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퍼지이론을 이용한 유고감지 알고리즘

시정개발연구원
이 시 복

ABSTRACT

This paper documents the development of a fuzzy logic based incident detection model for urban diamond interchanges. Research in incident detection for intersections and arterials is at a very initial stage. Existing algorithms are still far from being robust in dealing with the difficulties related with data availability and the multi-dimensional nature of the incident detection problem. The purpose of this study is to develop a new real-time incident detection model for urban diamond interchanges. The development of the algorithm is based on fuzzy logic.

The incident detection model developed through this research is capable of detecting lane-blocking incidents when their effects are manifested by certain patterns of deterioration in traffic conditions and, thereby, adjustments in signal control strategies are required. The model overcomes the boundary condition problem inherent in conventional threshold-based concepts. The model captures system-wide incident effects utilizing multiple measures for more accurate and reliable detection, and serves as a component module of a real-time traffic adaptive diamond interchange control system. The model is designed to be readily scalable and expandable for larger systems of arterial streets.

The prototype incident detection model was applied to an actual diamond interchange to investigate its performance. A simulation study was performed to evaluate the model's performance in terms of detection rate, false alarm rate, and mean time to detect. The model's performance was encouraging, and the fuzzy logic based approach to incident detection is promising.

INTRODUCTION

The high cost of congestion caused by incidents is a serious challenge to real-time traffic management in urban areas. Incidents are a major cause of urban congestion, and they require rapid remedial traffic management actions to ensure traffic safety and prevent serious accumulation of congestion. Incident-induced congestion is of particular concern for traffic adaptive control systems currently being tested as a part of Intelligent Transportation Systems (ITS). Successful operation of such systems heavily relies on their ability to rapidly detect incidents and effectively respond to incident-induced delays.

During the last two decades considerable research was dedicated to development of automatic incident detection algorithms and responsive control management for freeways. More recently (since the mid 1980's), similar research efforts have been initiated for arterial streets; however, relatively little work has been done on the arterial side because of differences between the freeway and the arterial streets. Freeways have directed access points, uninterrupted flow, minimal median and marginal friction and fewer geometric constraints. On the other hand, arterials feature a variety of traffic controls, turning movements, relatively easy rerouting of vehicles during incident conditions, characteristically more variable data, and, therefore, a more complex and challenging environment for incident detection (*1*).

The detection of traffic incidents in an urban arterial street is of more importance to traffic management and control than to traffic safety since the lower operating speeds on arterial streets are less likely to result in severe multiple collisions (*2*). As an integral part of traffic surveillance and control, automatic incident detection systems enable the traffic control center to minimize the response time and take essential actions before the incident-induced congestion spreads throughout the network.

Research Initiatives

When incorporated in a real-time traffic adaptive control system, the incident detection system can serve as an advisory module for the control system. The normal reaction of a control system to congestion on an intersection approach is increasing green time by sacrificing other less congested approaches to minimize delay and maximize traffic movements; however, when this congestion is caused by the incident, this type of control may not be appropriate. There is a need for special control strategies for incidents. These strategies must be developed and implemented so that they are responsive to the characteristics of incidents including their locations, severity, and the overall pattern of the incident effect.

An incident detection algorithm designed to detect an incident based on the traffic conditions resulting from the incident would not only identify the incident location and severity, but also naturally indicate what adverse effects the detected incident has created. The control system can utilize this incident information to activate the appropriate control actions in response to the incident. Existing incident detection algorithms were not designed for real-time traffic adaptive control systems where the incident detection model must connect to other system components including the signal controller. Thus, human operators must be involved between incident detection and any control actions in response to the incident, which takes substantially more time.

The most critical and common limitation in most existing incident detection methods is that they require threshold values to differentiate "significant" or "unusual" changes from "trivial" or "usual" variations in traffic conditions. The threshold values dictate the detection capabilities of the incident detection methods. Identifying an appropriate threshold value is a important problem in implementing these methods; however, these pre-defined "crisp" values can create a boundary condition problem (e.g., a measured value on the boundary can draw two different conclusions) and do not have the capability of adjusting themselves to changing traffic flow conditions. Additionally, threshold-based incident detection methods are not capable of compensating for errors during data acquisition and transfer (i.e., a small error when the system is operating in a condition near the threshold value can result in wrong conclusions).

A capacity-reducing incident affects not only the location of its occurrence, but also adjacent locations as long as traffic demands to and from the incident location exist. Any incident within the network results in a unique pattern of deterioration in operating conditions near its location of occurrence. Incident detection logic that takes into account this pattern captures the system-wide incident effects and, therefore, achieves more reliable detection and provides credible advisory information concerning the control strategy in response to the incident.

Diamond interchanges connect a freeway and the crossing arterial streets to serve the traffic entering and exiting the freeway. Due to the complexity of traffic movements within the interchange and increasing demand, many urban diamond interchanges are experiencing serious congestion. The two closely spaced traffic signals with high volume turning traffic makes for a challenging control environment. Developing a real-time, multi-modal, traffic adaptive interchange control system is a research objective of the Texas A&M ITS Research Center of Excellence. This objective requires an innovative research effort to integrate a variety of technologies into a single control system that will improve traffic performance. Incident detection is an essential component of the control system because incidents in congested interchanges require special attention. They can easily paralyze traffic movements and cripple the control in the interchange with its effects rapidly propagating through the freeway and adjacent streets. The timely and accurate detection of incidents and deployment of appropriate control strategies would provide significant benefits in reducing vehicle delay and maximizing vehicle/person movements in the diamond interchange area.

Research Objectives

The objective of this research is to develop a real-time incident detection model for urban diamond interchanges. The development of the algorithm is based on fuzzy logic which has been recognized as a viable solution approach for systems with uncertainty or approximate reasoning, especially for systems whose mathematical model is difficult to derive. This approach overcomes the boundary condition problem inherent in conventional threshold-based algorithms. The model captures system-wide incident effects utilizing multiple measures for more accurate and reliable detection. The model is a component module of a real-time traffic adaptive diamond interchange control system. The model is designed in such a way that it is readily scalable and expandable for larger systems of arterial streets.

METHODOLOGY

Definition of Incidents

Prior to introducing the new incident detection algorithm, it is necessary to clearly define the specific meaning of "incidents" supported by this research. As pointed out by Khan and Ritchie, "incidents" generally refer to "any problems on the surface street that require the attention of an operator or result in an operator formulating a response" (*1*). Lane blockages are an important subset of such problems. This research focuses on detecting lane-blocking incidents including mid-intersection blockages. Not all lane-blocking incidents, however, are equally important from the control perspectives. For example, an incident under very low volume conditions would not cause serious operational problems although it may require some actions for safety; therefore, lane blockages with significant magnitude of effects are of primary concern in real-time traffic adaptive control systems.

