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A KNOWLEDGE-BASED DECISION SUPPORT SYSTEM FOR INCIDENT TRAFFIC CONGESTION MANAGEMENT

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Abstract. A Knowledge-based Decision Support System (KB-DSS) based on a multi-stage Fuzzy Logic Controller (MS-FLC) is developed for traffic congestion management on expressways. The MS-FLC receives real-time traffic and incident data to analyse and anticipate the traffic conditions, to recommend alternative control measures in the form of natural languages for the human operator to select control decisions, and to calculate control settings to manage traffic congestion. In a case study, the KB-DSS is evaluated on a simulated network in comparison to ALINEA\Q, a popular ramp control method, across various traffic and incident situations. The results showed that: (i) the KB-DSS provides a systematic procedure in deriving control actions and a good capability to deliver linguistic expressions; (ii) the KB-DSS outperforms ALINEA\Q with respect to global objectives across many scenarios, attains significant improvements of mainline travel conditions and substantial reductions of ramp queues. These advantages make the KB-DSS a robust tool for traffic control for incident congestion management on expressways.

Keywords: congestion management, decision support system, knowledge-based, multi-stage fuzzy logic controller, fuzzy rule.

1. INTRODUCTION

Traffic congestion is a critical and pervasive problem confronting many metropolitan areas worldwide. Congestion can be broadly classified into two types: recurring congestion and non-recurring congestion. Characterised by time-critical constraints, the management of non-recurring congestion on expressways can be remedied by implementing effective control measures to ameliorate traffic conditions on the expressways, and at the same time to avoid imposing excessive congestion on adjoining sub-networks. Due to complex nature, an effective traffic control scheme for incident traffic congestion management often relies on techniques that deal efficiently with problems of uncertainty and imprecision.

Various approaches have been developed for real-time traffic management, including analytical optimisation and automatic control approaches [1]. The analytical optimisation models the state of traffic systems based on predefined assumptions about the system behaviour and dynamics [2,3]. They are often very complex, computationally expensive; thus, they can hardly satisfy real-time requirements. By contrast, although the automatic control approach [1,4] has the ability to model the behaviour of the control process and classify large patterns of input data [5-7], they provide no explanation instrument for the operators to determine appropriate control actions. Constrained by cognitive and time limits, the traffic operators require a support to solve problems more smoothly and rapidly, and at the same time to improve the effectiveness of decision making. To remedy this challenging problem, an interactive and flexible computerised systems that utilises available data, knowledge and control techniques with extensive user involvement is greatly needed to improve the quality of decision making [8]. Such component is known as a Decision Support System (DSS) [9-11].

Extensive research efforts have been made to employ knowledge representation and inference systems that are able to handle real-time traffic data to find solutions against traffic problems in a human-like fashion. Such systems, known as Knowledge-Based Decision Support Systems (KB-DSS), are suitable for ill-structured problems in well-defined domains where algorithmic and automatic procedures are not appropriate [12-14]. One of the most popular KB-DSS for traffic management and control is the rule-based reasoning system that has been investigated by many researchers [15-17]. In the rule-based reasoning system, fuzzy rules have a good capability in handling uncertainty to solve complex non-linear problems within a reasonable amount of time [18-20]. Fuzzy logic should therefore be a suitable solution to provide support to decision making on traffic control for incident congestion management.

Previous studies utilised the advantages of fuzzy logic in handling multi-variable incident traffic congestion problems, and the results have been encouraging. However, most of them discussed the decision-making process in a single stage [21-23]. Traffic control is a complex multivariable problem with a large number of input and output variables; thus, a single-stage fuzzy inference may not be suitable since the rule base becomes too cumbersome to handle effectively. To tackle the issue, a multi-stage Fuzzy Logic Controller (MS-FLC) should be deployed. In a MS-FLC, outputs from preceding stage are used as inputs to the current stage, and outputs from the current stage are used as inputs for the next stage. This decomposition reduces the problem complexity and the number of rules in each stage, thereby improves the overall performance.

This research develops a MS-FLC as a key component of the KB-DSS for traffic congestion management on expressways. The MS-FLC receives real-time traffic and incident data to analyse and anticipate the traffic conditions, to recommend alternative control measures in the form of natural languages for the human operator to select control decisions, and to calculate control settings to manage traffic congestion. In a case study, the KB-DSS is evaluated on a simulated network in comparison to ALINEA\Q, a popular ramp control method, across various traffic and incident situations.

2. METHODOLOGY

2.1. Conceptual framework

The complete structure of the proposed KB-DSS (see Figure 1) consists of four main components: the data base, the rule base, the MS-FLC (alternatively named as FLC for short), and the Graphical User Interface (GUI), wherein the rule base and the FLC are the key components.

The data base includes Historical Database (HDB) and Real-Time Database (RTDB). The HDB stores data for learning parameters of fuzzy rules and extracting rules [24]. In addition, traffic data from the HDB are used to construct historical profiles for traffic prediction. Historical incident data can be explored to identify incident-sensitive locations and to learn important incident attributes in the network. The RTDB, on the other hand, provides data as inputs for the FLC. The RTDB is continually rolled forward so that the state variables are continually updated with the latest data and information.

