Multi-Stage Fuzzy Logic Controller for Expressway Traffic Control During Incidents

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Abstract: In this research study, a multi-stage Fuzzy Logic Controller (MS-FLC) is developed for traffic control for incident management on expressways. The MS-FLC serves as the traffic operator's decision-making support tool at the operational level. The MS-FLC gathers real-time traffic and incident data in order to analyze and predict traffic conditions as well as to suggest alternative control measures to the traffic operator in the form of linguistic expressions. The MS-FLC is embedded in a traffic simulator controller (TSC) prototype and is evaluated by comparing its performance with no control scenario and ALINEA\Q, a popular local ramp control algorithm, across several incident scenarios in a simulation environment. In general, the MS-FLC outperforms ALINEA\Q with respect to global objectives. In particular, whereas the ALINEA\Q algorithm favors the mainline, the MS-FLC algorithm significantly improves mainline travel conditions while substantially reduces ramp queues. It is concluded that, if properly designed the MS-FLC serves as a robust tool for traffic control on expressways under incident conditions.

Keywords: Multi-stage fuzzy logic controller; Incident management; Traffic control; Traffic simulator; Ramp metering.

Introduction

Traffic congestion is a serious and widespread problem in many cities throughout the world. Congestion can be divided into two types: recurring and non-recurring congestion. Congestion management on expressways, which is characterized by time-critical constraints, should be enhanced by employing effective real-time control measures to improve traffic conditions. For real-time traffic control, various approaches have been developed, including analytical optimization and automatic control. The analytical optimization approach forecasts the current state of traffic systems based on certain assumptions about system dynamics and behavior, and projects the current network conditions into the future state (Ma et al. 2016; Luan et al. 2018). Mathematical models are usually quite sophisticated and computationally expensive in order to provide systematic solutions thus they can hardly meet real-time requirements. The automatic control approach, as opposed to the analytical optimization approach, has the ability to classify enormous patterns of input data in order to describe the behavior of measurable processes (Simoni and Claudel 2017; Hashemi and Abdelghany 2018; Wang et al. 2018; Lidbe et al. 2019). The technique, on the other hand, does not include an explanation tool to assist operators in determining appropriate control actions. To address this issue, a Decision Support System (DSS) is required to make better use of available data, information, and knowledge to improve the quality of the control decision-making process.

Traffic control is a multivariable problem. The control decision-making process progresses from a low to high degree of abstraction, that is, from data to information to knowledge. For complicated situations where there is a need to evaluate the current traffic situation and to anticipate the future state for determining control actions, the control decision-making process should ideally be stratified into a number of stages where the decision-making logic is executed sequentially from one stage to the next.

Traffic control decision-making is decision-making in the face of uncertainty. Imprecise data measurement, approximate information reasoning, uncertain forecasting of future traffic conditions, and imprecise human perception are all factors that contribute to the unpredictability of traffic control. Because it entails using many forms of traffic and incident data to arrive at control judgments under critical-time restrictions, traffic control in incident scenarios is even more uncertain and critical. Due to the complicated, important, and uncertain nature, an effective traffic control strategy during incidents often relies on techniques that deal efficiently with problems of uncertainty and imprecision.

Fuzzy logic has an attractive capability to deal with uncertainty problems. With the help of fuzzy sets, the vagueness and uncertainties of the real world are handled smoothly. The key motivations behind the application of fuzzy logic for traffic control rest on the following advantages: (i) the linguistic expressions are general and easy to be perceived by the traffic operator, which is important for a decision support system; (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 (Toan 2008; Toan and Wong 2021).

Support Vector Machine (SVM) is a family of machine learning algorithms. SVM possesses a good generalization capability, computational efficiency, and is very robust in high dimensions (Toan and Truong 2021). In traffic engineering, SVM has been successfully applied in many domains, including SVM real-time incident detection (Motamed 2016; Xiao et al. 2013; Motamed and Machemehl 2014), and traffic flow prediction (Yuanyuan and Weixiang 2018; Cai et al. 2018; Luo et al. 2019; Toan and Truong 2021). Short-term prediction of traffic flow is crucial for real-time traffic control.