For this research, an incident is defined as any lane-blocking event which degrades the performance of an arterial street such that the traffic signal control system should adjust its operation. The incident detection algorithm developed through this research is capable of detecting lane-blocking incidents when their effects are manifested by certain patterns of deterioration in traffic conditions and, thereby, require adjustments in signal control strategies.

Modeling Approach

This research utilizes fuzzy logic and its application concepts to design major components of the incident detection algorithm. The incident detection model detects incidents by observing abnormal traffic conditions resulting from the incident. The abnormal traffic conditions are manifested as abrupt changes in traffic measures (detection variables). These measures include: maximum queue length, speed, occupancy, and turning movements measured at each intersection approach of the diamond interchange. The model looks for abrupt changes in each measure by comparing the current values against the past five minute average values. This comparison process was modeled by fuzzy logic. The model identifies the incident location by comparing the actual incident patterns against plausible hypothetical (expected) incident patterns and identifying the location associated with the best-matching pattern. This matching process was designed using fuzzy logic. The logic for detection of incident termination was also based on fuzzy logic.

Development of the Fuzzy Inference Engine

A fuzzy inference routine serves as the main engine of the incident detection algorithm. Simulation runs were conducted to obtain traffic data required to determine membership functions and accompanying rule bases. A microscopic arterial street simulation model, TexSIM, was used for simulation. The TexSIM model was developed as a part of the research conducted by the Texas A&M ITS Research Center of Excellence. TexSIM has a capability of simulating various types of incidents and generating a variety of output. The simulated real-time traffic condition in a typical urban diamond interchange expressed in terms of various traffic measures was the basis for definition of the fuzzy membership functions and rules. The simulation results for normal and incident conditions were examined to determine the membership function categories and corresponding rules required to describe various possible states of the system.

Membership Functions

A membership function is represented as an X-Y plot with the X-axis representing the input variable and the Y-axis the degree of membership. The membership function assigns the degree of membership (ranging from 0 to 1) to an input value when found within its coverage along the variable axis. The resulting membership functions are illustrated in Figures 1, 2, and 3.

Rule Bases

The rule bases consist of a set of rules (statements) that describe the relationship between inputs and the consequences (outputs). In this research, rule bases describing normal and abnormal traffic conditions were constructed for each measure. Depending upon the number of partitioned input subspaces, different numbers of rules are required for each traffic measure employed. Figures 1, 2, and 3 include the rule bases for each measure along with the membership functions.

Fuzzy Inference Procedure

Let A(x), B(y), and C(z) denote the membership functions of fuzzy set A, B, and C, respectively. Fuzzy sets A and B are subsets of the input set X (percent change) and the input set Y (average), respectively. Fuzzy set C is a subset of the output set Z (traffic conditions in location *l*). In general, the fuzzy inference rules can be described as follows:

If x is A_1 and y is B_1, then z is C_k.
If x is A_2 and y is B_2, then z is C_k.
....
If x is A_m and y is B_n, then z is C_k.

Note that all the rules have the same consequent "z is C_k." For all the rules, the consequent is either "traffic conditions at location *l* (z) are Normal (C_1)" or "traffic conditions at location *l* (z) are Abnormal (C_2)." Therefore, two distinct rule sets and accompanying inferences are required to represent the normality and abnormality of traffic conditions at location *l*. Figure 4 illustrates the fuzzy inference procedure for these two instances.

For the inference on normality of traffic conditions, the rules can be expressed as follows:

If x is A_1 and y is B_1, then the condition of location *l* (z) is Normal (C_1).
If x is A_2 and y is B_2, then the condition of location *l* (z) is Normal (C_1).
....
If x is A_m and y is B_n, then the condition of location *l* (z) is Normal (C_1).

Now, let the input be $x=x_0$ and $y=y_0$. First, the compatibility between the input and each of the antecedent conditions of rules is determined. In general, the compatibility for antecedent "x is A" is denoted as $A(x_0)$. Since the antecedent is two-dimensional, the compatibility is determined as: $\omega_i = A_i(x_0) * B_i(y_0)$; I = 1, 2, ..., m n, where *I* is the number of the rule. The inference result for the *i*th rule is $\omega_i\, C_1$, where C_1=1.0. The complete inference result z^0 is constructed from Equation (1). The value of z^0 represents the grade of normality of location l and is defined as *the degree of matching* (μ_l) between the input data (the current traffic condition) and the inference rules (necessary conditions) for normality of location l.

$$z^0 = \mu_l = \frac{\sum_{i=1}^{m\times n}(\varpi_i \times C_1) + \sum_{j=1}^{m\times n}(\varpi_j \times C_2)}{\sum_{i=1}^{m\times n}\varpi_i + \sum_{j=1}^{m\times n}\varpi_j}$$

$$= \frac{\sum_{i=1}^{m\times n}(\varpi_i \times C_1)}{\sum_{i=1}^{m\times n}\varpi_i + \sum_{j=1}^{m\times n}\varpi_j} \qquad (\because C_2 = 0) \tag{1}$$

$$= \sum_{i=1}^{m\times n}\varpi_i \qquad (\because C_1 = 1,\ \sum_{i=1}^{m\times n}\varpi_i + \sum_{j=1}^{m\times n}\varpi_j = 1)$$

where,

m = number of partitioned input spaces representing the normal condition (=number of the normality rules),

n = number of partitioned input spaces representing the abnormal condition (=number of the abnormality rules),

μ_l = degree of matching for the location l,

ω_i = compatibility value from the ith rule from the normality rule base, and

ω_j = compatibility value from the jth rule from the abnormality rule base.

For abnormal conditions, the rules are as follows:

If x is A_1 and y is B_1, then the condition of location l (z) is Abnormal (C_2).
If x is A_2 and y is B_2 then the condition of location l (z) is Abnormal (C_2).
....
If x is A_m and y is B_n, then the condition of location l (z) is Abnormal (C_2).

