoning, is an alternative that may improve the reliability of incident detection systems (*5,6*).

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STUDY OBJECTIVES

This study examined a feasible software design to improve existing freeway incident detection algorithms through application of fuzzy set theory. The study used real-world traffic volume and occupancy data to improve existing incident detection algorithms. Finally, system performance is measured against conventional systems to enhance existing automatic freeway incident detection algorithms.

This paper investigated the potential application of fuzzy set theory to improve California Incident Detection Algorithm 8. Through the freeway volume and occupancy data collected, three feasible approaches were examined. Other possible enhancements that can be used to improve the existing automatic incident detection algorithms in most computerized FTMs also are summarized.

STUDY BACKGROUND

Most existing incident detection algorithms fall into four categories: pattern recognition approach, statistical analysis approach, catastrophe theory approach, and artificial intelligence approach. Among them, neural network and fuzzy set theory has demonstrated success in representing complicated knowledge and compensating for the difficulty encountered in the conventional decision approach. Experiments, performed initially by the Texas Transportation Institute (TTI), indicated that these two approaches are technologically feasible, especially during insufficient detector information or loss of part of data communication. The purpose of this study is to demonstrate operational performance of fuzzy logic against conventional incident detection algorithms using historical detector data observed from freeway control centers.

The following sections discuss the background of freeway incident detection algorithms, fuzzy set theory, and fuzzy applications. The development tools used in the proposed approaches are described briefly.

Incident Detection Algorithms

Two different incident detection algorithms are commonly used by monitoring data from one or a series of detector stations. The first or the most commonly used incident detection algorithm is the comparative or California-type algorithm (*4*). Ten comparative incident detection algorithms were developed by FHWA. Among these, Algorithm 8 is recommended for use during high-volume conditions. The algorithm can continuously assess freeway incident potential by analyzing volume and occupancy data from paired vehicular detectors at each freeway section.

The second approach uses incident detection triggered by the condition changes as observed at a single detector station (*7,8*). Although not being free from false alarms, the second or point-detection algorithm, such as the McMaster algorithm, was developed. This algorithm does not have to rely on the continuous measures from paired detectors but requires better understanding of freeway operating characteristics at each detector station. As these systems move into daily usage, evaluations of these incident detection elements are essential to improving the operational effectiveness of the traffic management system.

Both the comparative and point-based detection techniques, such as the California and McMaster algorithms, rely on several predefined thresholds to adjust the relative sensitivity for detecting freeway status changes. Because these status descriptors often are associated with uncertainty measures, the use of crisp thresholds cannot clearly distinguish operations among true incidents, congested operations, and impacts from previous incidents. The selection of improper threshold values may result in undesirable detection errors, such as generating high false alarms or failing to detect potential incidents. Fuzzy set theory provides a feasible alternative scheme that may improve the reliability of incident detection systems.

As shown in Figure 1, FHWA Incident Detection Algorithm 8 can be regarded as a series of binary decision trees (*9*). Nine "incident conditions" or "operating states" can be detected by Algorithm 8. The algorithm takes input occupancy data and calculates the following traffic measures: spatial difference in occupancies (OCCDF), relative temporal difference in downstream occupancy (DOCCTD), relative spatial difference in occupancies (OCCRDF), and downstream occupancy (DOCC). The system-operating states can be determined from the decision tree analysis.

Fuzzy Applications

Fuzzy set theory has been applied successfully to many fields, including structural engineering, damage evaluation, manufacturing, medical diagnoses, meteorology, and ramp control (*10–15*). In the crisp system, when the observation is imprecise, noise prone, or near the decision boundaries, the result is easily biased or mistaken. The fuzzy approach allows users to approximate reasoning by specifying boundaries in decision-making. Fuzzy logic provides the approximate reasoning that can improve classical expert system designs using fuzzy techniques by specifying the membership func-

