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A FUZZY-BASED METHODOLOGY FOR ANTICIPATING TREND OF INCIDENT TRAFFIC CONGESTION ON EXPRESSWAYS

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Abstract. Traffic control decisions for incident congestion management on expressways are often made in the face of uncertainty because it entails using many forms of both current and predicted traffic data and incident information to arrive at control decisions under critical-time pressure. For these reasons, an effective traffic control strategy during incidents often relies on techniques that deal efficiently with problems of uncertainty and imprecision. Motivated by this, the author has carried out a research project that develops a multi-stage Fuzzy Logic Controller (MS-FLC) as a tool to support traffic operator's decision-making at the operational level. The research project aims at establishing a systematic procedure in deriving control actions for ramp control during incidents on expressways following fuzzy-logic approach. For proactive ramp control, the trend of traffic condition on expressways during incidents should be properly anticipated. This paper presents the first two stages of the MS-FLC: (1) evaluation of traffic condition upon incident occurrences, and (2) anticipation of traffic condition during incidents. The results show that the MS-FLC provides a systematic procedure in deriving control actions using fuzzy-based methodology, which possesses excellent capabilities in data-handling and knowledge representation to deliver linguistic expressions that is easy to understand by the operators for making decisions. With both current and anticipated types of information obtained from these two stages, the MS-FLC operates on both reactive and proactive control manners so as to enhance performance of the incident management on expressways.

Keywords: fuzzy logic, traffic control, multi-stage, incident management, fuzzy rule, decision support system.

1. INTRODUCTION

Traffic congestion is a pervasive problem confronting many metropolitan areas in the world. Congestion can be broadly categorized into two types: recurring congestion and non-recurring congestion. Non-recurring congestion is a problem caused by unpredictable events (accident, vehicle breakdown, abnormal rises in traffic demand, etc.) known as incidents that make a temporary reduction in road capacity. Incidents are often characterized by complex nature and time-critical constraints. For these reasons, management of incident congestion should coordinate activities from responsible agencies to bring traffic to normal conditions [1]. From the traffic control perspective, incident management on expressways involves implementation of real-time traffic monitoring and control measures to ameliorate traffic conditions in expressways to avoid spreading congestion to urban streets.

Traffic control decisions are often made in the face of uncertainty that arises due to various reasons, including imprecise data measurement, approximate information reasoning, uncertain traffic forecast, and imprecise human perception [2,3]. Traffic control under an incident occurrence is even more uncertain because it entails using many forms of traffic and incident data to arrive at control decisions under critical-time pressures [1]. Due to the complicated and uncertain nature, an effective traffic control strategy during incidents often requires robust techniques that deal efficiently with the problem of uncertainty, in association with human judgment skills.

Fuzzy logic is a qualitative approach that is close to human observation, reasoning and decision-making. A fuzzy logic system (FLS) is a non-linear mapping of input to the output universe of discourse using fuzzy logic principles [3,4]. FLSs provide foundations for incorporating both subjective judgment and objective knowledge, for handling both numerical data and linguistic information. Fuzzy logic has an attractive capability to deal with uncertainty problems. FLSs have been widely applied in transport engineering, including traffic signal control [5,6], seaport operations [7], transit operation [8], lane-changing simulation model [9], evaluation of congestion intensity [3], and traffic management and control [10,11]. The rationales for applying fuzzy logic for traffic control include: (i) the linguistic expressions are general and easy to be perceived by the traffic operator; (ii) the transition from one fuzzy set to another is gradual, representing continuity in human perception; and (iii) the capability to combine several input quantities to provide a single output for the traffic operator to make a control decision [1,3,12]. In a fuzzy logic reasoning system, knowledge is represented in the form of condition-action rules: IF conditions are met, THEN actions are carried out.

Under complex situations such as traffic control during incidents it is necessary to analyze available data in order to understand the current problem and predict what might happen before deriving a control action. As a result, the decision-making logic in this context should be executed sequentially in several stages where the output from preceding stage is used as input to the following stage. The division of decision-making process into subsequent stages reduces the problem complexity and thereby improves the overall system performance since the number of rules increases exponentially with the number of variables, leading it too cumbersome to handle the rule base in a single stage. Furthermore, in reviewing previous literature, it is found that the works on control applications have mostly been reactive [11,13-15], and little effort has been devoted to traffic control for incident management following MS-FLC approach [16,17]. Essential issues such as evaluation of the current traffic situation and anticipation of the on-going incident traffic condition before making control decisions in the event of an incident have not been adequately addressed.

Motivated by this, in a broader research project [18], the author has developed a multi-stage fuzzy logic controller (MS-FLC) to support decision making in traffic control for congestion management on expressways. The MS-FLC model reflects a complex sequential structure of the decision-making logic for the multi-variable traffic control problem, and consists of three tasks: (1) evaluation of current traffic congestion, (2) prediction of traffic congestion tendency, and (3) recommendation of control strategies and control actions to alleviate congestion. For the MS-FLC validation and evaluation, a traffic simulator controller (TSC) that consists of a car-following model (CFM) [19] and the traffic controller (TC) was developed. The MS-FLC was evaluated across several incident scenarios by comparing its performance with ALINEA\Q, a popular local ramp control algorithm. The results show that the MS-FLC significantly outperforms ALINEA\Q with respect to global objectives, significantly improves mainline travel conditions, and substantially reduces ramp queues.

This paper presents the research work on stages 1 and 2 of the MS-FLC, i.e. evaluation of the current traffic situation and anticipation of incident traffic condition. The structure of this paper is as follow: Section 2 presents the overall framework of the MS-FLC, sections 3 and 4 describe the components and the formulation of rules in stages 1 and 2 respectively. Section 5 presents the resulting fuzzy rule base for anticipating the trend of incident traffic congestion. Section 6 provides conclusions and findings from this research.