The compatibility is determined as: $\omega_j = A_j(x_0) * B_j(y_0)$; $j = 1, 2, ..., m\ n$, where j is the number of the rule. The inference result for the jth rule is $\omega_j C_2$, where C_2=1.0. The complete inference result z^0 is constructed from Equation (2). The value of z^0 represents the grade of abnormality of location l and is the degree of matching (μ_l) between the input data (the current traffic condition) and the inference rules (necessary conditions) for abnormality of location l.

$$
\begin{aligned}
z^0 = \mu_l &= \frac{\sum_{i=1}^{m\times n}(\varpi_i \times C_1) + \sum_{j=1}^{m\times n}(\varpi_j \times C_2)}{\sum_{i=1}^{m\times n}\varpi_i + \sum_{j=1}^{m\times n}\varpi_j} \\
&= \frac{\sum_{j=1}^{m\times n}(\varpi_j \times C_2)}{\sum_{i=1}^{m\times n}\varpi_i + \sum_{j=1}^{m\times n}\varpi_j} \qquad (\because C_1 = 0) \\
&= \sum_{j=1}^{m\times n}\varpi_j \qquad (\because C_2 = 1,\ \sum_{i=1}^{m\times n}\varpi_i + \sum_{j=1}^{m\times n}\varpi_j = 1)
\end{aligned}
\tag{2}
$$

DESCRIPTION OF THE INCIDENT DETECTION MODEL

The incident detection model utilizes various measures as its input since those measures can be obtained through the extensive surveillance system (i.e., loop detectors or video image processing unit) built as a part of the real-time traffic adaptive control system. The algorithm consists of four major component modules: (1) normality inference module, (2) incident location inference module, (3) incident severity assessment module; and (4) incident termination inference module.

The normality inference module examines the normality of traffic conditions to determine the possibility of incident occurrence. The incident location inference module confirms the incident occurrence and determines the incident location. The incident severity assessment module determines the severity of the confirmed incident through a more detailed examination of a selected measure. The incident termination inference module monitors traffic conditions after the incident is detected to determine whether or not the incident is cleared.

The component modules are integrated and run sequentially as a single system. Running once every minute, the algorithm continuously observes traffic conditions in the intersection area and identifies conditions indicating the occurrence of incidents. If an incident is detected, the algorithm, upon completion of its run, reports the incident location and severity as the final results. If an incident is not identified during any inference procedure, the algorithm returns to the beginning of the process and waits for the next run.

Normality Inference Module

Normality Inference

The normality inference module assumes that if every approach in the network is normal in terms of queue length, then traffic conditions in the network are normal. This assumption is a basis for a set of propositions describing necessary conditions for normality of traffic conditions (e.g., queue length at Approach 1 is normal AND queue length at Approach 2 is normal AND ...). The module compares real-time data against these propositions to determine how well they match (degree of matching). The membership functions and rules to be used for inference are shown in Figure 1. The inference procedure for normal conditions introduced in the previous section can be directly used with the following substitutions:

x = AVGQUE, $A_1 \ldots A_m$ = small, medium, large,

y = PIQUE, $B_1 \ldots B_n$ = small, medium, large, very large,

z = condition of location l, and C_1 = normal.

The degree of matching resulting from the inference represents the grade of normality of a location. The inference is performed for all intersection approaches in the network. Then, the module seeks the approach possessing the minimum value among the degrees of matching for all approaches. This approach is presumably the one that was most affected by the incident.

If the degree of matching for the most affected approach falls under a pre-defined decision value (ALPHA1), the module classifies the approach for further examination during subsequent time intervals. If the degree of matching for the approach is smaller than the decision value during the next two time intervals, the module concludes that an incident is possible "near" that approach and activates the incident location inference module. This triple checking routine was designed to filter out random fluctuations of traffic measures under normal condition.

Case Classification

The normality inference module provides an indication of the likely locations of an incident (plausible incident locations) to scale down the problem. If an incident is possible, the module determines the plausible incident locations and passes the information to the incident location inference module. This process is referred to as "case classification" in this research. For the case-classification process, the most affected approach number identified during the normality inference must be provided along with information on network linkages.

Information on network linkages is static data in tabular form defining the geometric relationship between approaches in terms of origin, destination, and the required type of turn (e.g., left, through, right).

Given the most affected approach number, the incident must be located at one of the following locations: (1) the most affected approach itself, (2) mid-intersection, or (3) one of the departing legs of the intersection. This process is universally applicable not only for diamond interchanges, but also for any arterial street network as long as linkages between intersections and approaches are configured and provided.

Incident Location Inference Module

This module examines the plausible locations of the incident to confirm the incident occurrence and identify the location of occurrence.

Hypothetical Incident Patterns

Incidents can occur anywhere within the interchange area. Each incident location would have different effects on traffic conditions within the interchange resulting in unique patterns of changes in various measures. Hypothetical patterns of incident effects that are likely to result from each incident location can be developed based upon experts' knowledge and simulation of incidents. The hypothetical pattern for an incident location consists of a series of propositions describing the necessary conditions to be satisfied in order to assure the incident occurrence in that location. These propositions (i.e., necessary conditions) are represented by the condition descriptions of various measures at intersection approaches affected by the incident (e.g., the occupancy at Approach 1 is abnormal AND the queue length at Approach 2 is normal AND ...).

Every time the location inference module is activated, it examines all plausible incident locations near the most affected approach. The hypothetical patterns for the plausible incident locations must be mutually exclusive to avoid confusion. The hypothetical incident patterns given a plausible incident location can be generated by universally applicable logic. Given a plausible incident location, the unique pattern of incident effects pertaining only to that incident location is determined. The pattern is characterized by changes in various measures manifested at certain locations. The general concept for the pattern generation is as follows:

- The most affected approach itself: Since the incident is on the most affected approach, the most affected approach itself must be ABNORMAL, and other approaches feeding traffic into the same intersection are in NORMAL condition.

- Mid-intersection: Every approach to the intersection (all links whose downstream node number is the intersection node number) must be ABNORMAL.

- Departing legs: The approach adjoining the departing leg is NORMAL, and all other approaches feeding traffic into the departing leg must be ABNORMAL.

Location Inference

The module performs inference through one-by-one comparisons between the current data and each proposition in the hypothetical pattern of a plausible incident location. The current data used for the inference are the average values for three minutes during which the incident possibility was examined by the normality inference module. Based on the past five minute average and the current three minute average data, the percent change in each measure is calculated.

The inference procedure involves both normality and abnormality inferences introduced in the previous section. That is, if a proposition of the hypothetical pattern advocates normality of a location (e.g., "queue length at Left A is normal"), then Equation (1) and Figure 4(a) are employed for inference; whereas, if abnormality is advocated (e.g., "queue length at Left A is abnormally increased"), then Equation (2) and Figure 4(b) are used. Depending on which measure is involved in the proposition, appropriate substitutions are required for variables x, y, z, and fuzzy subsets $A_1,\ldots,A_m$, $B_1,\ldots,B_n$, C_1 and C_2 for fuzzy inference.