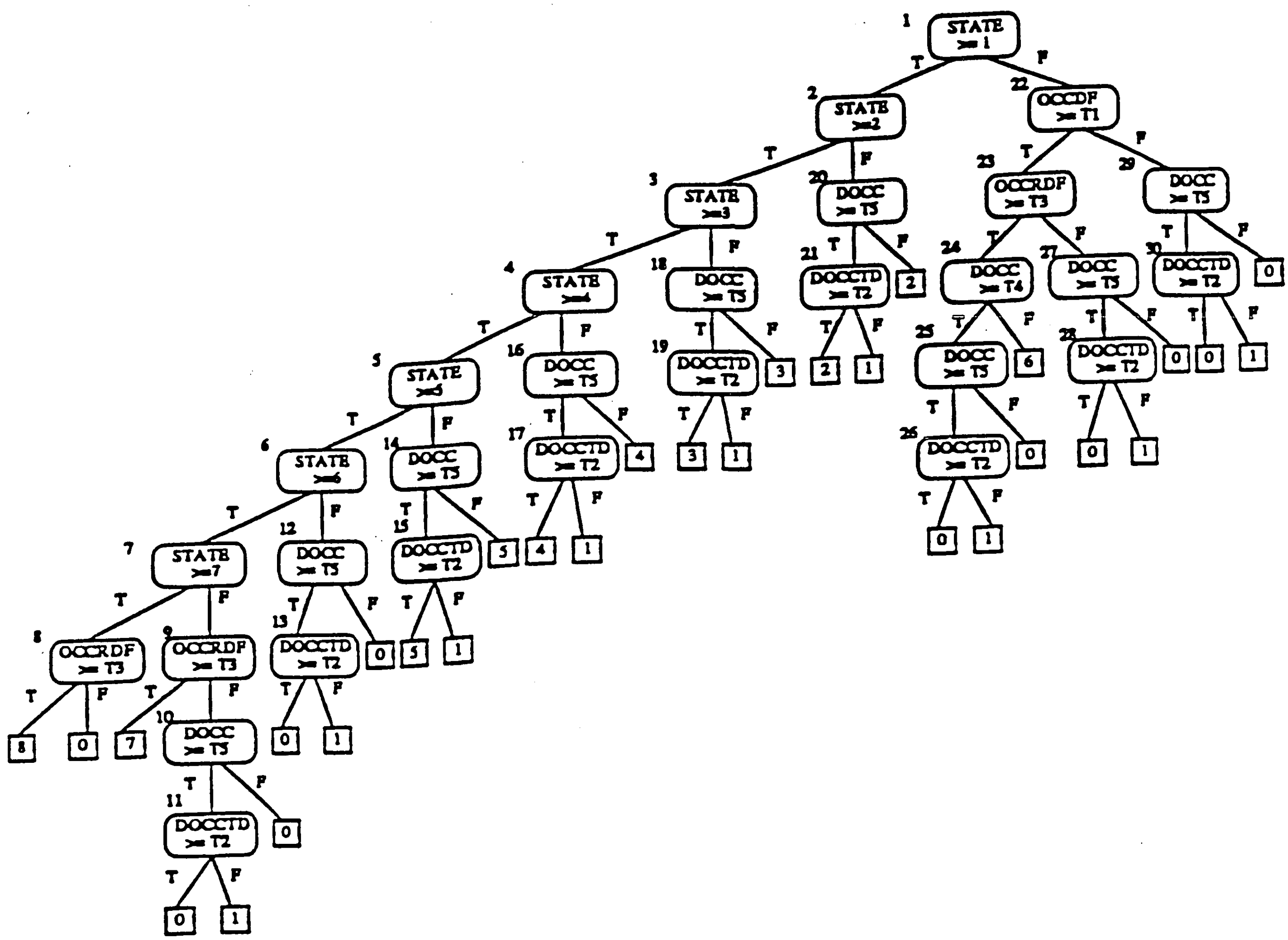

FIGURE 1 Decision tree of Algorithm 8.

tions to fine tune the system by the users. Therefore, when inputs fall near the fuzzy boundaries, fuzzy values show the significance of the inputs that can better tolerate imprecision and provide reliable results.

Fuzzy utilities are programs built with fuzzy logic. Fuzzy approach is an approach to develop "fuzzy expert systems" by combining the fuzzy utilities with existing functions of "crisp expert systems." During inferences, the fuzzy-logic–based fuzzy utilities use the membership functions to represent the likelihood of input values. The range of a membership function falls between 0 and 1, which represent the check boundaries. The membership functions can be modified when the fuzzy expert system is applied to a different location or jurisdiction to screen out the least possible inputs from the preconditions. Once the facts match the preconditions and fuzzy values are greater than the threshold, the postconditions will be propagated into the following stages.