In this study, a multi-stage Fuzzy Logic Controller (MS-FLC) is developed for traffic control for incident management on expressways. The MS-FLC serves as the traffic operator’s decision-making support tool at the operational level. The MS-FLC gathers real-time traffic and incident data in order to analyze and predict traffic situations, as well as to suggest alternative control methods to the traffic operator in the form of linguistic expressions. Given these functions, the decision-making support under these situations typically includes semi-structured decisions (Toan, 2008) that employ both structured modules for data collection, data analysis, and information processing, and non-structured component to help the operators when confronted with qualitative type of decisions. Thus, for the MS-FLC to execute in its totality, SVM is employed as a subset of MS-FLC model for short-term traffic flow prediction for anticipation of incident related traffic condition. Given the anticipated traffic, the MS-FLC calculates the signal settings at the ramp entrance once the operator selects the control measure. The MS-FLC is evaluated in the case study in the "Model evaluation" section. Herein, a traffic simulator controller (TSC) prototype was designed and evaluated across several incident scenarios in a simulation environment.

The remainder of this paper is organized as follows: Section 2 reviews the fundamental concepts and previous works on applications of fuzzy logic systems for expressway traffic control. Section 3 presents the methodology of the MS-FLC that includes the rule-base formulation and the structure of the MS-FLC. Section 4 presents the evaluation results of the MS-FLC, sensitivity analysis, and proposed extension of the MS-FLC for corridor-wide control. Finally, Section 5 summarizes the findings from this research and draws the conclusions.

Literature Review

The use of control devices such as traffic lights to regulate the number of cars entering the expressway in order to meet operational objectives such as balancing traffic demand and capacity on the mainline is known as expressway ramp traffic control. Measurable traffic characteristics such as reduced travel time, higher operational speed, or increased throughput have typically been used to evaluate the benefits of ramp control (Zhang et al. 2001). Ramp metering is used to regulate the rate at which traffic can enter an expressway.

Ramp metering control is classified into fixed-time and traffic-responsive strategies (Zhong et al 2014). In fixed-time strategy the ramp rates are calculated off-line for various times of the day using the available historical data. Given its static nature, fixed-time strategy may cause either under- or over-utilization of the expressway's mainline. Traffic-responsive ramp metering, on the other hand, adjusts the ramp control in response to the real-time traffic conditions on the mainline and the ramp during the metering period. The adjustment is conducted either in the reactive manner or proactive manner (Toan 2008; Zhong et al 2014). The former adjusts the ramp metering rates using real-time measurements in order to maintain a pre-specified value of the expressway traffic conditions, while the latter attempts to improve the traffic conditions based on traffic variables anticipated for a certain time horizon. In terms of network topology, ramp metering strategies can be classed as local or coordinated schemes (Zhang et al. 2001; Zhao et al 2016). Local strategy makes use of local measurements to adjust ramp metering rates, whereas coordinated strategy considers a coordination of several controllers in an expressway corridor. The latter utilizes data to simultaneously calculate ramp flows for all controlled ramps within the corridor. Because more extensive information is used and more robust control action is coordinated, this may give possible system-wide gains above local ramp metering. When there is local congestion, local control is appropriate. Coordinated control should be considered if congestion is widespread in different sections of the expressway corridor.

Previous research has shown that under recurring traffic congestion, local ramp metering performs compatibly as coordinated approaches, and that local ramp control is the most direct and is an effective strategy to relieve expressway congestion (Papageorgiou et al. 2003). Nonetheless, in the presence of many bottlenecks on the expressway, non-recurrent congestions, or limited ramp storage capacity, coordinated ramp metering systems are often more efficient than local ramp metering strategies (Zhong et al 2014). However, determining whether a ramp metering should be coordinated is not straightforward and is reliant on network topology, background congestion level, and the queue management policies. Rather than launching a complete system, a gradual ramp control strategy should be considered, with priority given to the areas with the largest risk of disrupting traffic flow. However, according to Papageorgiou et al. (1991), the employment of advanced algorithms does not always result in performance enhancement. A local ramp control algorithm ALINEA was tested against coordinated control algorithm METALINE on the Boulevard Peripherique in Paris, using a macroscopic traffic model. The results showed that under normal conditions, both ALINEA and METALINE control systems produced nearly the same results, and the METALINE was only slightly better than the ALINEA in the event of an unforeseen incident due to more comprehensive information.