The results from the inference are weighted and averaged across the columns (traffic measures) and rows (locations) in the pattern table to determine the overall degree of matching between the actual traffic condition and the hypothetical pattern. All traffic measures (columns) are equally weighted. Locations (rows) are weighted in proportion to their feeding volume into the plausible incident location. This process is repeated for the hypothetical patterns of each plausible incident location to determine which one matches best with the current traffic condition. The best match is further considered to ascertain that the degree of matching is satisfactory. If the degree of matching is satisfactory, having a value greater than the decision value ALPHA2, the incident is confirmed and its location of occurrence is identified.

Incident Severity Assessment Module

This module assesses the severity of the incident confirmed by the preceding two modules. The severity information must be provided in a form the control system can utilize to formulate new control strategies in response to the incident. Traditionally, incident severity is reported as the number of lanes blocked due to the incident. In many instances, however, incidents do not cause complete loss of a lane's functionality in processing vehicles as scheduled by the lane assignment and the signal timing unless the incident is located very close to the stop bar. The lanes with the incident may be capable of serving some vehicles entering the intersection. That is, some of the vehicles that switched lanes upstream of the incident would return to their original lanes after they pass the incident site if the space between the incident site and the stop bar is sufficient. Furthermore, when the incident is detected in the middle of or at a departing leg of the intersection, the lanes of the affected approaches are not physically blocked although some of their functionality might be lost. Therefore, information such as "the lane is *blocked*" would not be beneficial to determine control actions in response to the incident.

Depending upon the amount of traffic returning to the original lanes, the percent reduction in volume distribution on the lane can be determined as: 100*(AVGLVD - current lane volume distribution) / AVGLVD. The percent reduction indicates the part of a lane's functionality currently lost due to the incident. To assess the severity of an incident, the module determines the percent reduction in volume distribution for the lanes of the incident-affected approaches identified by the location inference module.

Incident Termination Inference Module

This module monitors traffic conditions after the incident is detected to verify termination of the incident. Upon receiving the current data, the module re-examines abnormality of the most affected approach identified by the normality inference module to look for a significant decrease in the degree of matching. The queue length (QUE) and speed

(SPD) measures are used for inference. The decreased (lower) degree of matching means that the current condition is less compatible with the necessary traffic conditions to assure that the incident effects persist. If the degree of matching decreases below a sufficient level (decision value, ALPHA3) during three consecutive 1 minute time intervals, the module concludes that the incident effects no longer exist, and declares termination of the incident.

INCORPORATION OF THE INCIDENT DETECTION MODEL INTO A REAL-TIME CONTROL SYSTEM

The incident detection model developed in this research was incorporated into a real-time traffic adaptive diamond interchange control system currently being developed as a part of the research conducted by the Texas A&M ITS Research Center of Excellence. The control system monitors and responds to real-time traffic conditions through an automated optimization process for green times and lane assignments. The control system will also be capable of granting signal priority to transit vehicles and heavy vehicles. Incident detection is one of the functions that the control system provides.

The controller system architecture for laboratory development includes video imaging equipment, a Versa-Module Eurocard (VME) bus computer system and software, a standard National Electrical Manufacturer's Association (NEMA) controller and signal hardware, a simulator resident on a microcomputer, fiber optic lane assignment signing, and sensing and communications capabilities. Figure 5 illustrates the system architecture of the diamond interchange control system. The field camera unit captures the real-time video image of the diamond interchange, and sends the signal to the video image processing unit, SSI (Smart Sensor Interface). The video image processing unit collects and analyzes the video image to generate traffic data in a usable form, and passes the data to the data base in the main system (VME) through the serial communication unit. The data base stores the data and releases them when requested by other system components. The PASSER III Optimization Manager receives data from the data base, and performs analyses to determine the optimal signal timing strategy and lane assignment for the current traffic condition. Then, the optimal control strategy is recommended to the controller manager. The controller manager examines whether or not the recommended strategy is feasible under the current control scheme. If it is feasible, the controller manager adjusts the NEMA controller with the recommended signal settings.

The dotted lines in the figure represent temporary system links required for the earlier phase of the research because some system components including video image processing units are currently under development. The simulator substitutes for the cameras, image processing unit, signal lights, and the physical system of the diamond interchange.

The incident detection model is functionally integrated and effectively communicates with other system modules of the control system. The incident detection module resides within the main system and communicates with the data base and optimization manager. It receives data required for incident detection from the data base. When an incident is detected, the incident detection module generates an incident report containing the time of detection, location of the incident, and severity information. The incident report is then sent to the data base for storage of historical incident data. At the same time, the incident information is reported to the optimization manager so that an appropriate control strategy in response to the incident can be determined.

EVALUATION OF THE INCIDENT DETECTION MODEL

The prototype incident detection model was applied to an actual diamond interchange to investigate its performance. The model performance was evaluated off-line using simulated traffic data generated by TexSIM.

Study Design

The study site used for performance evaluation was the First Street and IH 35 diamond interchange in Austin, Texas. The geometric configuration of the interchange is typical of urban diamond interchanges in Texas. It consists of two signalized intersections, two one-way frontage roads which serve the traffic demand on and off the freeway, and a crossing arterial street. Figure 6 illustrates the network configuration of the diamond interchange system. Incidents at various locations within the interchange under three different volume conditions (representing light, medium, and heavy volume conditions) were simulated for evaluation. For each volume condition, incidents were simulated at 12 different locations within the interchange with 3 different severity levels. One incident was simulated during each one hour simulation run; therefore, the total number of simulation runs was 102 requiring 102 hours of simulation time.

Model Performance

Performance of the incident detection model was evaluated using three major measures that are typically used to assess the performance of incident detection algorithms: detection rate, false alarm rate, and mean time to detect. Shown in Table 1 are the performance measures calculated for each volume level and incident severity level.

Detection Rate

Table 1 summarizes detection rates of the model determined for each volume case and severity. The model detected 74 incidents among the total of 102 incidents; therefore, the detection rate of the model was determined to be 73 percent. The detection rates increased from 62 percent for light volume conditions to 79 percent for heavy volume conditions. The difference in detection rate between medium and heavy volume conditions (77 versus 79 percent) was not as large as the difference between light and medium volume conditions. The detection rate was higher when the incident was more severe: 42 percent for 1 lane blocked, 86 percent for 2 lanes blocked, and 93 percent for 3 lanes blocked.

False Alarm Rate

The model produced 34 false incident decisions (false alarms) among a total of 6120 decisions; therefore, the false alarm rate of the model was determined to be 0.56 percent. As shown in Table 1, the false alarm rate tends to increase as volume level increases: 0, 0.74, and 0.93 percent for light, medium, and heavy volumes, respectively. For nearly all of the false alarms, the model immediately reported their termination because the random fluctuations that caused false alarms disappeared shortly after they were detected.