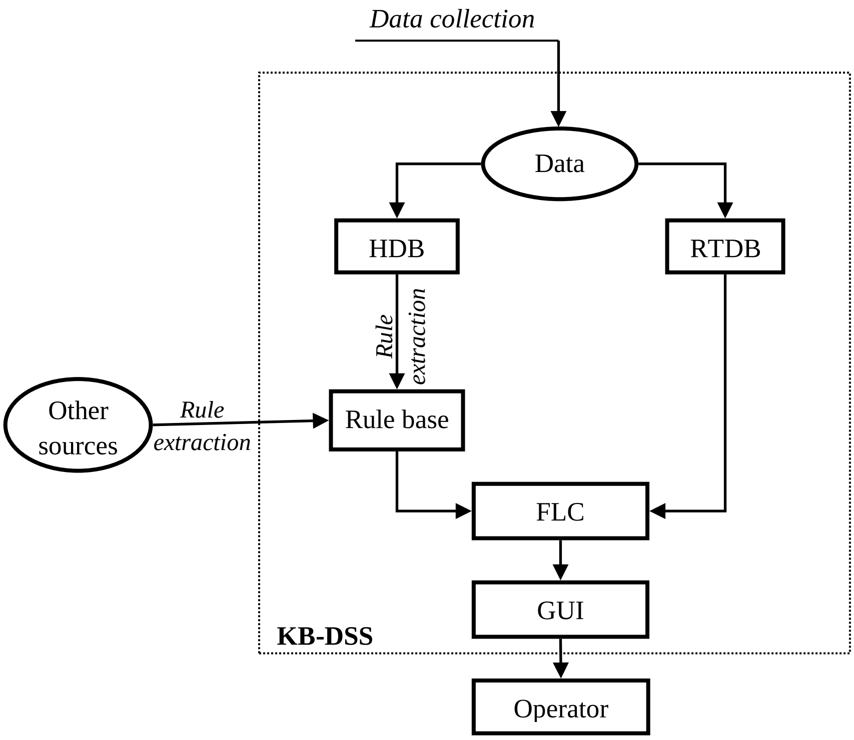

Figure 1. KB-DSS architecture.

The rule base is an essential component of the KB-DSS. It stores knowledge in the IF-THEN rule format. Two formal approaches to learn rules in the rule base include the data-driven that utilises data from the HDB for input-output mapping and the expert-oriented that extract rules using engineering knowledge and expert judgments. For traffic control, traffic operator's experience is a particular important source for rule extraction.

The FLC is the key component of the KB-DSS. The FLC (Figure 2) has 4 components: fuzzifier, fuzzy rule base, inference engine and defuzzifier [8]. The fuzzifier matches numerical inputs with the conditions of the rules and converts them into fuzzy sets. The fuzzy rule base holds a collection of IF–THEN rules. For each rule, the antecedent describes to what degree the rule satisfies, while the conclusion assigns a membership function to each of the output variables. The fuzzy inference engine maps input fuzzy sets to output fuzzy sets and combines outputs from constituent activated rules to obtain an aggregated fuzzy output. Finally, the defuzzifier converts the aggregated fuzzy output into non-fuzzy (crisp) values using defuzzification techniques such as the centroid and maxima.

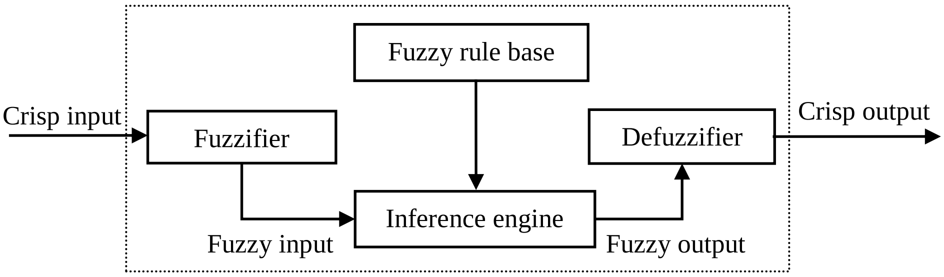

Figure 2. Schematic diagram of a Fuzzy Logic Controller.

The user interface (GUI) provides the traffic operator with a communication means (menus, commands, input-outputs, natural language interface, …) to integrate with the other components. In the KS-DSS, GUI facilitates graphical displays that make man-machine interaction efficient and user-friendly.

2.2. Multi-stage Fuzzy Logic Controller

A FLC employs a number of state (input) variables to produce control actions. The number of rules in the rule base depends on the number of state variables and the number of fuzzy sets in each variable. As the number of variables increases, the number of rules increases exponentially. For example, for a system consisting of M state variables each with N fuzzy sets, the maximum number of rules is N^M. Consequently, for complicated applications with a large number of input and output variables, the single-stage fuzzy inference may not be suitable since the rule base becomes too cumbersome to handle effectively. For a multi-variable FLC, the decomposition into several stages is desirable since it reduces the complexity of the problem and provides a hierarchical concept of association and reasoning.