To explore how fuzzy logic can be used to improve California Incident Algorithm 8, two different fuzzy logics are used. The first method uses commercial fuzzy expert system building tools. The other approach embeds the fuzzy utilities into crisp expert system building tools. The following section describes the development tools used to implement these two fuzzy inference systems.

Development Tools

Fuzzy expert system building tools provide built-in fuzzy features and operations so that users need not expend extra effort in developing system operational features. On the other hand, developing fuzzy systems by embedding fuzzy utilities into expert system building tools provides more flexibility in the software design that can be integrated with conventional programs, once the design can be finalized.

In this study, the first approach applies C-Language Integrated Production System (CLIPS) functions to implement fuzzy logic with Algorithm 8. The other two approaches use a fuzzy expert system building tool (FIDE or fuzzy inference development environment) with two different heuristic rules and membership functions, based on realistic freeway traffic measures, to improve the performance of the existing algorithm.

CLIPS System

The CLIPS system is a complete environment for developing expert systems, that is, programs that are specifically intended to model human expertise or knowledge (*16,17*). Designed originally by the NASA Johnson Space Flight Center, CLIPS is designed to allow artificial intelligence research, development, and delivery on conventional computers. CLIPS provides a cohesive tool for handling a wide variety of knowledge with support for three different programming paradigms—rule-based, object-oriented, and procedural paradigms.

The CLIPS system uses a "forward chaining rule language" that is based on the Rete algorithm. The term production system is an acronym of the rule-based programming paradigm. These languages include the fact lists, current state of the "world," if-then knowledge rules, and inference engine. Rule-based programming allows knowledge to be represented as heuristic, or "rule-of-thumb" that specifies a set of actions to be performed for a given situation. This object-oriented programming scheme allows complex systems to be modeled as modular components that can be easily reused to model other systems or create new components.

The procedural programming used in CLIPS 5.1 allows CLIPS to represent a knowledge base in ways similar to those allowed in languages such as C, Pascal, Ada, and LISP. Using CLIPS, one can develop expert system software using either rule-based programming, object-oriented programming, procedural programming, or combinations of the three approaches.

FIDE System

FIDE provides a user-friendly working environment for users to develop fuzzy applications (*18*). At first, the users need to prepare fuzzy sets and fuzzy rules. Several descriptive words can be used to modify the system input. For example, the users may use adjectives such as hot, warm, or cold to represent a variable temperature. These adjectives or labels can be used to associate with a membership function in the fuzzy subset. Finally, fuzzy rules can be constructed on the basis of the system analysis results.

After preparing the needed fuzzy sets and fuzzy rules, FIDE can be used for fuzzy inference (*19*). The input values are fuzzified according to the membership functions of labels. The fuzzified values can be used to refine fuzzy rule evaluation. After the system evaluation is completed, the results are defuzzified. To provide user interface capability, various equations can be further added to provide various degrees of defuzzification in the system interference analysis.

SYSTEM DESIGN APPROACH

Initial experiments, performed by TTI and others, indicated that the advanced techniques can be used to improve incident detection. These techniques include data-smoothing techniques; neural networks and fuzzy set theory are technologically feasible. Many approaches suggested that advanced techniques can improve system operations using historical detector information from preobserved freeway incidents.

The main operational advantage of fuzzy incident detection systems is to eliminate the sharp decision boundaries caused by the predefined crisp thresholds. The systems can also provide approximate reasoning to consider the uncertainty characteristics of incident detection. The proposed development, as discussed, can lead to the possible development scheme for providing the automatic training of decision thresholds.

Study Variables

The California algorithm and its variations detected an incident by determining whether the following three criteria are met:

1. The absolute difference between upstream and downstream occupancy level exceeds an established threshold value;
2. The relative difference between upstream and downstream occupancy levels, with respect to the observation from upstream detector stations, exceeds a second threshold value; and
3. The current downstream occupancy level is significantly different from the occupancy level recorded downstream 2 min before the current system reading.

As shown in Table 1, the analysis results or operating state values will be mapped to nine corresponding operating states to record the intermediate decision-making points and state of the potential incidents. The algorithm uses two basic analyses, including simple features and time series analysis. The simple feature measures site characteristics, such as occupancy and volume on the incident occurrence. The time series features, based on data consistency analysis, detect any temporal discontinuity in occupancy and volume.