2. CONCEPTUAL MODEL

The decision-making process for traffic control during incidents on expressways involves three stages as figured out in Figure 1:

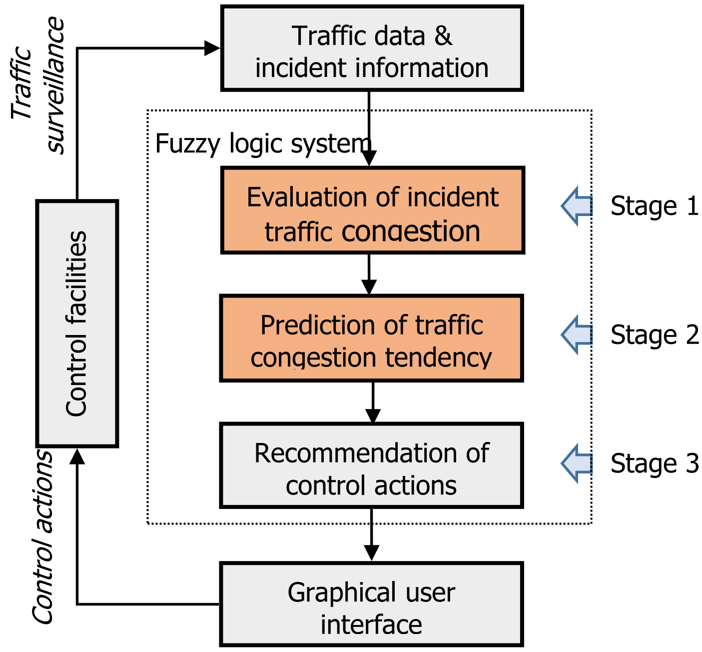


Figure 1. Traffic control decision-making procedure during incidents.

Stage 1: Evaluation of the current incident traffic condition: A traffic stream is characterized by its *state* and the *change in state.* This stage involves evaluation of the state of traffic prevailing at the current time. The purpose is to answer the questions *what is* *happening*, and *how critical* is the event. To evaluate the current traffic condition, the MS-FLC uses incident attributes and traffic data upstream of the incident location. The state of traffic is prescribed by three principal quantities: congestion level, congestion mobility, and congestion status (Figure 2). Congestion level reflects the severity of traffic, congestion mobility determines the dynamics of the congestion, and the congestion status refers to the magnitude of the queue length on the expressway. Each component (rule block) requires various treatments in the subsequent stages. The congestion mobility and congestion status blocks deal specifically with the heavy congestion category: if the congestion problem is critical, urgent control interventions need to be implemented immediately, and the corresponding rules in stage 3 are executed. By contrast, if the traffic congestion is not yet critical, the system proceeds with traffic forecasting module and rules in the second stage will be triggered. Depending on the critical level of the congestion, the MS-FLC continues the second stage – the prediction of traffic tendency, or proceeds to the third stage – recommendation of control actions. The rules in this stage can be categorized as *fact-state rules* since the reasoning logic uses numerical data to evaluate the state of traffic.

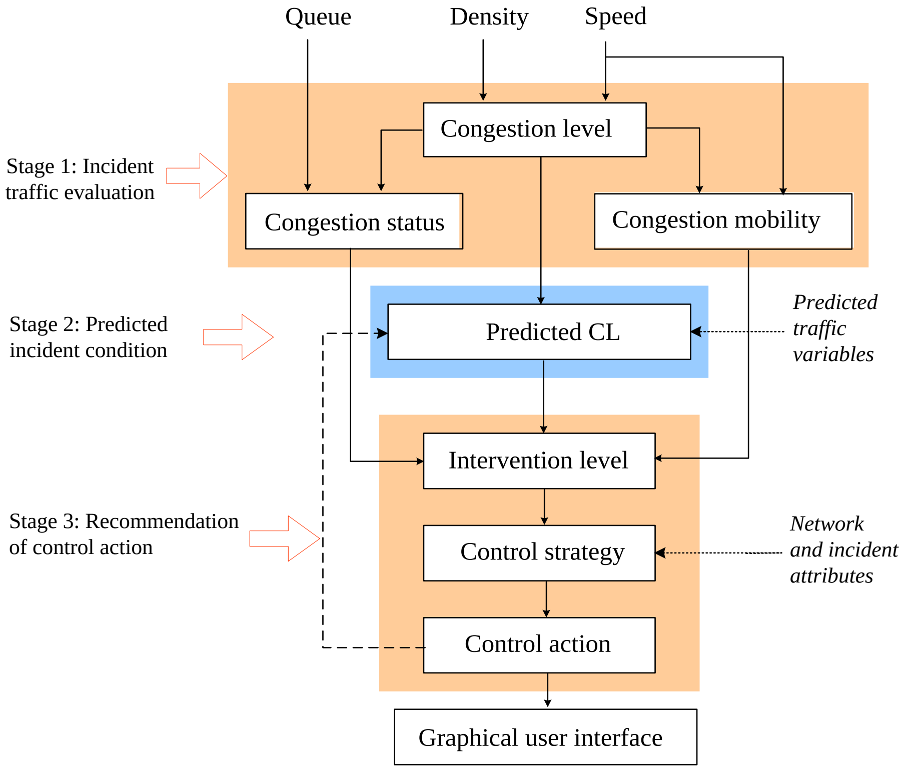


Figure 2. Conceptual model of MS-FLC for incident-related traffic control.

Stage 2: Prediction of incident traffic congestion tendency: This stage involves the prediction of the *change in the state* of traffic as well as the evolution of the incident problem. Given the outcome from the first stage, the second stage continues to anticipate the traffic and incident conditions in the immediate future, which is typically 5, 10, 15 minutes, known as time-series short-term traffic prediction. This task involves the employment of an advanced traffic forecasting technique based on Support Vector Machine (SVM), as introduced in [20, 21] as part of this research project. The SVM is linked with a real-time database so that data can be continually retrieved for the MS-FLC operation using the rolling-horizon approach proposed in [22]. The rules in this stage are typically *state-state* rules, since the reasoning sequence infers the future state from the current state using external variables from the traffic-forecasting module.