Mean Time to Detect

The mean time to detect was 4.1 minutes. As shown in Table 1, the mean time to detect decreases as volume level increases: 4.6, 4.0, and 3.7 minutes for light, medium, and heavy volumes, respectively. Under higher volume conditions, incident effects develop faster because the interchange experiences a higher level of congestion under normal conditions; therefore, it took less time for incident effects to reach the level that the model can detect.

The mean time to detect was shorter when the incident was more severe: 4.4, 4.1, and 3.9 minutes for light, medium, and heavy volumes, respectively. The impact of more severe incidents on traffic conditions is greater; therefore, congestion builds up more rapidly to reach the level that the model can detect.

CONCLUSIONS

This research was a pioneering effort in applying fuzzy logic to the arterial street incident detection problem. The following conclusions can be drawn from the results of this research:

- The incident detection model was tested under a laboratory setting, and its performance was encouraging in terms of detection rate, false alarm rate, and mean time to detect. The model developed by this research is a prototype model that runs under a simulated real-time environment; therefore, the model should be properly validated and calibrated to be deployed in the field as a component of a real-time traffic adaptive control system. The model was designed for (but, not limited to) paired intersections typified by urban diamond interchanges. Calibration will be required for the model to be operative for larger systems that involve more signalized intersections.
- The model addresses technical difficulties inherent in existing algorithms including the threshold problem, modeling of input variables, and filtering of random fluctuations. The model captures overall incident effects on the network using multiple data for accurate incident detection, and features improved real-time capabilities. These benefits were

made possible by applying fuzzy logic. Therefore, it can be concluded that fuzzy logic would be a promising approach for developing an arterial street incident detection model.

RECOMMENDATIONS FOR FUTURE RESEARCH

This research was an initial attempt to develop a fuzzy logic based incident detection model for arterial streets. Further research is recommended to enhance the model as follows:

1. The model was developed based on off-line data generated by a simulation model. The model should be calibrated and validated in the field using real-time traffic data in an actual diamond interchange to confirm its benefits.
2. Fuzzy systems, including the model developed by this research, are not capable of learning and tuning their membership functions and fuzzy rules. The model can be enhanced for learning capability through hybrid system approaches such as fuzzy-neural or fuzzy-genetic algorithms.
3. A study is recommended to assess incident information needs for a real-time traffic adaptive control system to determine effective control strategies in response to the incident. The proposed model can be refined to provide the specific incident information required by the control system.

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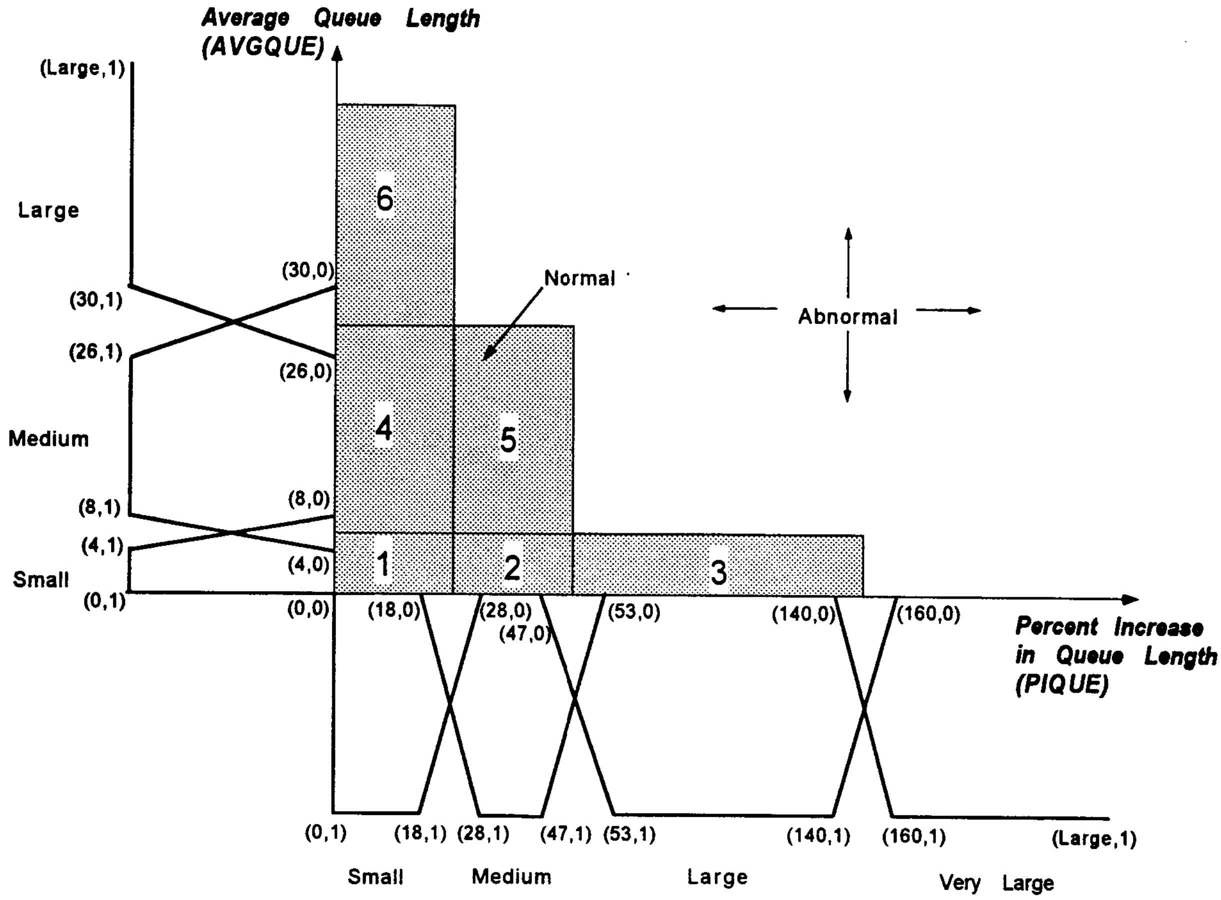
ENDNOTES

1. Khan, S.I., and S.G. Ritchie, "Incident Detection on Surface Streets Using Artificial Neural Networks," *Proceedings of the Int'l Conference on Advanced Technologies in Transportation and Traffic Management*, Singapore, May 18-20, 1994, pp. 261-268.

2. Bell, M.G.H., and B, Thancanamootoo. "Automatic Incident Detection Within Urban Traffic Control Systems," *Proceedings of International Road and Traffic Conference - Roads and Traffic 2000*, Vol. 4:2, 1988, pp. 35-38.