A fuzzy logic system (FLS) is a non-linear mapping of input to the output universe of discourse using fuzzy logic principles. FLS is an attractive approach in handing uncertainty problems. There has been a great deal of works for various applications in traffic engineering such as incident management (Lawrence and Huang 2006; Hatri and Boumhidi 2018; Hawas et al. 2020; Tariq et al. 2020), route choice (Arslan and Khisty 2005; Dhulipala et al. 2017; Bhandari and Cho 2019), safety analysis (Imprialou et al. 2014; Ali et al. 2017; Chowdhury and O'Sullivan 2018), and so on. In the aforementioned applications, FLS in general has delivered promising results. For knowledge representation, many researchers have investigated the rule-based reasoning system for traffic management and control (Toan and Lam 2005; Memon et al. 2015, 2016; Yan et al. 2018; Tariq et al. 2020). In the rule-based reasoning system, the knowledge is represented in the form of condition-action pairs: IF conditions (premises) are met, THEN actions (conclusions) are carried out. There are two types of rules: regular rules that evaluate state and control variables using crisp sets, and fuzzy rules that use fuzzy sets. The primary distinction between regular and fuzzy rules is that fuzzy rules allow for partial set membership and a progressive transition from one fuzzy set to the next. The problem-solving capability of fuzzy rules is more competent, thus fuzzy rules are more suitable for complex situations.

Traffic control is one of the earliest applications of FLSs in traffic engineering (Toan and Wong 2021; Chen et al. 2021). Attempts have been made in this area to use a fuzzy logic technique to improve control at signalized junctions. Pappis and Mamdani (1977) were the first to use fuzzy logic theory to control traffic at a single signalized intersection. Nakatsuyama et al. (1983), Sasaki and Akiyama (1987, 1988), and others have since made significant contributions to fuzzy logic applications in traffic engineering. Zhan and Prevedouro (2011) introduced a fuzzy logic-based methodology for determining the level of service (LOS) at signalized intersections. The LOS thresholds were replaced with fuzzy values, and fuzzy inferences were used to integrate key factors in order to create a composite LOS measure. The results demonstrated that using fuzzy logic to assess user perceptions of signalized intersection LOS is a viable alternative. Collotta et al. (2015) introduced a traffic signal dynamic control system with multiple fuzzy logic controllers, each handling vehicle turning movements, allowing real-time traffic monitoring. The results showed the system outperformance with considerable reduction of vehicle waiting times. Using a formal description of traffic control on crossroads, Yusupbekov et al. (2015) proposed adaptive fuzzy-logic traffic control systems. The results demonstrated that the synthesized adaptive fuzzy control system was robust and capable of directing road traffic over a wide range of parameters. More references on previous literatures in using fuzzy logic for traffic control can be seen in Taylor and Meldrum (2000), Zaied and Al Othman (2011), and Collotta et al. (2015), Kalinic and Krisp (2019), and Tariq et al. (2020).

There have been variety of applications of multi-stage fuzzy logic for traffic control. Ge (2014) presented a two-stage traffic signal control method. The first stage calculates traffic urgency degree for all red phases, the second stage determines green delay of the current green phase using fuzzy inference. The comparisons were made with pre-timed controller and fuzzy logic controller. The results showed that fuzzy control had a better effect on traffic urgency than pre-timed control and common fuzzy control. Based on the Takagi–Sugeno type FLC algorithm, Xu et al. (2013) proposed an efficient local ramp metering approach. The resulting parameters are fine-tuned by particle swarm optimization and microscopic traffic simulations with PARAMICS. Simulation studies show that a balance between traffic on the freeway mainstream and on-ramp link has been achieved; Hawas et al. (2019) proposed formulation of a multistage fuzzy-logic model (FLM) for incident detection and management of traffic signals in urban traffic networks. Three distinct non-linear regression models were utilized to find the resilient incident detection and traffic management parameters that are most likely to reduce total network travel time. Other studies on merits of applications for FLC for traffic control are summarized in Yusupbekov et al. (2015), Collotta et al. (2015), and Pandey et al. (2017).

Previous research has taken advantage of fuzzy logic's advantages in dealing with multi-variable traffic control problems, and the results have been promising. Earlier research has shown that in complex situations where it is necessary to analyze available data and information in order to understand the current problem and predict what might happen before proposing a control action, the rules must be executed sequentially according to a decision-making logic. Another reason is that the number of rules increases exponentially as the number of variables increases, thus for a complicated multi-variable control problem the rule base becomes too cumbersome to handle effectively in a single stage, but a multi-stage structure can handle much better. To tackle such complex multi-variable control problems, this research represents the decision-making process by a three-stage control architecture, known as the MS-FLC: output variables from preceding stage are used as input variables to the next stage. The decision-making process in MS-FLC during incident (as presented in the Methodology section) serves to reduce the problem complexity and thereby improves the overall system performance.

In summary, while there has been a lot of work done in the area of fuzzy logic traffic management, the majority of the control applications have been reactive. Little effort has been devoted to traffic control for incident management following MS-FLC approach. Essential issues such as the evaluation of the current traffic situation and anticipation of the immediate incident condition have not been adequately explored, and a systematic procedure in deriving control decisions in the event of an incident have not been adequately addressed.