Given the prescribed functionalities and relationships, the rules in the proposed multi-stage FLC can be expressed in the general form:

$$\boldsymbol{Y} = f(\boldsymbol{X}, \boldsymbol{U}) \tag{1}$$

where $\boldsymbol{X}$ is the vector of input variables, $\boldsymbol{U}$ is the vector of intermediate variables, and $\boldsymbol{Y}$ is the vector of the output variables.

$$\mathbf{X} = (x_1, x_2, \ldots, x_n)^T \tag{2}$$

$$\mathbf{U} = (u_1, u_2, \ldots, u_m)^T \tag{3}$$

$$\mathbf{Y} = (y_1, y_2, \ldots, y_n)^T \tag{4}$$

where

$$y_i = f_i(x_1, x_2, \ldots, x_n, u_1, u_2, \ldots, u_m); \forall i = 1, \ldots, n \tag{5}$$

$$u_j = \psi_j(x_1, x_2, \ldots, x_n); \forall j = 1, \ldots, m \tag{6}$$

Equations (2) to (6) represent non-linear relationships of a fuzzy multi-variable control model. In multi-stage FLC, the primary parameters of input variables are employed in the first stage, while in the second and the third stages both intermediate inputs from the previous stage as well as external variables are utilised. Basically, the rules have multiple-inputs-single-output structure. Given these, the formation of rules in three stages can be described as follows:

$$\text{Stage 1: } \left\{ \begin{array}{l} R_1 : If\ X_1\ is\ A^1_{1,x} \cap ... \cap X^1_N\ is\ A^1_{1,x}\ then\ Y_1\ is\ C^1_{1,y} \\ .... \\ R_{n_1} : If\ X_1\ is\ A^1_{n_1,x} \cap ... \cap X^1_N\ is\ A^1_{n_1,x}\ then\ Y_1\ is\ C^1_{n_1,y} \end{array} \right\} \Rightarrow \text{ to the 2}^{\text{nd}} \text{ stage} \tag{7}$$

$$\text{Stage 2: } \left\{ \begin{array}{l} R_1 : If\ Y_1\ is\ A^2_{1,x} \cap ... \cap X^2_E\ is\ A^2_{1,x}\ then\ Y_2\ is\ C^2_{1,y} \\ .... \\ R_{n_2} : If\ Y_1\ is\ A^2_{n_2,x} \cap ... \cap X^2_E\ is\ A^2_{n_2,x}\ then\ Y_2\ is\ C^2_{n_2,y} \end{array} \right\} \Rightarrow \text{ to the 3}^{\text{rd}} \text{ stage} \tag{8}$$

$$\text{Stage 3: } \left\{ \begin{array}{l} R_1 : If\ Y_2\ is\ A^3_{1,x} \cap ... \cap X^3_E\ is\ A^3_{1,x}\ then\ Y_3\ is\ C^3_{1,y} \\ .... \\ R_{n_3} : If\ Y_2\ is\ A^3_{n_3,x} \cap ... \cap X^3_E\ is\ A^3_{n_3,x}\ then\ Y_3\ is\ C^3_{n_3,y} \end{array} \right\} \Rightarrow \text{ defuzzification} \tag{9}$$

where: $X_{(;)}$, $Y_{(;)}$: input and output variables respectively

n_1, n_2, n_3: number of rules in stages 1, 2, 3 respectively

$A^i_{j,x}$: fuzzy number in antecedent part; i = 1, 2, 3: the stage; j : rule j^{th} in each stage

$x = 1,2,\ldots,M$: any fuzzy number in antecedent fuzzy sets; M is number of fuzzy sets in each input variable

y =1,2, …, O: any fuzzy number in conclusion fuzzy sets; O is number of fuzzy sets in each output variable

N: number of input variables employed by 1st stage; $C^i_{j,y}$: fuzzy number in conclusion part

E: number of external input variables employed by stages 2 and 3.

2.3. Overall framework

Figure 3 describes the MS-FLC proposed for incident congestion management. The model reflects a complex sequential structure of the decision-making logic for the multi-variable traffic control problem. Given the nature of the control problem, we propose the MS-FLC to be decomposed into 3 stages: (i) incident traffic evaluation; (ii) predicted incident traffic condition; and (iii) recommendation of control actions. The rules in the first stage are executed first to give results to the second stage. The second stage receives the results as its internal inputs, and predicted traffic data as external inputs. Similarly, the third stage employs both internal and external inputs to produce the output in the form of control actions.

Stage 1: Evaluation of current states of traffic during incidents

The goal of this stage is to assess the state of traffic at the time the incident occurs. In order to determine severity of the traffic congestion, it is critical to properly assess the level of traffic severity, on this basis, appropriate recommendations for the next step can be made. Three primary quantities used to define the state of traffic are congestion level, congestion mobility, and congestion status.