Variations of this basic incident detection algorithm were further developed to distinguish incidents from normal bottleneck congestion, previous incident compression shock wave, and random traffic fluctuation by analyzing volume and occupancy from paired detectors.

Development Process

As shown in Figure 2, each fuzzy system can be divided further into three analysis stages, such as fuzzification, fuzzy inference, and defuzzification. In addition to the basic input variables, the current incident condition can be used as an input for the next interval in the fuzzy system.

Fuzzification

The fuzzification part of the fuzzy system is a mapping from the crisp inputs into fuzzy subsets. The fuzzier decides the corresponding degrees of membership functions from the crisp inputs. The resulting fuzzy values are then fed into the fuzzy inference engine.

Fuzzy Inference

The inference compositional rule is mostly adopted in the fuzzy inference (*20*). The fuzzy rule base contains a set of IF-THEN fuzzy rules. The output is obtained from the data input and fuzzy relation. The MAX-MIN operator is used.

Defuzzification

The defuzzification process generates crisp outputs from the fuzzy results. Output membership functions may be discrete or continuous. The weighted average defuzzification is mostly used for discrete membership functions. The commonly used continuous defuzzification strategies are centroid of area and mean of maximum.

Alternative Approaches

The basic idea behind development of fuzzy incident detection systems is to eliminate the sharp boundaries set by the predefined thresholds often needed in the decision-making process. In the fuzzy approaches, the thresholds are defined as fuzzy sets instead of crisp values. The decision tree can then be replaced by fuzzy rules to represent the decision-making process.

Three approaches are proposed for applying fuzzy logic to Incident Detection Algorithm 8. The first approach embeds fuzzy utilities into CLIPS. Approaches 2 and 3 use the fuzzy expert system building tool, FIDE, to develop the systems.

Approach 1

The first fuzzy system approach is developed by embedding fuzzy utilities into the CLIPS system. The original decision tree of Algorithm 8 is used in the inference process along with the MAX-MIN operations. The input variables are compared with fuzzified threshold values in each node of the decision tree. The output is the state with the highest fuzzy value.

Approach 2

The second approach uses the fuzzy expert system building tool, FIDE, to develop the system. Linguistic terms are defined for input variables and operating states. One fuzzy rule is created for each path of the decision tree of Algorithm 8. The weighted average defuzzification is recommended for generating crisp outputs for the discrete membership functions of states.

Approach 3

The third approach uses basically the same structure as that defined in Approach 2. However, simplified fuzzy rules are used to represent the decision-making functions used in Approach 3. Therefore, the

TABLE 1 Operating States of Incident Detection

NO	INCIDENT DETECTION OPERATING STATE	
	STATE	MESSAGE
1	0	INCIDENT-FREE
2	1	COMPRESSION WAVE DOWNSTREAM IN THIS INTERVAL
3	2	COMPRESSION WAVE DOWNSTREAM 2 INTERVALS AGO
4	3	COMPRESSION WAVE DOWNSTREAM 3 INTERVALS AGO
5	4	COMPRESSION WAVE DOWNSTREAM 4 INTERVALS AGO
6	5	COMPRESSION WAVE DOWNSTREAM 5 INTERVALS AGO
7	6	TENTATIVE INCIDENT
8	7	INCIDENT CONFIRMED
9	8	INCIDENT CONTINUING