TABLE 1 Performance of the Proposed Model

Performance Measures	Volume Cases	1 lane blocked	2 lanes blocked	3 lanes blocked	*Overall*
Detection Rate (%)	Light	17	75	100	**62**
	Medium	50	92	90	**77**
	Heavy	58	92	90	**79**
	Overall	**42**	**86**	**93**	**73**
False Alarm Rate (%)	Light	0	0	0	**0.00**
	Medium	0.69	0.97	0.42	**0.74**
	Heavy	1.11	0.69	0.83	**0.93**
	Overall	**0.60**	**0.56**	**0.50**	**0.56**
Mean Time to Detect (minutes)	Light	6.5	4.4	4.3	**4.6**
	Medium	4.0	4.2	3.8	**4.0**
	Heavy	4.2	3.8	3.4	**3.7**
	Overall	**4.4**	**4.1**	**3.9**	**4.1**



Normal Rule Set

Rule 1: If AVGQUE is Small AND PIQUE is Small, then Location l is Normal (w_1)

Rule 2: If AVGQUE is Small AND PIQUE is Medium, then Location l is Normal (w_2)

Rule 3: If AVGQUE is Small AND PIQUE is Large, then Location l is Normal (w_3)

Rule 4: If AVGQUE is Medium AND PIQUE is Small, then Location l is Normal (w_4)

Rule 5: If AVGQUE is Medium AND PIQUE is Medium, then Location l is Normal (w_5)

Rule 6: If AVGQUE is Large AND PIQUE is Small, then Location l is Normal (w_6)

where l = 1A, 1B, 1C, 2A, 2B, 2C

Abnormal Rule Set

Rule 1: If AVGQUE is Small AND PIQUE is Very Large, then Location l is Abnormal (w_1)

Rule 2: If AVGQUE is Medium AND PIQUE is Large, then Location l is Abnormal (w_2)

Rule 3: If AVGQUE is Medium AND PIQUE is Very Large, then Location l is Abnormal (w_4)

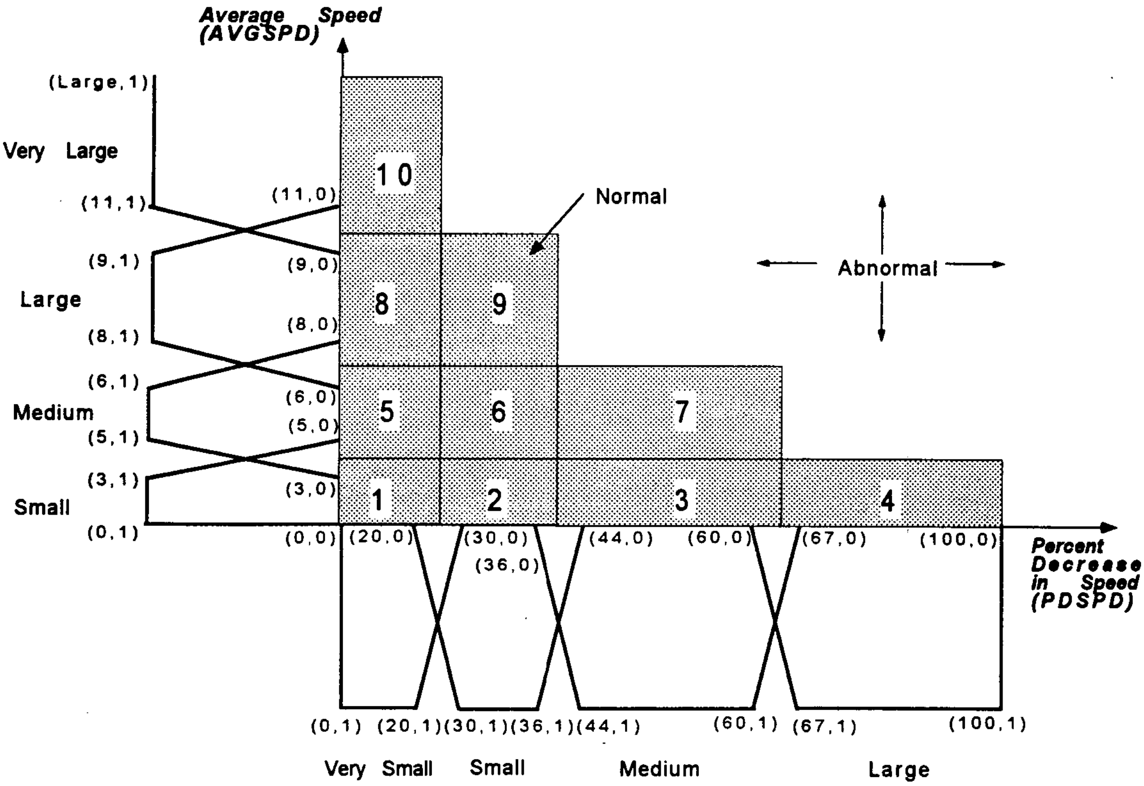
Rule 4: If AVGQUE is Large AND PIQUE is Medium, then Location l is Abnormal (w_3)

Rule 5: If AVGQUE is Large AND PIQUE is Large, then Location l is Abnormal (w_5)

Rule 6: If AVGQUE is Large AND PIQUE is Very Large, then Location l is Abnormal (w_6)

where l = 1A, 1B, 1C, 2A, 2B, 2C

FIGURE 1 Fuzzy Membership Functions and Rules for Queue Length (QUE)



Normal Rule Set

Rule 1: If AVGSPD is Small AND PDSPD is Very Small, then Location *I* is Normal (w_1)

Rule 2: If AVGSPD is Small AND PDSPD is Small, then Location *I* is Normal (w_2)

Rule 3: If AVGSPD is Small AND PDSPD is Medium, then Location *I* is Normal (w_3)

Rule 4: If AVGSPD is Small AND PDSPD is Large, then Location *I* is Normal (w_4)

Rule 5: If AVGSPD is Medium AND PDSPD is Very Small, then Location *I* is Normal (w_5)

Rule 6: If AVGSPD is Medium AND PDSPD is Small, then Location *I* is Normal (w_6)

Rule 7: If AVGSPD is Medium AND PDSPD is Medium, then Location *I* is Normal (w_7)

Rule 8: If AVGSPD is Large AND PDSPD is Very Small, then Location *I* is Normal (w_8)

Rule 9: If AVGSPD is Large AND PDSPD is Small, then Location *I* is Normal (w_9)