The congestion level indicates the severity of traffic, the congestion mobility determines the dynamics of the congestion, evaluated by traffic speeds and the congestion status refers to the length of queues on expressways. Congestion mobility and congestion status rules are specifically designed to deal with the heavy congestion. Each component requires various treatments: if the congestion is critical, control interventions should be carried out urgently, and the rules in stage 3 should be executed accordingly. By contrast, if the traffic congestion is not yet critical, the traffic forecasting model and rules in the stage 2 will be fired. The rules in this stage belong to fact-state rules since the numerical data are used to define the state of traffic.

Stage 2: Prediction of incident traffic conditions

Given the outcome from the first stage, the second stage continues to anticipate the traffic and incident conditions in the immediate time steps, which is typically 5, 10, 15 minutes, known as short-term traffic prediction. The prediction of short-term traffic conditions is crucial to ensure success in any proactive-traffic control scheme. In anticipation of traffic and incident conditions, the essence is the prediction of short-term traffic and incident variables. This task involves the employment of an advanced traffic forecasting technique for prediction of traffic variables and the use of fuzzy logic for data processing. 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. The details on evaluation of current states of traffic and prediction of incident traffic conditions are elaborated in [25].

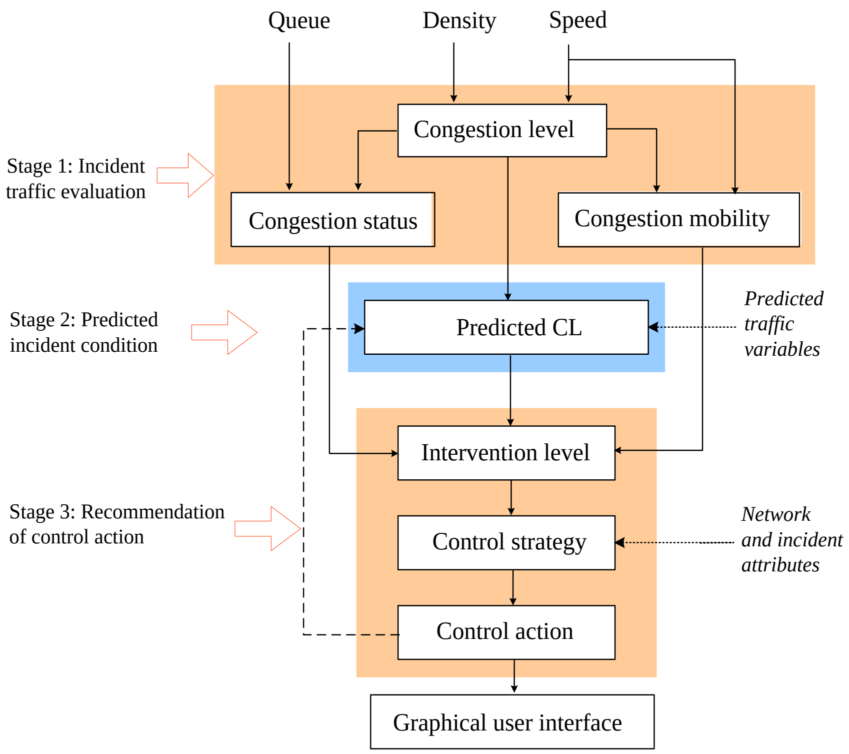

Figure 3. Conceptual model of FLC for incident-related traffic control.

Stage 3: Recommendation of control measures

The outputs from stages 1 and 2 will firstly be used to determine the strength of necessary control intervention (no_control, moderate, strong, and very_strong control level), upon which an appropriate control strategy is recommended. The control strategy rules offer a broad view of control solutions based on the evaluated control intervention level and the availability of control facilities. The traffic operator may adopt isolated, coordinated, or integrated control strategy. Once a control strategy is selected, concrete control actions are fired. For example, for isolated local ramp control, the control action considers adjustment of ramp flow and variable message sign (VMS) display; for integrated control the control action considers ramp flow and VMS diversion directives. The outputs of the FLC system are defuzzified to deliver crisp values. 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 rules for control actions are basically state-action rules for the given input-output mapping.

For the MS-FLC to operate in totality, the model is linked with a traffic data collection package for real-time traffic data and incident information (RTDB in Figure 1) in the 1st stage, and is integrated with a short-term traffic flow prediction model in the 2nd stage. Given the predicted traffic data, MS-FLC calculates the signal settings at the ramp entrance having the operator's selection of a control measure in the 3rd stage. In the model evaluation, MS-FLC is embedded in a traffic simulator controller (TSC) [26], and is evaluated across several incident scenarios in a simulation environment. Details of the MS-FLC is described in Figure 5.

3. MODEL EVALUATION

3.1. General setting

For model evaluation, a basic expressway segment as shown in Figure 4 is used. The segment has three links: the link upstream of the ramp, the link downstream of the ramp (upstream of the incident), and the link downstream of the incident. For local ramp control, most of the measurements are made in the vicinities of the incident, namely the upstream and downstream links. The lengths of the links used in this experiment are $L_{upstr} = 1000\,m$, $L_{downstr} = 500\,m$. The lane-blocking incident reduces the capacity of the expressway, and the local ramp control by traffic signal is implemented to regulate traffic demand from the ramp to maintain a balance between demand and capacity, to improve expressway travel condition, and to prevent congestion during the incident.