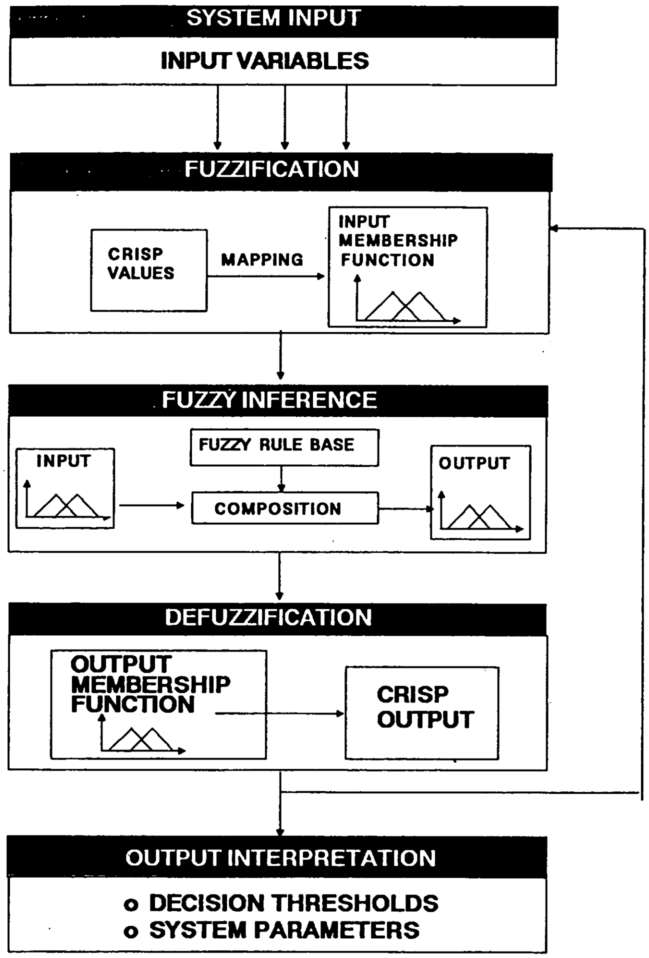

FIGURE 2 System development process.

total number of decision rules can be significantly decreased because one fuzzy rule can represent a group of paths of the decision tree.

Continuous membership functions are defined for all the operating states to reflect the different degrees of incident conditions. The left-most maximum defuzzification is used in this formulation. Figure 3 describes the exact membership functions as used in Approach 3.

SYSTEM EVALUATION

This section describes the results of the proposed approaches, evaluates the operational performance of the fuzzy systems, and summarizes the further development directions.

System Comparisons

Experimental Approaches 1 through 3 were implemented and compared with the original Algorithm 8. As shown in Figure 4, each approach proposes different methods of organizing the main components of the fuzzy systems. Approaches 2 and 3 fuzzify the input values before the fuzzy inference, whereas Approach 1 compares input variables with fuzzified thresholds during the inference process.

Because the fuzzy utilities are not provided in CLIPS, Approach 1 uses more primitive fuzzification and defuzzification processes than Approaches 2 and 3. However, the fuzzy system of Approach 1 has more potential for extending with automatic system learning abilities that can be integrated with conventional system software in the future.

Performance Evaluation

Three types of measures of effectiveness (MOEs) are often used to evaluate the automatic incident detection systems. These measures usually include the following (*21*):

1. Fraction of incidents detected,
2. Fraction of false alarms, and
3. Time to detect.

To illustrate the feasibility of the proposed approaches, several sets of occupancy data are used to test the experimental systems (*9*).

Figure 5 illustrates one example that summarized the comparison of the evaluation results with a known incident occurring at Time 11. All systems detect the incident at Time 13. The bottom half of the graph indicates the results of a set of incident-free data in which all the outputs with state Values 7 and 8 are considered as false alarms.

From this example, it was observed that all the fuzzy systems produced better results than were produced in the original Algorithm 8. The total number of false alarms is obviously reduced and the time to detect remains basically the same as that in Algorithm 8. Applying fuzzy logic to the conventional incident detection algorithm should be a feasible and practical development approach that can improve the accuracy of incident detection.

Approach Evaluation

Because of the development process required, the production rules used in the fuzzy systems can be represented in the form of plain English. As shown in Figure 6, the fuzzy approaches are much easier to understand than the original algorithm.

On the other hand, the binary decision tree of Algorithm 8 takes more time to trace, is difficult to debug, and is hard to understand. The fuzzy systems are also easier to implement initially and provide a tool that allows the user to improve the definition of a specific decision-making process that can be used in the future to maintain the workable decision thresholds.

Further Development

Two challenges still remain for the effective development of an automatic incident detection algorithm based on fuzzy set logics. At first, the performance of both nonfuzzy and fuzzy approaches depends heavily on how to generate and develop suitable thresholds, that is, membership functions in the fuzzy systems. Defining and fine tuning the membership functions in the fuzzy systems are as difficult as determining the right thresholds to be used in the original algorithm. However, if the membership functions can be systematically tuned through an automated procedure, the fuzzy systems can be developed as an effective tool to find the best threshold values (*22*).