This research study develops a MS-FLC for expressway traffic control during incidents. The MS-FLC design targets application for corridor-wide control for traffic management under both recurrent and non-recurrent congestion. Since the MS-FLC is a highly non-linear system with complex stability behavior, and using the MS-FLC model for corridor-wide management necessitates a significant amount of model calibration effort, the authors propose an incremental development roadmap. Before extending to a corridor-wide control, the MS-FLC is initially built and its performance evaluated using a local ramp control technique, as well as the model's performance sensitivity analysis. Herein, the main focus is on the development and assessment of the MS-FLC performance for local ramp control in comparison to competing control algorithms. In the last section, an overall model architecture for corridor-wide control is described. Due to the rarity of off-ramp control, the phrase "ramp control" in this study refers to on-ramp control.

Methodology

Overall Framework of the MS-FLC

Fig. 1 describes the proposed architecture of the MS-FLC for incident management. The model reflects a complex sequential structure of the decision-making logic for the multi-variable traffic control problem. The rule base in the MS-FLC consists of 3 stages: (i) incident traffic evaluation; (ii) predicted incident condition; and (iii) recommendation of control action. The rules in the first stage need to be executed first to give results to the second stage. The second stage uses the output from the first stage as its internal input, and external inputs from traffic forecasting. Similarly, the third stage employs both internal and external inputs to provide output in the form of control actions.

Stage 1: Evaluation of Current States of Traffic during Incidents

The objective of this stage is to evaluate the current state of traffic in the event of an incident. The traffic state is prescribed by three principal quantities: congestion level (CL), congestion mobility, and congestion status. The congestion level reflects the severity of traffic, estimated by traffic speed and density. The congestion mobility determines the dynamics of the congestion, quantified by traffic speeds. The congestion status refers to the existence and magnitude of queue lengths on expressways. The congestion mobility and congestion status specifically deal with the heavy congestion category. Each component (rule block) requires various treatments in the subsequent stages. If the congestion problem is critical, immediate control measures must be made, and the rules in stage 3 will be 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 fired. The rules in this stage can be categorized as fact-state rules since the reasoning logic uses numerical data to estimate the state of traffic.

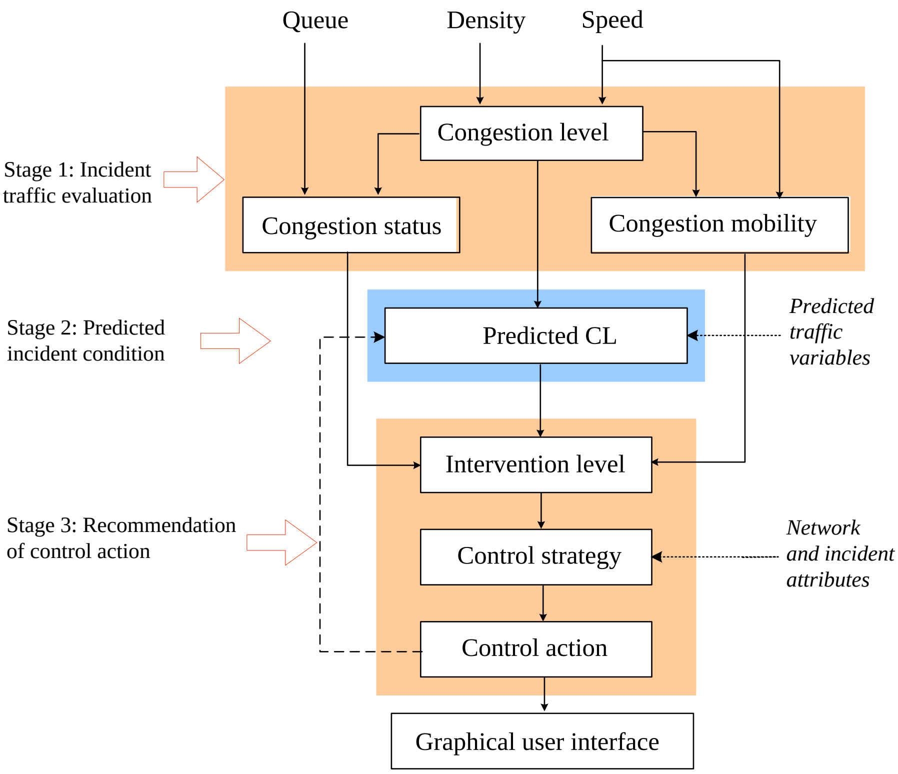

Fig. 1. Conceptual model of MS-FLC for incident-related traffic control

Stage 2: Prediction of Incident Traffic Conditions

Predicting short-term traffic conditions is critical to any proactive traffic control scheme's success. The key to anticipating traffic and incident conditions is to predict short-term traffic variables. The second stage, employing short-term traffic prediction advanced traffic forecasting technique for traffic variable predictions and fuzzy logic for data processing, continues to anticipate traffic and incident conditions in the immediate time interval based on the results of the previous stage. The rules in this stage are typically state-to-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 Measures