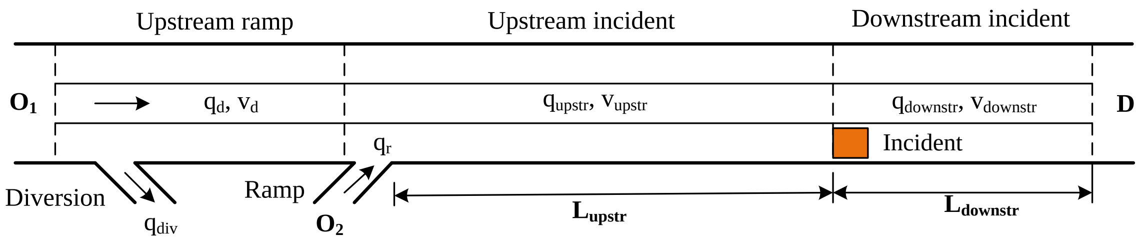

Figure 4. Layout of the study network.

The inputs in evaluation involve 2 pairs of time-dependent OD demands (O_1D and O_2D), speed profile of the first vehicles, and time-varying splits at the diversion route. The time varying splits are specifically considered in the rules in the FLC algorithm. The evaluation investigates a wide range of traffic conditions and incident situations. The traffic O_1D flows can be loaded at Low, Medium, and High demand levels, the values of which are defined based on local conditions. In addition to traffic conditions on the expressway and on the ramp, the evaluation investigates various incident scenarios, including capacity reduction and incident location.

In this experiment the ramp is assumed to have a storage capacity of 60 vehicles. Once the ramp queue reaches this level, the urban traffic will not join the ramp queue but will be diverted to the surface street sub-network and enter the expressway through downstream ramps. The availability of diversion alternatives encourages the local traffic to utilise the parallel sub-network in case of critical mainline traffic conditions.

The parameters of interest used for control and evaluation are aggregated variables including traffic flow rate $q_{(;)}(t)$, speed $v_{(;)}(t)$, and density $k_{(;)}(t)$ for every interval t, where (;) denotes the locations upstream and downstream of the incident. Apart from that, the queues on expressway and on the ramp are also collected. The total study time is 90 minutes, including: the first one third part (30 min.) is normal traffic, the second one third part (30 min.) is incident period, and the last one third part (30 min.) is again normal traffic. There are 8 measures of effectiveness (MOEs) that are used as the evaluation criteria, including total travel time (TTT) on expressway, total waiting time (TWT) on the ramp, total time spent (TTS) in the system, total travel distance (TTD), average speed (MS) and mean density (MD) on the expressway, maximum length of queues on the expressway (max Q_exp), and maximum length of queues on the ramp (max Q_ramp).

Three control methods are considered: No control; ALINEA (ALINEA\Q) control, and FLC control. ALINEA is the most widely used technique in the close-loop control [4]. ALINEA determines the metering rates such that the traffic state on the expressway approaches a pre-defined condition. Developed as an enhancement of ALINEA, ALINEA\Q [1] incorporates ramp control with ramp queue management by considering two metering rates. The first rate is calculated exactly the same as that in the ALINEA algorithm, while the second rate is calculated so as to maintain the ramp queue within a desirable queue length. The FLC control monitors the ramp flow by considering both the congestion level of the expressway and the ramp queues, with priority given to the mainline traffic. Results from initial scenarios will be used to train the FLC before the actual evaluation. The MS-FLC controller architecture is elaborated using SIMULINK in MATLAB as in Figure 5.