Stage 3: Recommendation of control strategies and actions: Given the outcomes from the first two stages, the MS-FLC performs a sequential analysis to arrive at recommended solutions. Given this reasoning process, the rules in stage 3 pertain to both strategic level (for intervention level, control strategy) and operational level (for control settings). The traffic operator may consider isolated, coordinated, or integrated control strategy. During the control implementation, the traffic surveillance system continually observes and provides updated data and information to the MS-FLC. Since the control input is a function of the system input, the MS-FLC behaves like a closed-loop control system. The rules for control actions are basically *state-action* rules for the given input-output mapping.

3. EVALUATION OF INCIDENT TRAFFIC CONGESTION

Figure 3 outlines a schematic representation of the first stage of the MS-FLC. The stage consists of three blocks: congestion level (*CL*), congestion mobility (*C_Mob*) and congestion status (*C_Stat*). Each of the blocks constitutes a sub-system of multiple-input-single-output (MISO) type, which employs several state variables to supply a single control variable. The *CL* evaluates the current level of traffic congestion based on speed and density; *C_Mob* estimates the dynamics of traffic stream given the speed, and the *C_Stat* determines the spatial extent of congestion, given the queue length.

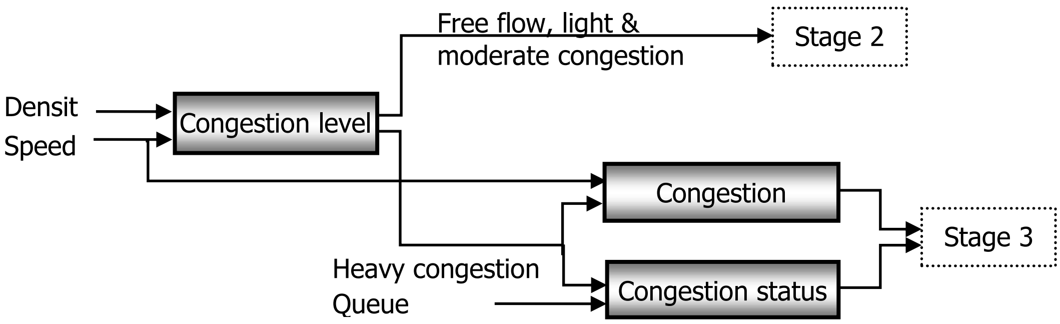


Figure 3. Rule base configuration for the first stage.

The current traffic congestion in the *CL* block is quantified into fuzzy predicates such as free flow, light, moderate, and heavy congestion. Under free flow, light, and moderate congestion, the MS-FLC proceeds to the second stage that forecasts the evolution of the traffic condition. Under heavy congestion, the rules will be fired to evaluate congestion mobility and congestion status respectively before making control actions in the 3rd stage.

The following section presents some issues in fuzzy logic design of the three blocks outlined in Figure 3. Fundamental issues in fuzzy logic design include the shape of membership functions and the fuzzy partition. This study uses the piece-wise linear style of the membership functions since the style is simple, straightforward, and it requires less computational effort. Fuzzy partition involves determination of location of control points of the fuzzy predicates. In this study, the control points of fuzzy predicates are basically determined following expert-oriented approach for simple problems, or data-based approach when the data are obtainable. Specifically, knowledge in traffic engineering is used for fuzzy partition of the congestion level (Figure 4), common sense reasoning for congestion mobility

(Figure 5), and a combination of both engineering judgments and common-sense reasoning for queue length (Figure 6) and congestion status (Figure 7). In the figures, the notation "μ" indicates the degree of membership functions, that is normalized in the the numerical scale [0, 1], where 0 represents complete uncertainty and 1 represents the opposite absolute certainty.

3.1. Evaluation of Traffic Congestion Level

Rules for the congestion level are characterized by two predicates (speed and density) in the antecedent, and one predicate (congestion level) in the consequent as a multiple input - single out (MISO) model. The use of both of speed and density is necessary to better represent the operational conditions of expressway traffic: density reflects freedom to maneuver as related to service quality, and speed is a major concern of drivers as related to traffic dynamics. They are both quantitative measures that characterize operational conditions of a traffic stream on the expressways [3, 23]. The antecedent predicates are connected with an AND operator. The general expression of rules is of the form:

$$\text{If speed is } V_{(x)} \text{ AND density is } K_{(x)} \text{ then congestion level is } CL_{(x)} \quad (1)$$

For example: if speed is low and density is medium then congestion level is moderate.

Figure 4 shows an example of partition of the fuzzy sets for congestion level. Setting boundaries of predicates of the control variable (Figure 4) is made with reference to [24]. Specifically, the predicate FreeFlow is associated with LOS A and partly to LOS B, while Light congestion corresponds to LOS C and partly to LOSs B and D, with speed reducing, flow increasing and the freedom to maneuver within the traffic stream is noticeably limited. Moderate congestion describes operation that approaches the road capacity (LOS E) and partly to LOS D, where speed deceases significantly, density increases quickly with increasing flows, and maneuverability within the traffic stream is limited. Moderate congestion may also be associated with LOSs C and F with low possibility, represented by low membership degree. Heavy congestion describes breakdowns in vehicular flow, which can be considered as approaching the LOS F at which point queues may form with potential propagation upstream. It is characterized by low speed and high density. Heavy congestion may also be associated partly with LOSs D and F. Finally, VeryHeavy represents an extreme breakdown of flow of very low traffic dynamics. It is strictly associated with LOS F.

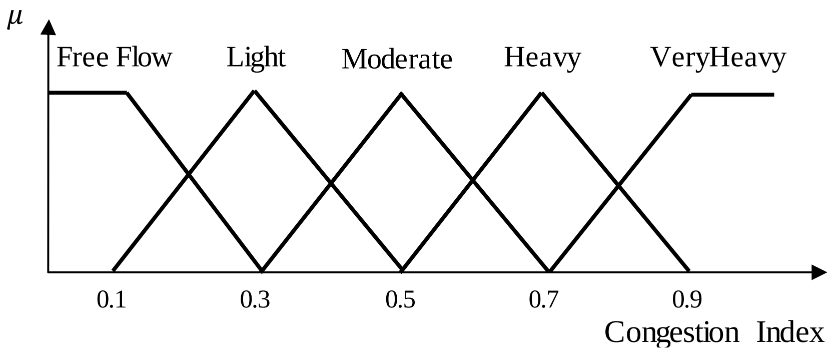


Figure 4. Fuzzy partition of the congestion level (source: [3]).