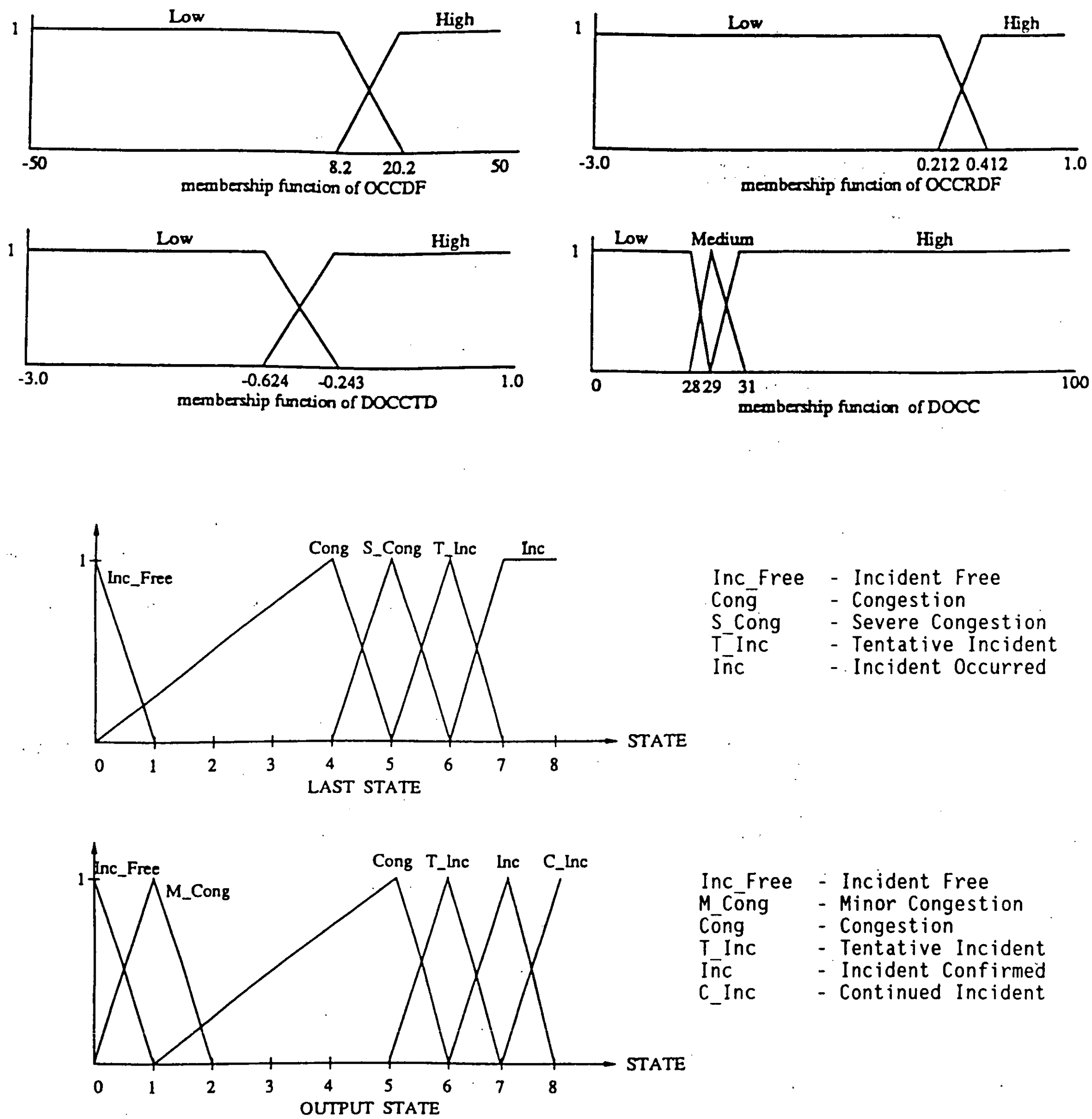

FIGURE 3 Input variable and state function.

Because most commercial fuzzy expert system building tools allow only fixed sets of membership functions and fuzzy rules, it would be difficult to include learning ability in Approaches 2 and 3. Therefore, Approach 1 can be used as the basis for enhancing freeway incident detection systems with learning ability, whereas Approaches 2 and 3 provide insights for understanding fuzzy utilities and validating the test evaluation results. Figure 7 is proposed as one design that can allow for automatic thresholds training in a computerized FTMS. The system learning function may include a meta rule base and a computational unit to automatically learn the membership functions and interface within the fuzzy system.