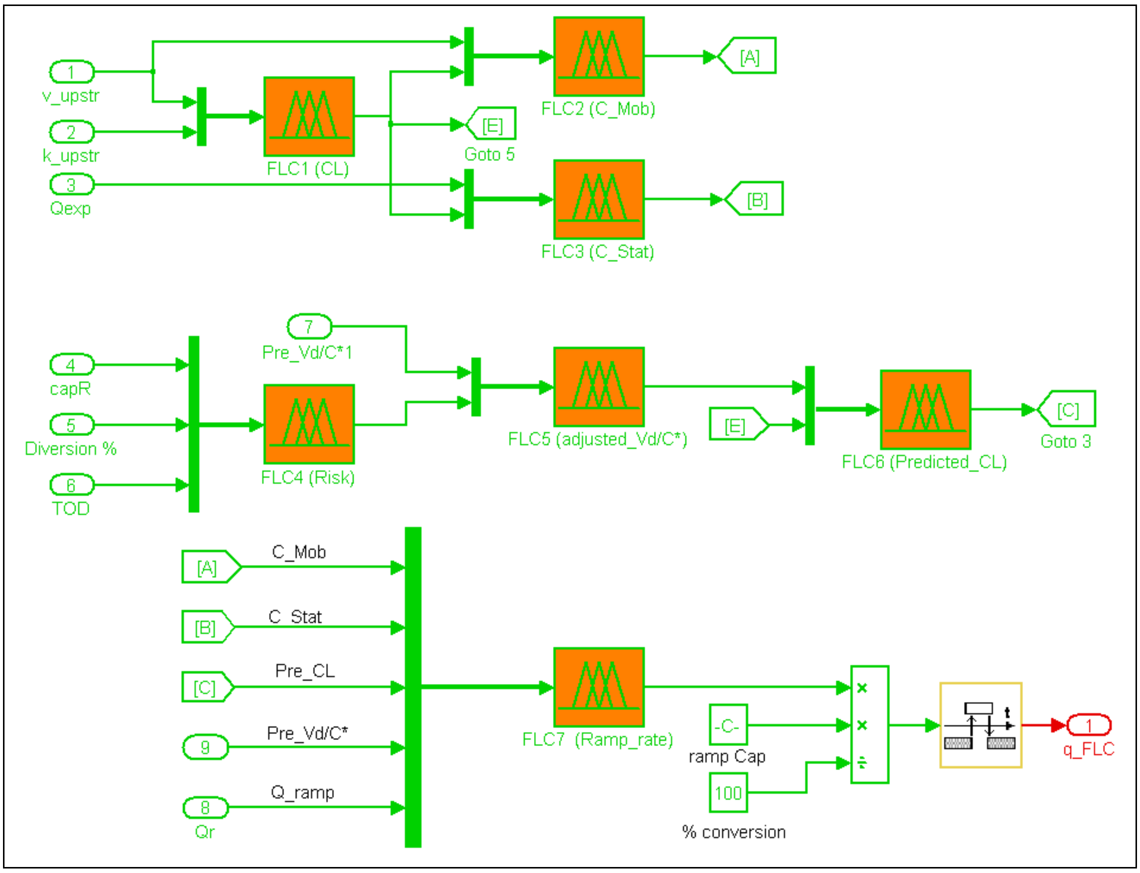

Figure 5. The MS-FLC controller in MATLAB.

In the evaluation, the setting of traffic demand is evaluated approximately based on the V/C^* ratio, where V is the traffic volume, and C^* is the remaining capacity. Although technically the traffic under various situations can be investigated, for purposes of discussion in this paper, only a *high-expressway demand* scenario, wherein the traffic demand is about 1,000-1,100 veh/h/lane, is presented here. This scenario encompasses several cases in which the high level of mainline traffic demand is associated with various levels of ramp traffic demand, capacity reduction, and incident location. More specifically, the following scenarios are investigated:

- Scenario 1: medium ramp demand.
- Scenario 2: high ramp demand.

Since the experiment focuses on congested conditions, Scenario 2 was extended to:

- Scenario 3: more severe capacity reduction (less remaining capacity); and

To see the effect of the incident location, Scenario 3 was extended to:

- Scenario 4: incident location moved upstream, to 500m after ramp.

The settings in each scenario are listed in Table 1.

Table 1**.** Settings in each scenario.

Scenario	Mainline demand *(veh/h/lane)*	Ramp demand *(veh/h)*	Remaining capacity C^* *(%)*	Incident location *(downstream)*
Scenario 1	1,000-1,100	300±10%	45-50%	1,000m
Scenario 2	1,000-1,100	400±10%	45-50%	1,000m
Scenario 3	1,000-1,100	400±10%	30-40%	1,000m
Scenario 4	1,000-1,100	400±10%	30-40%	500 m

3.2. Results

The values and percentile changes for the MOEs are summarised from Tables 2 to 5. It is noted that for the temporal MOEs (TTT, TWT, TTS), a negative sign of the percentile change indicates time savings, while for spatial MOEs (MD, max Q_exp, max Q_ramp), a negative sign indicates improvements.

Scenario 1: Medium ramp demand

The outcomes from Scenario 1 are shown in Table 2. The table demonstrates that in general significant advantages were obtained under both ALINEA and FLC. In comparison to No control, ALINEA increased MS by 15.12%, decreased MD by 13.12%, and saved TTT by 13.13%. ALINEA obtained significant decrease in Max Q_exp by 32.38%. Nonetheless, ALINEA incurred a TWT of 9.54 veh.h. and a max Q_ramp of about 46 vehicles.

Table 2**.** MOEs for Scenario 1.

MOE	Unit	No Control	ALINEA		FLC	
		Value	*Value*	*% change*	*Value*	*% change*
TTT	*veh.h*	55.62	48.32	-13.13	48.36	-13.06
TWT	*veh.h*	0	9.54	---	6.56	---
TTS	*veh.h*	55.62	57.86	4.03	54.91	-1.28

TTD	*veh.km*	2541.43	2541.43	0	2541.43	0
MS	*km/h*	45.69	52.60	15.12	52.56	15.02
MD	*veh/km*	29.55	25.67	-13.12	25.69	-13.05
max Q_exp	*veh*	112.47	76.05	-32.28	77.62	-30.99
max Q_ramp	*veh*	0	46.54	--	20.55	---

The FLC method achieved a comparable degree of benefits of 13.06%, 15.02%, and 13.05% for TTT, MS, and MD respectively. The TWT and max Q_ramp under FLC were less severe than under ALINEA, which resulted in a save in TTS of 1.28% as opposed to a loss of 4.03% under ALINEA. Since the traffic conditions at the start and the end of the evaluation period were identical among three control methods (there was no queue on the mainline and on the ramp at these time points), the TTDs were also identical.