Table 1 summarizes the collection of rules for congestion level. In this study, the congestion level is classified into 5 linguistic terms: "free flow" (FF), "light congestion" (L), "moderate congestion" (M), "heavy congestion" (H), and "very heavy congestion" (VH).

Table 1. Rule decision matrix for congestion level (source: [3]).

		Density				
	Relation	VeryLow	Low	Medium	High	VeryHigh
Speed	VeryLow	---	---	H	VH	VH
	Low	---	M	M	H	VH
	Medium	L	L	M	H	H
	High	FF	L	M	M	---
	VeryHigh	FF	FF	L	---	---

Some of combinations such as “VeryHigh” speed - “VeryHigh” density, “VeryHigh” speed - “High” density, “High” speed - “VeryHigh” density, … are unlikely to occur, thus they are removed from the Table.

3.2. Congestion Mobility

The congestion mobility rule block examines another aspect of incident traffic condition: the *dynamics* of congestion. Having evaluated the congestion level in the first rule bock, congestion type *heavy* is tracked in another block and treated together with traffic speed to see *how fast* the so call heavy traffic moves. This rule block takes two input variables, speed and congestion level, to evaluate one output variable (*C_Mob*). The membership functions of the state variables are the same as in the first block. The universe of discourse of the control variable *C_Mob* is normalized in scale:

$$C\_Mob = [0, CM_{max}] = [0,10] \quad (2)$$

The congestion mobility consists of two fuzzy sets:

$$C\_Mob = \{SM\_HC, MV\_HC\} \quad (3)$$

The abbreviations stand for *“slow moving - heavy congestion”* and *“medium moving - heavy congestion”*, respectively. The term *"fast moving - heavy congestion"* is not included since *fast moving* and *heavy congestion* are mutually exclusive.

The membership functions of *C_Mob* are all convex and normal, constructed by equally partitioning the output space (Figure 5).

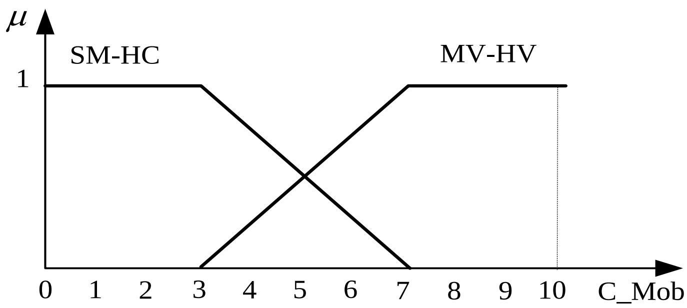


Figure 5. Membership functions of congestion mobility (source [1]).

3.3. Congestion Status

Congestion status quantifies the *spatial magnitude* of the congestion being considered given the number of vehicles in queue. A queue starts as demand exceeds (remaining) capacity. A lane-block incident temporarily reduces the road capacity, leading to potential traffic breakdown and formation of queue upstream of the incident location. The queue length or the number of vehicles in queues signifies the spatial magnitude of the incident congestion, thus the evaluation of the queuing status is important before proposing control actions.

Given that queues only form under heavily congested situations, in the third rule block, the MS-FLC evaluates the status of congestion based upon the queue length (number of vehicles in the queue) under the heavy congestion category. Figure 6 plots membership functions for queue length on expressways.

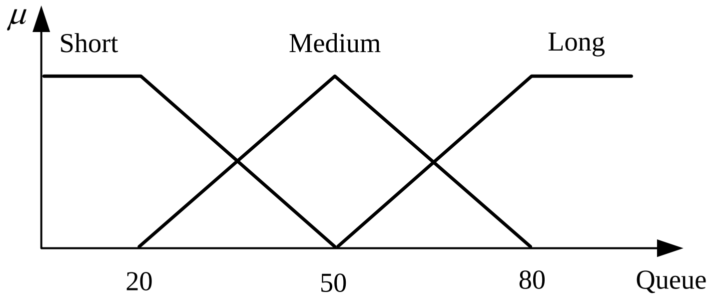


Figure 6. Linguistic values of queue length (source [1]).

The linguistic values of the queue length variable are set as:

$$Queue = \{Short, Medium, Long\} \quad (4)$$

and linguistic values for the congestion status are set as (Figure 7):

$$C\_Stat = \{SQ - HC, MQ - HC, LQ - HC\} \quad (5)$$

The abbreviations stand for *"short queue – heavy congestion"*, *"medium queue – heavy congestion"*, and *"long queue – heavy congestion"*, respectively.

It is logical to note that the term *queue* only refers to slow-moving traffic streams. As an example, the queue average spacing is between 10 and 20 m, and the queue average speed is between 5-15 km/h [25].

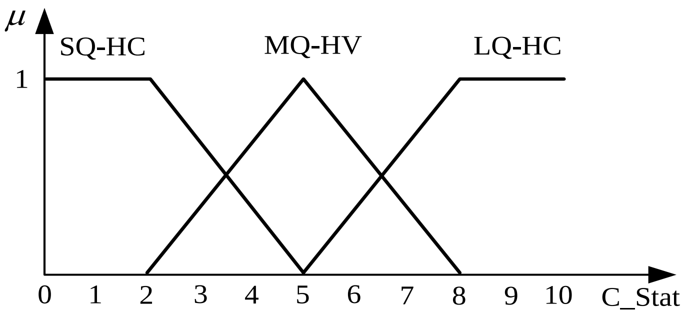


Figure 7. Fuzzy sets of congestion status (source [1]).