The outputs from stages 1 and 2 will be utilized to assess the strength of the necessary control intervention (no control, moderate, strong, and very strong control levels), after which an appropriate control approach will be advised based on the results. Based on the estimated control intervention and the availability of control facilities, the control strategy rule block presents a broad view of alternative control solutions. If concrete control actions are translated, the traffic operator may choose a local or corridor-wide control strategy. Local ramp control, for example, considers ramp traffic and VMS display; corridor-wide control is divided into coordinated ramp control, which coordinates numerous ramp metering controls, and integrated control, which incorporates ramp control as well as VMS diversion directives. The FLC system's outputs are defuzzified to provide crisp values. The rules in stage 3 apply to both the strategic (for intervention level, control strategy) and operational levels, as based on the reasoning process (for control settings). Control action rules are essentially state-action rules for the given input-output mapping.

Rule Base Architecture

Given the prescribed relationships, the rules in the proposed MS-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 output variables.

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

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

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

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

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

Eq.s (2) to (6) represent non-linear relationships of a fuzzy multi-variable control model. In MS-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 first stage as well as external variables are utilized. Basically, the rules have multiple-inputs-single-output structure, where multiple inputs are used to produce a single output. Given these, the formation of rules in the three stages can be described as follows:

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

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

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

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

Note that in Eq.s (7) to (9) the rules are assumed homogeneous using the AND operator for simplicity. As will be seen in the following sections, in this MS-FLC the AND operator is predominant in the compositional operation, even though the OR operator is occasionally used.

The Eq.s (7), (8), and (9) are elaborated in section "Formation of Rules" below.

Formation of Rules

Stage 1: Evaluation of Current States of Traffic during Incidents

Stage 1 evaluates three principal quantities: congestion level, congestion mobility, and congestion status. The congestion mobility and congestion status specifically deal with the heavy congestion category, and the rule formation of these quantities are simple and straightforward. In the multiple input - single out (MISO) model, rules for the congestion level are characterized by two predicates (speed and density) in the antecedent, connected with an AND operator, and one predicate (congestion level) in the consequent. The general expression of rules is of the form:

$$\text{If speed is } V_{(x)} \text{ AND density is } K_{(x)} \text{ then congestion level is } CL_{(x)}. \tag{10}$$

Fig. 2 shows an example of partition of the fuzzy sets for congestion level variable.

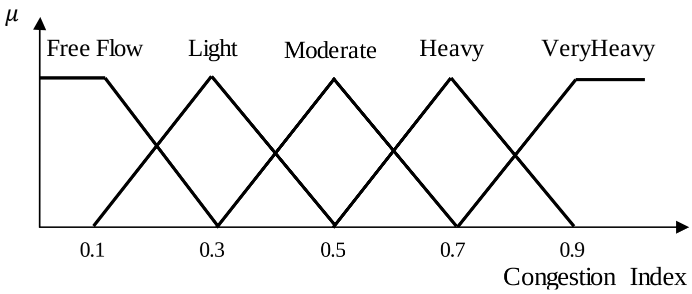

Fig. 2. Fuzzy partition of the congestion level

The collection of rules for congestion level is summarized in the rule decision matrix (Table 1). 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.

Table 1. Rule decision matrix for congestion level (source: Toan and Wong, 2021)

(FF: Free flow, L: Light congestion, M: Moderate congestion, H: Heavy congestion, VH: Very heavy congestion)

		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	---	---

Stage 2: Prediction of Incident Traffic Conditions

In prediction of incident traffic conditions, it is essential to predict short-term traffic flow in the incoming period. This is an exogenous component from the MS-FLC (see Fig.1), but the prediction execution can be accomplished by a prediction software, and the result provided accordingly. As part of this research, Toan and Truong (2021) presented an efficient short-term traffic flow prediction using support vector machine (SVM) and model training using nearest neighbor approach. The results are promising and proposals are made on extended research for online application.