Rule 10: If AVGSPD is Very Large AND PDSPD is Very Small, then Location *I* is Normal (w_{10})

where *I* = 1A, 1B, 1C, 2A, 2B, 2C

Abnormal Rule Set

Rule 1: If AVGSPD is Medium AND PDSPD is Large, then Location *I* is Abnormal (w_1)

Rule 2: If AVGSPD is Large AND PDSPD is Medium, then Location *I* is Abnormal (w_2)

Rule 3: If AVGSPD is Large AND PDSPD is Large, then Location *I* is Abnormal (w_3)

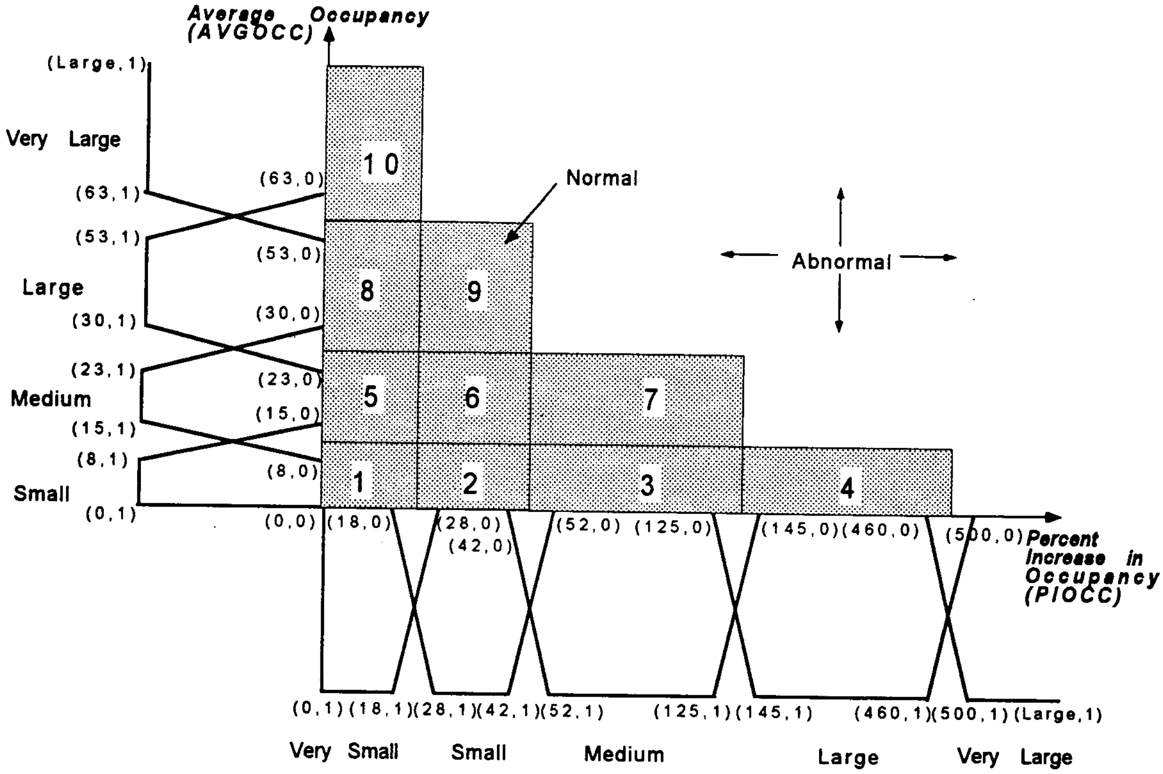
Rule 4: If AVGSPD is Very Large AND PDSPD is Small, then Location *I* is Abnormal (w_4)

Rule 5: If AVGSPD is Very Large AND PDSPD is Medium, then Location *I* is Abnormal (w_5)

Rule 6: If AVGSPD is Very Large AND PDSPD is Large, then Location *I* is Abnormal (w_6)

where *I* = 1A, 1B, 1C, 2A, 2B, 2C

FIGURE 2 Fuzzy Membership Functions and Rules for Speed (SPD)



Normal Rule Set

Rule 1: If AVGOCC is Small AND PIOCC is Very Small, then Location I is Normal (w_1)

Rule 2: If AVGOCC is Small AND PIOCC is Small, then Location I is Normal (w_2)

Rule 3: If AVGOCC is Small AND PIOCC is Medium, then Location I is Normal (w_3)

Rule 4: If AVGOCC is Small AND PIOCC is Large, then Location I is Normal (w_4)

Rule 5: If AVGOCC is Medium AND PIOCC is Very Small, then Location I is Normal (w_5)

Rule 6: If AVGOCC is Medium AND PIOCC is Small, then Location I is Normal (w_6)

Rule 7: If AVGOCC is Medium AND PIOCC is Medium, then Location I is Normal (w_7)

Rule 8: If AVGOCC is Large AND PIOCC is Very Small, then Location I is Normal (w_8)

Rule 9: If AVGOCC is Large AND PIOCC is Small, then Location I is Normal (w_9)

Rule 10: If AVGOCC is Very Large AND PIOCC is Very Small, then Location I is Normal (w_{10})

where I = 1A, 1B, 1C, 2A, 2B, 2C

Abnormal Rule Set

Rule 1: If AVGOCC is Small AND PIOCC is Very Large, then Location I is Abnormal (w_1)

Rule 2: If AVGOCC is Medium AND PIOCC is Large, then Location I is Abnormal (w_2)

Rule 3: If AVGOCC is Medium AND PIOCC is Very Large, then Location I is Abnormal (w_3)

Rule 4: If AVGOCC is Large AND PIOCC is Medium, then Location I is Abnormal (w_4)

Rule 5: If AVGOCC is Large AND PIOCC is Large, then Location I is Abnormal (w_5)

Rule 6: If AVGOCC is Large AND PIOCC is Very Large, then Location I is Abnormal (w_6)

Rule 7: If AVGOCC is Very Large AND PIOCC is Small, then Location I is Abnormal (w_7)

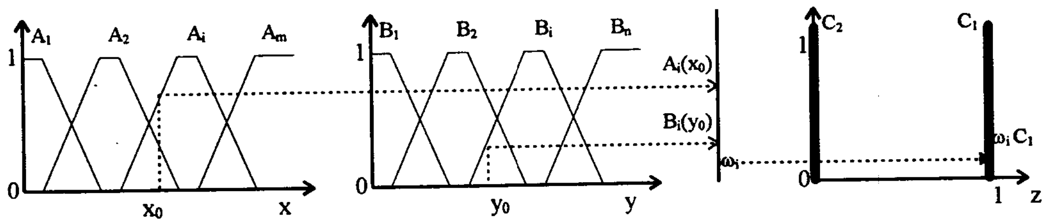
Rule 8: If AVGOCC is Very Large AND PIOCC is Medium, then Location I is Abnormal (w_8)