4. ANTICIPATION OF TREND OF TRAFFIC CONDITIONS

The anticipation of incident-related traffic conditions is the 2nd and the intermediate stage of the MS-FLC. The stage attempts to see how incident-related traffic conditions evolve so that suitable proactive traffic control solutions are recommended. The anticipation of traffic conditions under incident situations is a complex multivariate process that involves short-term forecast of traffic variables. Given that traffic conditions during incidents are characterised by random fluctuations, a risk factor is necessary to cater for unknown and unexpected impacts from the traffic environment that may reduce the prediction accuracy.

Figure 8 describes the schematic process of the 2nd stage of the MS-FLC. The stage consists of the estimation of the risk factor, the prediction and adjustment of traffic variables, and the anticipation of incoming traffic condition.

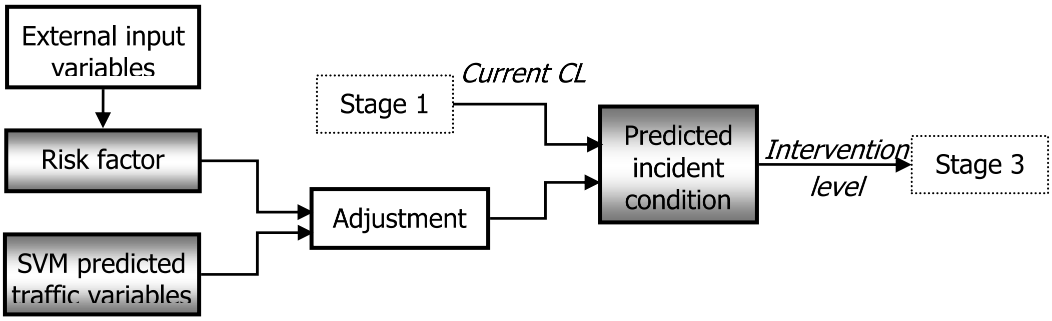


Figure 8: Schematic rule flow for the 2nd stage.

Risk factor. In effects, traffic forecasting techniques are essentially data-driven, relying purely on data collected within a current time window, thus they have limited reasoning capability to take account of random fluctuations of traffic environment in the future, which may be particularly high under incident situations. Thus, the predicted data should be adjusted to cater for external risks that exist exogenously with the prediction being made. The application of a risk factor is an attempt to take advantage of reasoning capabilities in fuzzy logic to compensate for shortcomings of data-driven traffic forecast. Other than the congestion level produced in the first stage that is known as an internal input, the risk factor considers a number of external variables. Since the consideration of all influencing factors is not possible, it may be more feasible to focus on the most influencing factors. The author recommends considering the effectiveness of control strategy, incident severity, and time of day.

Effectiveness of the control strategy: since the predicted traffic parameters and the implemented control actions are mutually dependent, it is desirable to take into account the effectiveness of the control actions in prediction of traffic variables. The control effectiveness can be represented by the proportion of drivers who conform to the control directives at the ramps, such as to follow route-diversion or lane-changing messages. Eq. (6) describes the level of conformity by a set of three linguistic terms:

$$Conform\_lev = \{Weak, Medium, Strong\} \tag{6}$$

The level of conformity depends on a number of factors, such as the strength and content of VMS messages, driver behaviour, network attributes, incident severity, and traffic congestion level. It is apparently site specific, thus the fuzzy terms should be calibrated locally [1].

Incident severity: the incident severity is estimated from the number of lane closure in comparison to the total number of available lanes. Without loss of generality, it is assumed that the higher the capacity reduction, the higher error-prone the prediction will be. In Eq. (7), the capacity reduction (CapR) is represented by three fuzzy sets:

$$CapR = \{Slight, Medium, Severe\} \tag{7}$$

The time of day: the time of day (TOD) reflects the global tendency of repeating background traffic patterns prevailing for a longer period. The TOD should be a profound risk factor in the sense that with the same prediction error it may be highly risky in peak hours, but less risky in off-peak or nighttime since the traffic demands during these periods are lower, and the road still has available capacity to accommodate the error surcharge. The fuzzy sets for TOD differentiate the peak from the off-peak (day time) and the nighttime:

$$TOD = \{Peak, OffPeak, NightTime\} \tag{8}$$

Given the three state variables *(*$Conform\_lev$, $CapR$, and *TOD),* the risk factor is evaluated using linguistic terms. In Eq. (9) the risk factor is labelled by 4 fuzzy sets:

$$Risk = \{Low, Medium, High, Very\_high\} \tag{9}$$

The mapping (Table 2) between the state variables and the control variable *(Risk)* is empirically made so that it forms an elegant transition from one fuzzy value to another, where the fuzzy values cover the whole of the output space: if the state variables indicate that traffic is in favourable conditions (strong conformity level, low-capacity reduction, off-peak period), the risk will be evaluated as “Low”. By contrast, when state variables indicate critical conditions, the risk will be evaluated as “High” or “Very_high”.

Table 2. Decision table for the risk factor.

Rule	**If**			**Then**
	$Conform\_lev$	$CapR$	TOD	$Risk$
1	Weak	Severe	Peak	Very_high
2	Weak	Severe	OffPeak	High
3	Weak	Severe	NightTime	Medium
4	Weak	Medium	Peak	High
5	Weak	Medium	OffPeak	Medium
6	Weak	Medium	NightTime	Low
7	Weak	Slight	Peak	Medium
8	Weak	Slight	OffPeak	Medium
9	Weak	Slight	NightTime	Low
10	Medium	Severe	Peak	High
11	Medium	Severe	OffPeak	Medium
12	Medium	Severe	NightTime	Low
13	Medium	Medium	Peak	Medium
14	Medium	Medium	OffPeak	Low
15	Medium	Medium	NightTime	Low
16	Medium	Slight	Peak	Medium
17	Medium	Slight	OffPeak	Low
18	Medium	Slight	NightTime	Low
19	Strong	Severe	Peak	High
20	Strong	Severe	OffPeak	Medium
21	Strong	Severe	NightTime	Low
22	Strong	Medium	Peak	Medium
23	Strong	Medium	OffPeak	Low
24	Strong	Medium	NightTime	Low
25	Strong	Slight	Peak	Low
26	Strong	Slight	OffPeak	Low
27	Strong	Slight	NightTime	Low