Apart from the predicted traffic demand, the incident severity (the lane closure) is used to estimate the capacity remaining $\left(C^*\right)$. Furthermore, the evaluation of the risk factor is necessary to anticipate the incident traffic conditions. The risk factor caters for external risks that exist exogenously with the prediction, ranging from the incident location, incident type, incident severity (capacity reduction), the time of day (peak/off-peak). The risk factor is decomposed into low/medium/high risk level. From the predicted traffic demand, the V/C^* is calculated, and then adjusted with the risk factor. There are 16 rules for this adjustment.

$$\text{If predicted } V/C^* \text{ is Low and risk factor is high then the adjusted } V/C^* \text{ is medium} \tag{11}$$

The evolution of traffic trend depends heavily on the balance between traffic demand and supply, represented by the ratio of the predicted traffic demand (V) upstream and the capacity remaining $\left(C^*\right)$ at the incident location. Fig. 3 shows the membership functions for adjusted V/C^* ratio.

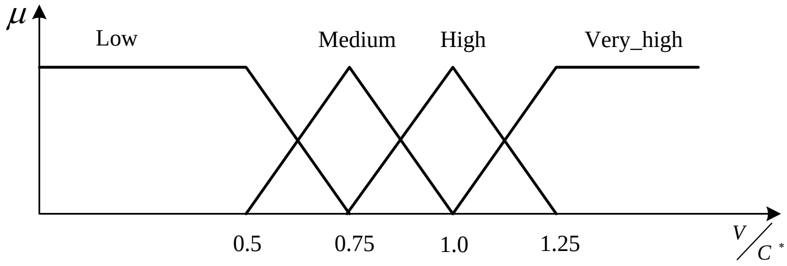

Fig. 3. Membership functions for adjusted V/C^* ratio

Given the congestion level estimated in the first stage and the adjusted V/C^* ratio, the MS-FLC evaluates the predicted congestion level. An example of rule of this type is as follows:

If adjusted V/C^* is High and CongestionLevel is Light then predicted-CongetionLevel is Moderate. (12)

The collection of predicted congestion level consists of 16 rules. Note that in this sub-stage, the variable CongestionLevel indicates the prevailing current congestion level, which does not include the Heavy congestion level since it is tracked directly from the 1st stage into the 3rd stage of the MS-FLC.

Stage 3: Recommendation of control action

Stage 3 receives the evaluated and predicted traffic conditions from previous stages, and other traffic and incident information to provide recommended solutions. The expressway operation management during incidents undertakes important tasks, including the dissemination of prevailing information to motorists, the regulation of ramp access, the control of route diversion, and the management of queues. The tasks employ appropriate control measures to target the control goals: the amelioration of the mainline congestion and prevention of excessive ramp queues. The goals are translated into specific measurable and tangible objectives such as to maximize mainline utilization, to prevent mainline congestion, to prevent excessive ramp queue, or to balance between objectives. Subsequently, the objectives are evaluated using specific measures of effectiveness (MOEs) as described in Section on “Results and Analysis”. Since the two objectives may be conflicting to each other, rules should be designed to compromise them at a balance point. For incident management, the control objectives target efficient incident responses for the mainline without incurring excessive ramp queues.

Table 2 summarizes the decision rules for the local ramp control strategy. Each rule is a mapping between two (three) predicates in the rule conditions and one predicate in the rule conclusion. The rule conditions are joined with AND connectives. The rule conclusion reflects the control action that infers ramp flow based upon the rule conditions in the direction of the key control objective that elaborates the control goals: in correspondence to the key control objective, the conditions of the rules consider the traffic condition (congestion level, CL) upstream of the incident (downstream of the ramp), the traffic demand (indicated by the V/C^* ratio) upstream of the ramp, and the ramp queue (see Fig. 5 later). For scenarios such that the traffic condition upstream of the incident and the V/C^* upstream of the ramp favor high ramp flows, the rules can be generated regardless of the queue status. Specifically, if the traffic condition upstream of the incident is *Free-flow* or *Light* and traffic demand is *Low/Medium*, the ramp flow is set to *High/Very_high* level so as to *maximize mainline utilization* (rules 1, 2, 7). In contrast, if the traffic demand (V/C^* ratio) upstream is *High/Very_high* the ramp flow is set to *Low/Very_low* levels to *prevent mainline congestion* (rules 3, 6, 9, 10, 18, 20, 23, 24). In addition, the ramp flow is adjusted according to the ramp queue status so as to *maintain acceptable ramp queue* (rule 4), to *prevent excessive ramp queue* (rules 5, 11, 21, 22), or to *maintain a balance between objectives* (rules 8, 13, 14, 19). Finally, if the traffic on the mainline is congested, the restriction of the ramp flow is to target *preventing a secondary ramp queue* at the ramp merge (rules 12, 15, 16, 17). The reason for this restriction is that when the mainline is congested, the ramp traffic will hardly find an acceptable gap to join the mainline, so a secondary queue of the metered vehicles may form spontaneously. If a secondary queue persists, ramp metering is not beneficial. At the extreme, vehicles in the secondary queue may try to encroach the mainline, breaking down traffic upstream of the ramp and creating safety risk. Therefore, in the presence of a secondary queue, it is imperative that the vehicles be stored on the ramp to wait for an opportunity in the next period rather than being metered. The inputs are combined in such a way that predicates are scaled gradually over the input domains, and the outputs are translated elegantly from one fuzzy value to another. For example, in rules 7, 8, and 9, given the *Light* congestion level, when the V/C^* changes from *Low* to *Medium* to *High*, the *Ramp_Flow* changes from *High* to *Medium* to *Low*, respectively.