Scenario 2: High ramp demand

The outcomes of Scenario 1 (Table 3) demonstrate that the standard ALINEA gained significant advantages for the mainline, where important MOEs (TTT, MS, MD, and max Q_exp) were greatly enhanced, and even slightly better than FLC control. However, it is noted that the ALINEA algorithm favours the mainline particularly without taking ramp traffic into account, resulting in unbearable traffic conditions on the ramp under high ramp demands. In effect, the goal of traffic control should be to maintain a manageable ramp traffic situation while achieving a seamless mainline driving condition. The control objectives should focus on effective incident responses to the mainline traffic without causing an excessive ramp queue length. Thus, in Scenario 2 the ALINEA\Q is used instead of standard ALINEA.

Table 3**.** *MOEs* for Scenario 2.

MOE	Unit	No Control	ALINEA\Q		FLC	
		value	*value*	*% change*	*value*	*% change*
TTT	*veh.h*	70.31	60.52	-13.92	55.14	-21.58
TWT	*veh.h*	12.91	22.62	75.24	24.71	91.40
TTS	*veh.h*	83.22	83.15	-0.09	79.85	-4.05
TTD	*veh.km*	2728.41	2715.12	-0.49	2719.53	-0.33
MS	*km/h*	38.80	44.86	15.61	49.32	27.10
MD	*veh/km*	37.42	32.36	-13.50	29.44	-16.70
max Q_exp	*veh*	153.87	135.22	-12.12	92.73	-39.73
max Q_ramp	*veh*	33.40	45	34.73	50	49.70

The simulation's outcomes for Scenario 2 are summarized in Table 3. The table demonstrates that significant improvements were made using both the ALINEA\Q and FLC: Under ALINEA\Q, the MS increased by 15.61%, TTT reduced by 13.92%, and MD fell by 13.50%. In particular, ALINEA\Q handled the ramp queue better than FLC and slightly better than the standard ALINEA under Case 1 (Table 2). With the exception of ramp-related qualities, the FLC control option outperformed ALINEA\Q for primary gains: TTT, MS, and MD increases were 21.58%, 27.1%, and 16.7%, respectively. Particularly, FLC also obtained 4.05% decrease in TTS.

Scenario 3: More severe capacity reduction

Findings from Scenario 1 and Scenario 2 demonstrate that the mainline has excessively long queues. Particularly in Table 3, the expressway line-ups for ALINEA\Q, FLC, and No control were 153.87, 135.22, and 92.73 vehicles, respectively. This is partly explained by the underlying presumption that the ramp will only collapse once the mainline queue has reached it. This passive ramp closure will tolerate a very severe mainline situation if the incident happens far from the ramp. The mainline traffic will take longer to disperse if there is a significant queue on the mainline since extra discharge from the ramp might not help the ramp traffic but instead worsen the mainline conditions. To prevent extreme congestion, an active action of ramp closure should be conducted from a control standpoint. Since this operational feature is not available under No control in Scenario 3, the ramp closure in Scenario 3 under ALINEA\Q and FLC is set when the mainline queue reaches 50% of the length of the upstream-incident segment.

Table 4 displays the outcomes of Scenario 3. It is assumed that the incident occurrence results in a more significant capacity drop (capacity remaining 30–40%). The table demonstrates that, in comparison to the previous scenarios, the benefits of ALINEA\Q and FLC gained for the mainline in this Scenario were greater. ALINEA\Q achieved a TTT saving of 22.14%, a rise in the MS of 26.82%, a decrease in the MD of 23.44%, and a reduction in the maximum Q_exp of 41.86% when compared to No control. With gains in TTT, MS, MD, and max Q_exp of 23.13%, 27.98%, 23.11%, and 42.61%, respectively, the FLC benefits were even more significant. The enhancements of ALINEA\Q and FLC were unquestionably brought about by strict regulation of ramp traffic and responsive mainline conditions. The results under No Control also show that the system performances significantly worsen in absence of substantial control intervention. Notwithstanding this, it is certain that ALINEA\Q and FLC impose greater TWT, and more vehicles must be diverted from approaching the ramp, due to the early ramp closure subjected to the mainline queue.

Table 4. *MOEs* for Scenario 3.