For instance, rule 1 is expressed as:

$$\begin{aligned}&If\ Conform\_lev\ is\ Weak\ and\ CapR\ is\ Severe\ and\ TOD\ is\ Peak\\ &then\ Risk\ is\ Very\_high\end{aligned} \tag{10}$$

5. RESULTS AND DISCUSSIONS

Having obtained the predicted traffic volume (V), the MS-FLC anticipates the evolution of traffic conditions using the current congestion level estimated in the first stage, the risk factor, and the predicted traffic demand. The evolution of traffic trend is heavily governed by the balance between traffic demand and supply, represented by the ratio between traffic volume (V) upstream and remaining capacity (C^*) at the incident location, which is the available full road capacity in normal condition minuses the capacity reduction $(CapR)$. In these regards, the V/C^* ratio is used as a principal parameter for the anticipation. The V/C^* (or *adjusted* V/C^*) ratio is represented by four fuzzy sets (Figure 9):

$$V/C^* = \{Low, Medium, High, Very\_high\} \quad (11)$$

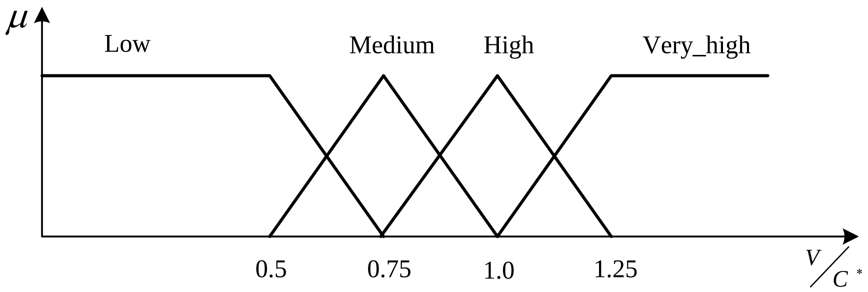


Figure 9. Membership functions for (adjusted) V/C^* ratio (source: [18]).

The process to anticipate congestion level involves two sub-stages: first, the predicted V/C^* ratio and the *Risk* are used to estimate the *adjusted* V/C^*, then the *adjusted* V/C^* and the current congestion level is used to infer the predicted congestion level. As stated previously, the division of the process into sub-stages simplifies the rule base, hence the number of rules can be cut off.

Figure 10 describes the fuzzy inference system (FIS) architecture for the 1st sub-stage in the reasoning process that derives the predicted congestion level. The risk factor and (predicted) V/C^* ratio are the two inputs, used to make adjustment for the V/C^* ratio. The inference engine is of Mamdani type [26].

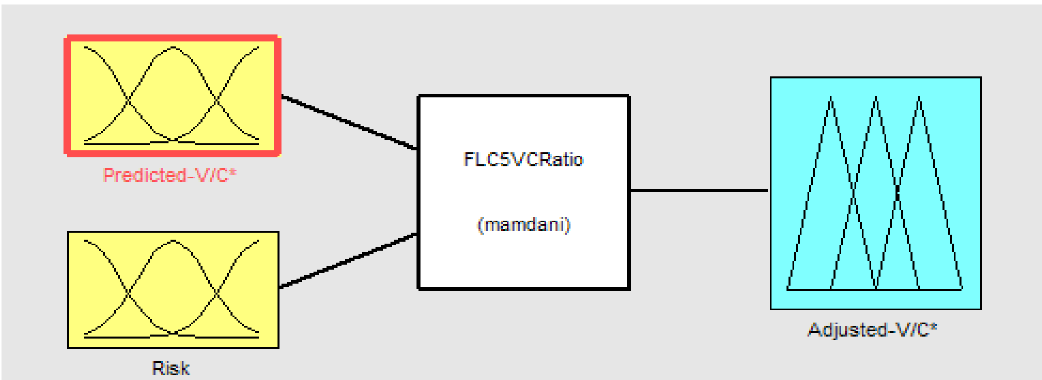


Figure 10. FIS architecture for the 1st sub-stage.

Given the fuzzy sets of the two input variables, the author proposes a set of 16 rules for the 1st sub-stage, as shown in Table 3.

Table 3. Rules for the 1st sub-stage.

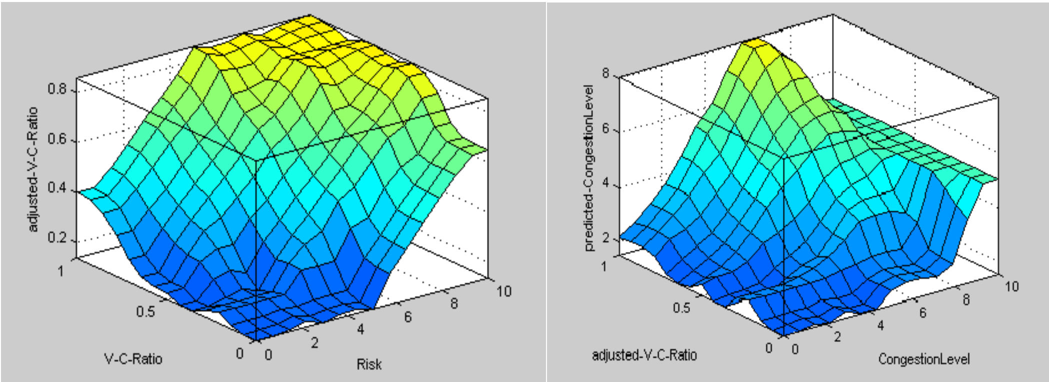
Rule No.	**Rule condition**		**Rule conclusion**
	predicted V/C^*	**Risk**	**adjusted V/C^***
1	Low	Low	Low
2	Medium	Low	Low
3	High	Low	Medium
4	Very_high	Low	High
5	Low	Medium	Low
6	Medium	Medium	Medium
7	High	Medium	High
8	Very_high	Medium	Very_high
9	Low	High	Medium
10	Medium	High	High
11	High	High	Very_high
12	Very_high	High	Very_high
13	Low	Very_high	High
14	Medium	Very_high	Very_high
15	High	Very_high	Very_high
16	Very_high	Very_high	Very_high

Given the adjusted V/C^* and congestion level in the current stage, the FIS infers the predicted congestion level using a collection of 16 rules in the 2nd sub-stage (Table 4). It is worth noting that in this sub-stage, the variable *CongestionLevel* indicates the prevailing current congestion level, which does not include the *Heavy* congestion level since this level is tracked directly from the 1st into the 3rd stage of the MS-FLC.