Table 2. Decision table for rules with local ramp control

(Note: SQ-HC: short queue-heavy congestion)

	Rule condition		Rule conclusion		
Rule	Congestion level (CL) upstr. of the incident	V/C^* upstr. of the ramp	Ramp Queue	Ramp Flow	Key Control objective
1	Free-flow	Low	--------	Very_high	Maximize mainline utilization
2	Free-flow	Medium	--------	High	Maximize mainline utilization
3	Free-flow	High	Short	Low	Prevent mainline congestion
4	Free-flow	High	Medium	Medium	Maintain acceptable ramp queue

5	Free-flow	High	Long	High	Prevent excessive ramp queue
6	Free-flow	Very_high	--------	Low	Prevent mainline congestion
7	Light	Low	--------	High	Maximize mainline utilization
8	Light	Medium	--------	Medium	Balance between objectives
9	Light	High	Short	Low	Prevent mainline congestion
10	Light	High	Medium	Medium	Prevent mainline congestion
11	Light	High	Long	Medium	Prevent excessive ramp queue
12	Light	Very_high	--------	Very_low	Prevent secondary queue
13	Moderate	Low	--------	Medium	Balance between objectives
14	Moderate	Medium	--------	Medium	Balance between objectives
15	Moderate	High	Short	Low	Prevent secondary queue
16	Moderate	High	Medium	Low	Prevent secondary queue
17	Moderate	High	Long	Medium	Prevent secondary queue
18	Moderate	Very_high	--------	Very_low	Prevent mainline congestion
19	SQ-HC	Low	--------	Medium	Balance between objectives
20	SQ-HC	Medium	Short	Low	Prevent mainline congestion
21	SQ-HC	Medium	Medium	Medium	Prevent excessive ramp queue
22	SQ-HC	Medium	Long	Medium	Prevent excessive ramp queue
23	SQ-HC	High	--------	Low	Prevent mainline congestion
24	SQ-HC	Very_high	--------	Very_low	Prevent mainline congestion

Development of the TSC

This section presents the development and validation of a Traffic Simulator and Control (TSC) model and the implementation and evaluation of the MS-FLC framework presented in previous sections. The TSC model (Fig. 4) is developed in SIMULINK in MATLAB, following the decision-making logic for incident-related traffic control presented in the conceptual model (Fig. 1). The TSC consists of two main components (Fig. 4): the car-following model (CFM), and the traffic controller (TC).

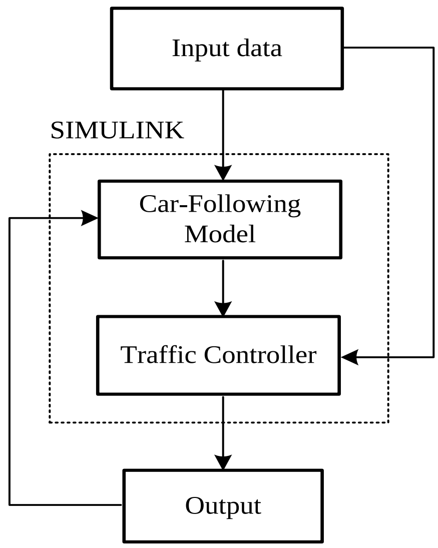

Fig. 4. Conceptual model of the TSC

The CFM simulates the car-following behavior and delivers the aggregated traffic parameters to the TC for traffic control. In this study, the CFM is developed using the modelling concepts provided by Gazis-Herman-Rothery (GHR) type of models. Although the CFM simulation keeps track of individual vehicles, only aggregated traffic variables (flow rate, density, total travel time, mean speeds - see the MOEs in Tables 4-7 also) are parameters of interest. In other words, by using the microscopic simulation, the model explains the macroscopic behavior of systems and obtains macroscopic traffic metrics.