The second challenge is to devise a performance analysis that can distinguish performance among various fuzzy systems because most MOEs were developed initially to evaluate end states from conventional algorithms. Furthermore, instead of being cut off after each incident decision, the outputs from the previous fuzzy system decision-making state are further aggregated. For instance, during this evaluation, it was found that three different fuzzy systems under evaluation have almost the same detection rates and times to detect, and close false alarm rates. Without a specific evaluation of the intermediate state detection, the currently used MOEs cannot effectively reflect and evaluate the detection of intermediate states. Therefore, a composite evaluation index should be developed for evaluating different fuzzy system designs.

CONCLUSIONS AND RECOMMENDATIONS

AID, based on the real-time detector measurements from the computerized FTMS, are increasingly used to reduce the impacts of unexpected incidents. The successful operations can minimize undesirable congestion and regional mobility loss and provide necessary motorist information. The operations of the overall surveillance,

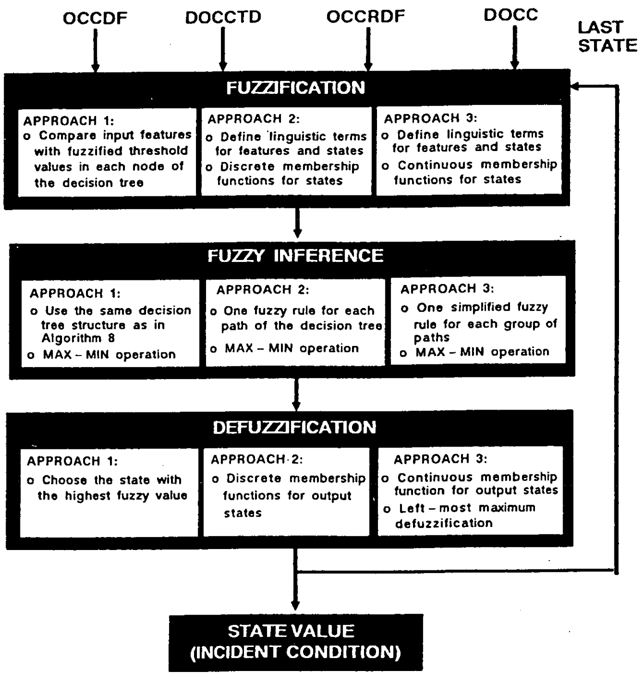

FIGURE 4 Comparison of three approaches.

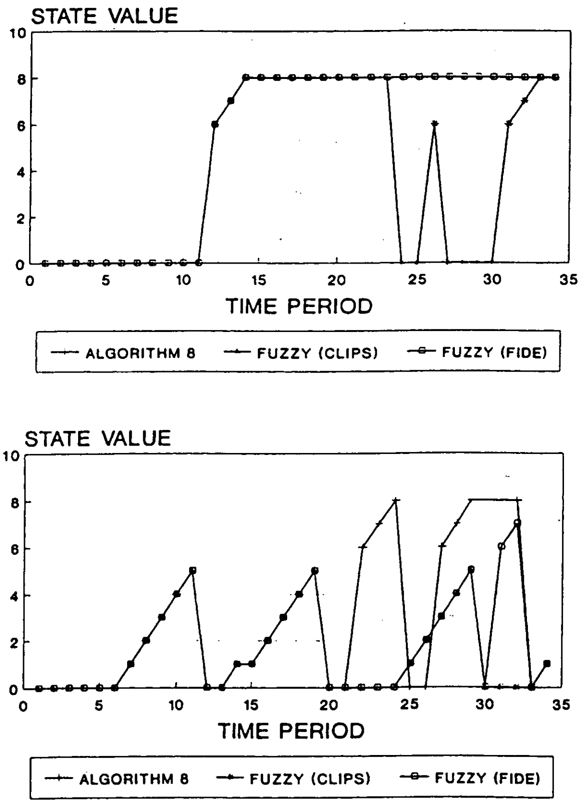

FIGURE 5 Incident test results. Results of fuzzy and nonfuzzy systems: *top*, incidents occurred at Time 11, *bottom*, incident-free data.