Table 4. Rule for the 2nd sub-stage.

Rule No.	**Rule condition**		**Rule conclusion**
	adjusted V/C^*	**CongestionLevel**	**predicted-CongestionLevel**
1	Low	Free-flow	Free-flow
2	Medium	Free-flow	Free-flow
3	High	Free-flow	Pre-con
4	Very_high	Free-flow	Light
5	Low	Pre-con	Free-flow
6	Medium	Pre-con	Pre-con
7	High	Pre-con	Light
8	Very_high	Pre-con	Moderate
9	Low	Light	Pre-con
10	Medium	Light	Light
11	High	Light	Moderate
12	Very_high	Light	Heavy
13	Low	Moderate	Light
14	Medium	Moderate	Moderate
15	High	Moderate	Heavy
16	Very_high	Moderate	Heavy

Figure 11 illustrates the surfaces of knowledge for the two sub-stages, which are obtained using the *centroid* defuzzification method. The figure represents the projection of a hyperspace of knowledge into one three-dimensional space.



a) The 1st sub-stage b) The 2nd sub-stage

Figure 11. Knowledge surfaces for two sub-stages.

Discussion: The above section presents the rule formulation in the two sub-stages. In the first sub-stage both the quantitative measurement (V/C^*) and qualitative estimation (*Risk* factor) are employed, where the *Risk* factor is used to adjust the predicted V/C^* ratio. As presented earlier, the use of the risk factor is to cater for external risks that exist exogenously with the prediction being conducted. The *Risk* factor accommodates potential uncertain elements in the traffic environment and is used as a scale. It is classified into 4 predicates with the basic idea: the *Low* risk level adjusts the V/C^* ratio down; the *Medium* keeps the ratio the same, and the *High* and *Very_high* risks scale the V/C^* up.

In the 2nd sub-stage, the *adjusted* V/C^* and the current congestion level are used to infer the anticipated congestion level for the next control stage. Obviously, the anticipated traffic condition depends not only on the current condition, but also on the trend and the rate of change of the state, and the prediction interval. The current congestion level is used as the baseline for reference, whereas the *adjusted* V/C^* is used as the determinant that orientates the *trend* toward which the current traffic condition evolves. It is worth noting that the volume *V* indicates the *latent traffic demand* (that can be measured far upstream) but not the flow rate measured in the immediate upstream of the incident. Therefore, the ratio does not incur the double effect as in the fundamental speed-volume relationship (for example, a low value of flow rate indicates either free-flow traffic *or* heavy congestion). From traffic engineering perspective, *"V"* carries the meaning of true traffic demand, *Low* V/C^* is associated with *Free-flow*; *Medium* V/C^* with *Pre-congestion*; *High* V/C^* with *Light* or *Moderate*; and *Heavy* congestion level with *Very_high* V/C^*.

In mapping of two state variables ($\Re^2 \rightarrow \Re^1$ mapping), there are some overlaps of rule conclusions (for example rules 1 and 2 in both Tables 3 and 4). However, the overlaps do not destroy the principle of consistent rule mapping: different inputs may produce the same output, but the same set of inputs must produce the same output. It is worth noting that the same fuzzy output in different conclusions does not deliver the same fuzzy membership values. For example, the value *"Low"* in the conclusions of rules 1 and 2 in Table 3 produces different values of membership functions.

Although the rule formulation seems to be highly subjective, it reflects inherent nature of the fuzzy-based methodology to confronting with uncertain problems to foresee what might happen in the future, since there exists no mathematical equation for such an uncertain and multivariable problem. Alternatively, the anticipated congestion level can be inferred from predicted traffic speed and density, in the same manner as is used to evaluate the current congestion level. However, as traffic congestion during incident changes unexpectedly, this direct inference without referring to the prevailing current congestion and the risk factors may be highly erroneous.

6. CONCLUSIONS

For traffic control for incident congestion management on expressways following fuzzy-logic approach, the author has carried out a research project that develops a multi-stage Fuzzy Logic Controller (MS-FLC) that aims at establishing a systematic procedure in deriving control actions to support traffic operator's decision-making at an operational level. The procedure includes three consecutive stages. This paper focuses on the 1st and 2nd stages of the MS-FLC. In the 1st stage the traffic conditions are evaluated using three quantities: congestion level, congestion mobility and congestion status, in the 2nd stage incident-related traffic conditions are anticipated using predicted traffic variables and the risk factor that cater for random fluctuations during the incident occurrence. Given the inputs from these two stages, rules in the 3rd stage is fired to recommend ramp control actions accordingly.

The results from this study allow the following conclusions to be made:

- MS-FLC provides a systematic procedure in deriving control actions, and the fuzzy-based procedure presented in this paper constitutes an important part to achieve this goal.
- Following fuzzy logic, the procedure possesses excellent knowledge representation capability, and delivers linguistic expressions that is easily understood by the operators for making decisions.
- With both current and anticipated types of information, the fuzzy-based procedure ensures that the MS-FLC operates on both reactive and proactive control to assist decision making in a systematic and structured manner.
- Flexibility of the performance: although the fuzzy-based procedure is designed for incident congestion management, it could also be applied to recurring congestion management, since the problem-solving strategy for both types of congestion aims at demand-capacity balance on the mainline and the ramp.

Nevertheless, as part of the MS-FLC the fuzzy-based procedure has certain limitations: (i) it employs a considerable number of input parameters, thus extensive observations from the network are required; and (ii) the MS-FLC is a highly non-linear system with complex behavior. However, a systematic procedure for the system's stability analysis is not yet available.