MOE	Unit	No Control	ALINEA\Q		FLC	
		value	*value*	*% change*	*value*	*% change*
TTT	*veh.h*	71	55.28	-22.14	54.57	-23.13
TWT	*veh.h*	20.28	25.75	26.99	23.90	17.86
TTS	*veh.h*	91.28	81.04	-11.22	78.47	-14.03
TTD	*veh.km*	2543.77	2511.95	-1.25	2502.36	-1.63
MS	*km/h*	35.83	45.44	26.82	45.85	27.98
MD	*veh/km*	37.89	29.01	-23.44	29.14	-23.11
max Q_exp	*veh*	181.85	105.72	-41.86	104.37	-42.61
max Q_ramp	*veh*	60	60	0	60	0

Scenario 4: Incidence location closer to the ramp

In Scenario 4, there is a mainline demand of 1,000–1,100 veh./h/lane, a ramp demand of veh/h, and 30–40% of the available capacity. Compared to scenarios 1 to 3, the incident happened 500 m downstream of the ramp. The simulation's results are shown in Table 5, which demonstrates that ALINEA\Q and FLC had less significant advantages than the earlier scenarios. ALINEA\Q gained a TTT saving of 6.49%, a MS rise of 5.6%, a MD decrease of 6.72%, and a max Q_exp decrease of 13.97%. FLC significantly outperformed ALINEA\Q in terms of increases in TTT, MS, MD, and max Q_exp, with improvements of 11.34%, 11.88%, 13.13%, and 19.69%, respectively. However, compared to No control, ALINEA\Q and FLC incurred 22.27% and 10.19% greater TWT, respectively. The two control algorithms, in particular, produced results that were 1.25 and 0.81% of the total mileage TTD less than No control. This is probable because vehicles that arrive at the ramp will not continue to join the queue but will instead be diverted to the parallel streets when the ramp queue approaches the ramp's physical storage limit.

Table 5. *MOEs* for Scenario 4.

MOE	Unit	No Control	ALINEA\Q		FLC	
		value	*value*	*% change*	*value*	*% change*
TTT	*veh.h*	57.41	53.68	-6.49	50.89	-11.34
TWT	*veh.h*	23.05	28.18	22.27	25.40	10.19
TTS	*veh.h*	80.45	81.86	1.75	76.29	-5.18
TTD	*veh.km*	2509.66	2478.26	-1.25	2489.29	-0.81
MS	*km/h*	43.72	46.16	5.60	48.91	11.88
MD	*veh/km*	30.72	28.65	-6.72	26.68	-13.13
max Q_exp	*veh*	127.19	109.42	-13.97	102.14	-19.69
max Q_ramp	*veh*	60	60	0	60	0

Discussions: Through the evaluation in comparison with the No-control scenario and ALINEA (ALINEA\Q) ramp control algorithm, it can be concluded that the proposed KB-DSS with the FLC controller achieved appreciable advantages. The FLC significantly reduces travel times and improves traffic conditions on both the mainline and the ramp, especially in situations of heavy traffic demand and severe capacity reduction. The FLC not only manages ramp traffic better than ALINEA\Q, but it also manages the mainline flow under critical incident congestion. We do, however, draw attention to the fact that the advantages of control intervention (ALINEA and FLC) rely on the level of traffic demand and incident circumstances. Under conditions of heavy traffic demands and catastrophic incidents, benefits are typically more significantly than under more favourable circumstances. Furthermore, we point out that this comparison is based on a simplified network with a single ramp. The benefits should be adjusted correspondingly since the ramp may have two lanes instead of the assumed one lane with a storage capacity of 60 vehicles.

4. CONCLUSIONS

For the control of traffic congestion on expressways, a Knowledge-based Decision Support System (KB-DSS) based on a multi-stage Fuzzy Logic Controller (MS-FLC) has been created. It is intended to help traffic operators make decisions for non-recurring congestion management in a methodically systematic and structured manner. The MS-FLC uses real-time traffic and incident data to analyse and predict traffic situations, suggest other control measures in the form of natural languages for the human operator to choose control decisions, and determine control settings to manage traffic congestion. In the case study, the KB-DSS is compared to ALINEA\Q, a prominent ramp control approach, across various traffic and incident situations. The results showed that the KB-DSS outperforms ALINEA\Q with respect to global objectives across many scenarios, attains significant improvements of mainline travel conditions and substantial reductions of ramp queues.

In considering the KB-DSS features, further conclusions can be made as follow:

- The KB-DSS offers a methodical and systematic process for determining control actions through a systematic assessment of current and future traffic circumstances, the MS-FLC (key component of KB-DSS), ensures that profound elements are taken into consideration prior to making control decisions.
- With an excellent data-handling capability that analyses various traffic data and incident information to provide operators with simplified language expressions for control actions, KB-DSS facilitates the operators to enhance the control decisions substantially.
- Although KB-DSS is specifically developed for incident congestion management, it can also be used for recurring congestion, since both recurring and non-recurring congestion share the same problem-solving strategy that aims at demand-capacity balance on the mainline and the ramp.

Despite the stated advantages, a number of issues should be considered: (i) the KB-DSS is a highly nonlinear system with complex stability behaviour. However, there exists no methodology for the system's stability analysis; (ii) the KB-DSS uses a large number of input parameters, necessitating extensive network observations and measurements even though data analytics should become faster as computing technology advances at an accelerated rate. These issues will be the subject of future research.

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