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if last_s is Inc and OCCRDF is High then state is C_Inc;
if last_s is Inc and OCCRDF is Low  then state is Inc_Free;
if last_s is T_Inc and OCCRDF is High then state is Inc;
if last_s is T_Inc and OCCRDF is Low  and DOCC is High and
    DOCCTD is High then state is Inc_Free;
if last_s is T_Inc and OCCRDF is Low  and DOCC is High and
    DOCCTD is Low  then state is M_Cong;
if last_s is T_Inc and OCCRDF is Low  and DOCC is notHigh
    then state is Inc_Free;
if last_s is S_Cong and DOCC is High and DOCCTD is High then
    state is Inc_Free;
if last_s is S_Cong and DOCC is notHigh then state is Inc_Free;
if last_s is Cong and DOCC is High and DOCCTD is High then
    state is Cong;
if last_s is Cong and DOCC is notHigh then state is Cong;
if last_s is Inc_Free and OCCDF is High and OCCRDF is High and
    DOCC is Medium then state is Inc_Free;
if last_s is Inc_Free and OCCDF is High and OCCRDF is High and
    DOCC is Low    then state is T_Inc;
if last_s is Inc_Free and OCCDF is High and OCCRDF is Low  and
    DOCC is notHigh then state is Inc_Free;
if last_s is Inc_Free and OCCDF is Low  and DOCC is notHigh
    then state is Inc_Free;
if last_s is Inc_Free and DOCC is High and DOCCTD is High then
    state is Inc_Free;
if last_s is notInc and DOCC is High
    and DOCCTD is Low then state is M_Cong;
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FIGURE 6 Example of linguistic rules.

communications, and control system, however, relies on the accurate and effective usage of incident detection algorithms.

Conclusions

This study explores the use of fuzzy logic to improve the operations of California Incident Detection Algorithm 8. Three design approaches were investigated and found to be equal or superior in performance to the conventional systems for effective freeway management. Several issues still remain for the practical development of automatic incident detection techniques, including the following:

1. Evaluation of the operational effectiveness of existing incident detection algorithm(s) in the field;
2. Assistance in developing users' guidelines to provide the suitable operator interface and settings during different conditions; and
3. Recommendations on how to integrate alternative data sources and improve existing automatic incident detection system design.

Recommendations

The fuzzy rules represented by the linguistic terms in fuzzy set systems are much easier to understand and debug than the decision tree commonly used in the nonfuzzy conventional approach. Fuzzy systems are also easier to maintain and adjust to various traffic control environments. Because different operating states can be used to represent degrees of severity of the freeway incidents, fuzzy rules can be grouped to simplify the operating states with similar behavior in

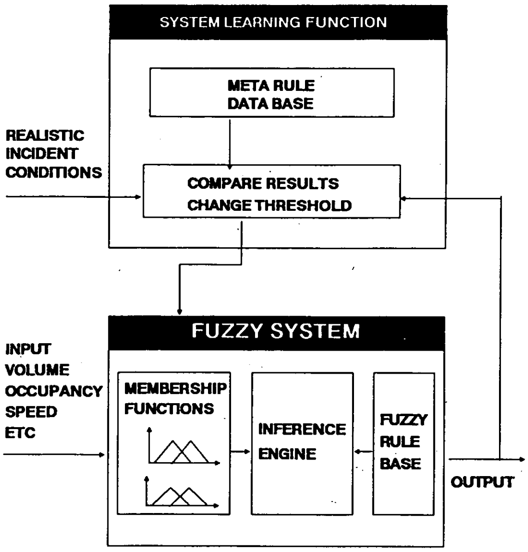

FIGURE 7 Automatic process to train thresholds.

the decision tree analysis. These simplified rules can further improve future operational efficiency and maintenance of fuzzy systems.

However, the performance of incident detection systems depends on how to generate suitable "threshold values" or "membership functions" in the fuzzy systems. Two problems still exist with the uses of fuzzy reasoning, including the lack of methods to determine proper thresholds and lack of automatic learning functions or adaptability in the algorithm (*22*). A fuzzy incident detection system design with automatic learning design can greatly improve the performance of an incident detection system. In addition, the conventional MOEs are not sufficient to evaluate among different fuzzy systems. A composite index is needed to improve the incident detection evaluation during intermediate states. Furthermore, the index can be used to reflect the degree of information usage and to measure the quality of information received for further system improvements.

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