Since this paper covers only a part of a larger research project, the ultimate numerical results of the system (i.e. control actions, ramp metering rates, etc.) are not readily available.

Given the limited space, there are a considerable number of points that could not be elaborated in detail, but only methodological framework is presented. The significance of this paper, to a great extent, can be focused on engineering judgments within the context of the wider research scope. Since the 1st and 2nd stages constitute essential components of the MS-FLC that determines control strategies and implements ramp control actions, the merit of this paper can further be linked to [18] that validates and evaluates the MS-FLC's performance in totality.

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REFERENCES

[1]. T.D. Toan, Development of a fuzzy knowledge-based system for local traffic control for incident management, PhD Thesis. School of Civil & Environmental Engineering, Nanyang Technological University, 2008.

[2]. S. R. Kukadapwar, D.K. Parbat, Modeling of traffic congestion on urban road network using fuzzy inference system, American Journal of Engineering Research, 4 (2015) 143-148.

[3]. T.D. Toan, Y.D. Wong, Fuzzy logic-based methodology for quantification of traffic congestion. Physica A: Statis. Mec. and its App. 570, 2021, 125784.

[4]. J. Mendel, Fuzzy logic systems for engineering: a tutorial, Proceedings of the IEEE, 83 (1995) 345-377.

[5]. D. Zhao, Y. Dai, Z. Zhang, Computational intelligence in urban traffic signal control: a survey. IEEE Transactions on Systems, Man, and Cybernetics, (2012) 485-494.

[6]. U. F. Eze, I. Emmanuel, E. Stephen, Fuzzy logic model for traffic congestion, IOSR Journal of Mobile Computing & Application, 1 (2014) 15-20.

[7]. A. John, Z. Yang, R. Riahi, Application of a collaborative modelling and strategic fuzzy decision support system for selecting appropriate resilience strategies for seaport operations, Journal of Traffic and Transportation Engineering (English Edition), 1 (2014) 159-179.

[8]. X. Li, Y. Liu, Y. Wang, Evaluating transit operator efficiency: an enhanced DEA model with constrained Fuzzy-AHP Cones, Journal of Traffic and Transportation Engineering (English Edition), 3 (2016) 215-225.

[9]. Q. Li, F. Qiao, L. Yu, Socio-demographic impacts on lane-changing response time and distance in work zone with drivers' smart advisory system, Journal of Traffic and Transportation Engineering (English Edition), 2 (2015) 313-326.

[10]. T. D. Toan, S. H. Lam, Development of a rule-based system for congestion management, in Transportation Research Board 84th Annual Meeting. Washington, D.C.: Transportation Research Board, 2005.

[11]. M.T. Tariq, A. Massahi, R. Saha, M. Hadi, Combining machine learning and fuzzy rule-based system in automating signal timing experts' decisions during non-recurrent congestion, Transp. Res. Rec., 2674 (2020) 163-176

[12]. K. Hamad, S. Kikuchi, Developing a measure of traffic congestion - fuzzy inference approach, Transportation Research Record: Journal of the Transportation Research Board, 2770 (2002) 77-85.

[13]. L. Zhan, P. D. Prevedouro, User perceptions of signalized intersection level of service using fuzzy logic, Transportmetrica, 7 (2011) 279–296.

[14]. M. Collotta, L.L. Bello, G. Pau, A novel approach for dynamic traffic lights management based on Wireless Sensor Networks and multiple fuzzy logic controllers, Exp. Sys. with App, 42 (2015) 5403-5415. http://dx.doi.org/10.1016/j.eswa.2015.02.011

[15]. M. Kalinic, J.M. Krisp, Fuzzy inference approach in traffic congestion detection, Annals of GIS, 25 (2019) 329-336.
[16]. Y. Ge, A two-stage fuzzy logic control method of traffic signal based on traffic urgency degree, Mod. and Sim. in Eng., (2014) 694185. http://dx.doi.org/10.1155/2014/694185
[17]. Y.E. Hawas, M. Sherif, M.D. Alam, Optimized multistage fuzzy-based model for incident detection and management on urban streets, Fuz. Sets and Syst., 381 (2019) 78-104.
[18]. T.D. Toan, M. Meng, S.H. Lam, Y.D. Wong, Multi-stage fuzzy logic controller for expressway traffic control during incidents, Forthcoming paper, Journal of Transp. Eng. Part A: Systems (2022), in press (expected time: March 2022), https://doi.org/10.1061/JTEPBS.0000679
[19]. T.D. Toan, S.H. Lam, Y.D. Wong, M. Meng, Development and validation of a driving simulator for traffic control using field data, Physica A: Statis. Mec. and its App., 596 (2022)127201. https://doi.org/10.1016/j.physa.2022.127201
[20]. T. D. Toan, V. H. Truong, Support vector machine for short-term traffic flow prediction and improvement of its model training using nearest neighbor approach, Transp. Res. Rec., 2675 (2021) 362–373. https://doi.org/10.1177/0361198120980432
[21]. M. Meng, T.D. Toan, Y.D. Wong, S.H. Lam, Short-term travel-time prediction using support vector machine and nearest neighbor method, Transportation Research Record, (2022) 1–13. https://doi.org/10.1177/03611981221074371.
[22]. S. Peeta, H.S. Mahmassani, Multiple user classes real-time traffic assignment for online operations: A rolling horizon solution framework, Transp. Res. Part C: Emerging Technol., 3 (1995) 83-98.
[23]. T.D. Toan, Fuzzy based quantification of congestion for traffic control, Transport and Communications Science Journal, 72 (2021) 1-8.
[24]. J.G. Nicholas, L.A. Hoel, Traffic and Highway Engineering, fourth ed., University of Virginia, 2009.
[25]. Quadstone Paramics V5.1: Modeller Reference Manual. Quadstone Limited, Version No. 1.0. Quadstone Limited, Scotland, 2004.
[26]. MATLAB User Manual, R2016a, 2016.