Rule 9: If AVGOCC is Very Large AND PIOCC is Large, then Location I is Abnormal (w_9)

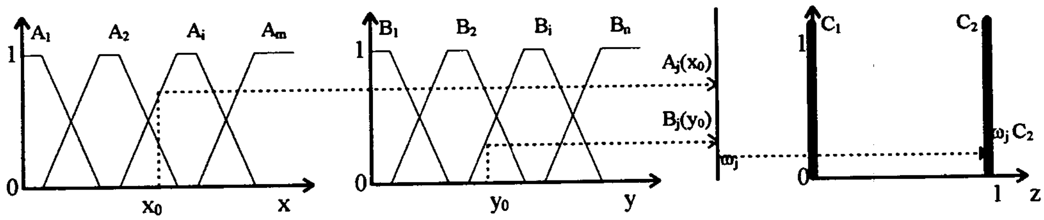
Rule 10: If AVGOCC is Very Large AND PIOCC is Very Large, then Location I is Abnormal (w_{10})

where I = 1A, 1B, 1C, 2A, 2B, 2C

FIGURE 3 Fuzzy Membership Functions and Rules for Occupancy (OCC)



(a) Normal Condition



(b) Abnormal Condition

FIGURE 4 Fuzzy Inference Procedure

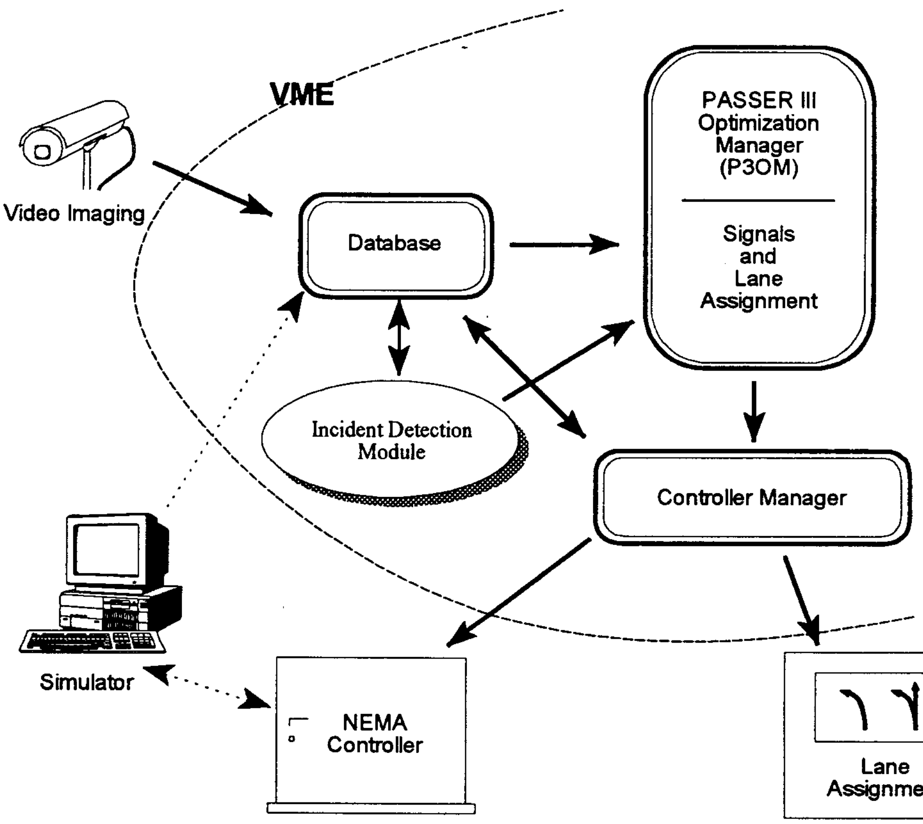


FIGURE 5 System Architecture of the Diamond Interchange Control System

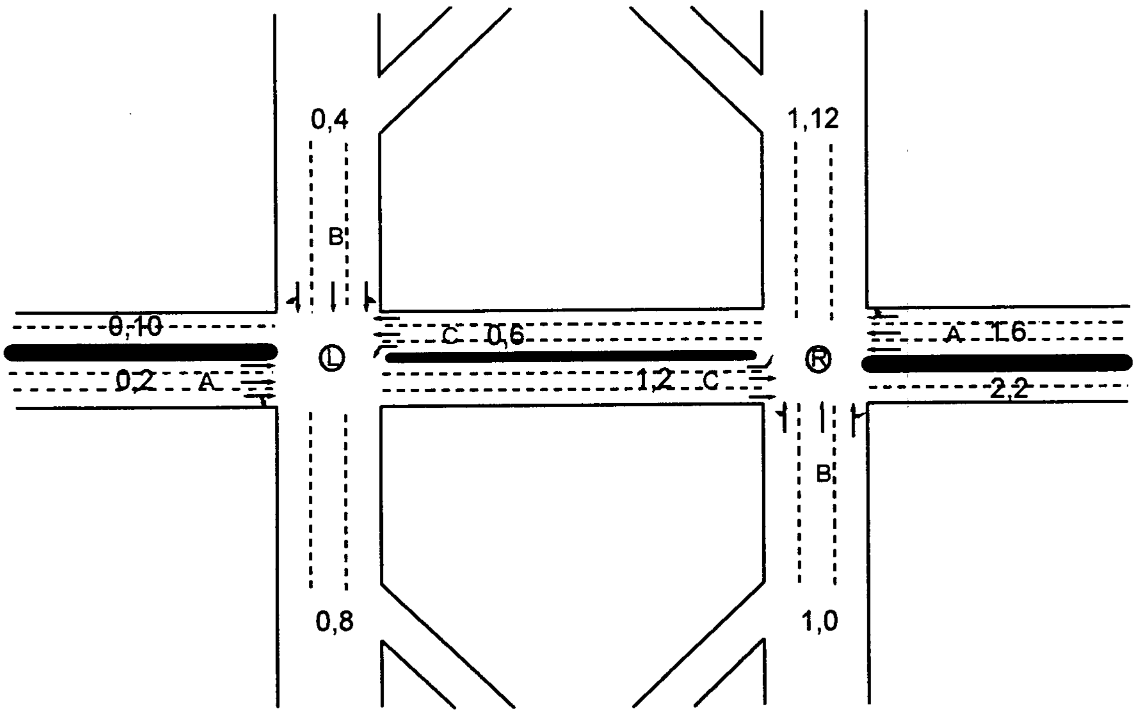


FIGURE 6 Network Configuration of the Diamond Interchange System

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