Although individual vehicles are tracked, the TSC functions more like a macroscopic traffic simulation model since only aggregated traffic variables, which are the parameters of interest, are generated. By including the CFM component in the model, the dynamic longitudinal interactions between vehicles, namely car-following behaviors, are replicated. The TC receives the aggregated outputs for traffic control purposes. The traffic on the multi-lane expressway where the data was collected is represented as an equivalent single-lane system for model calibration and validation.

In a multi-lane highway, a standard microscopic traffic simulation package examines both car-following and lane-changing behavior. Unfortunately, SIMULINK lacks the ability to capture lane-changing behaviors. Lane-changing maneuvers may have a significant impact on the speeds and travel times of vehicles in the traffic stream in free-flow conditions, but there are few lane-changing opportunities in congested conditions. Furthermore, because the parameters of interest are the overall macroscopic traffic variables that are averaged across lanes, they may not be highly sensitive to cars changing lanes, and traffic control for non-recurring congestion often concentrates on congested scenarios. As a result, through the calibration of its parameters, the CFM developed in this research implicitly integrates lane-changing effects.

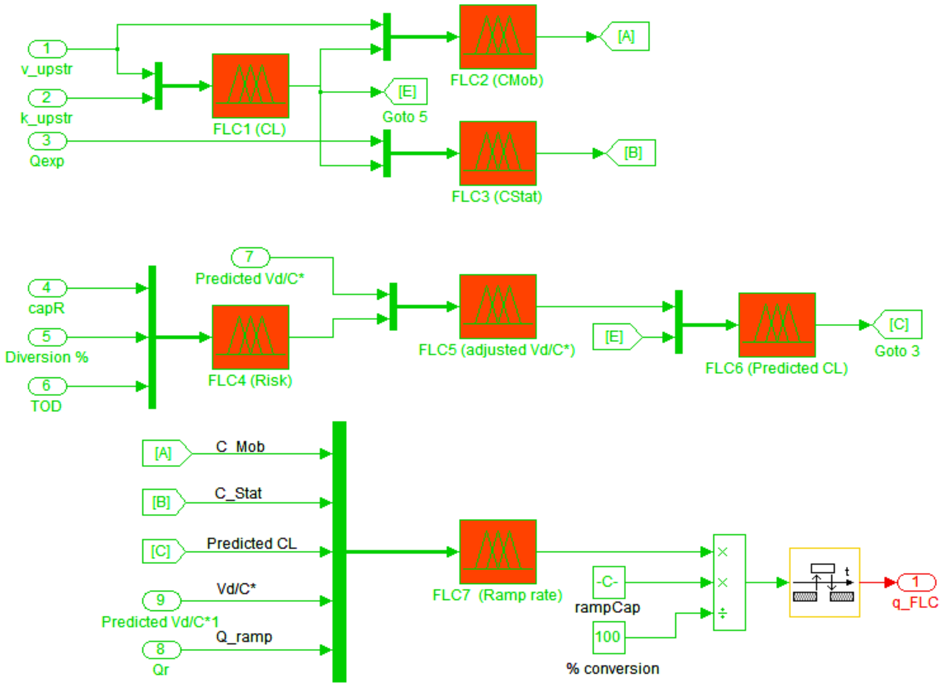

Fig. 5. The MS-FLC in SIMULINK

An iterative process of calibration simultaneously refines the model's parameters, ensuring that the model accurately replicates real-world behavior. The calibration of the CFM identifies the most influential parameters: desired gap, gain factor for acceleration, gain factor for deceleration, maximum acceleration, maximum deceleration, speed limit, and reaction time. Having calibrated, the CFM validation was performed at the macroscopic levels where speeds and flow rates for simulated platoons are aggregated in one-minute intervals and are compared with those of field data on a segment of the Singapore's Pan Island Expressway (PIE) under various traffic conditions (free-flow, medium congestion and heavy congestion). The result shows that the simulated speed is not significantly different from the field speed (at the significance level) for both upstream and downstream segments, and the aggregated flow rate discrepancies fall within small ranges.

The designed MS-FLC (Fig. 5) was embedded in the TC component for MS-FLC evaluation. Over different traffic situations and incident scenarios, the MS-FLC performance was compared to that of the No-control scenario and the ALINEA ramp controller. For the MS-FLC to execute in its totality, the model requires predicted short-term traffic flow for the incoming period to anticipate incident related traffic condition. The data are provided by an external SVM short-term traffic flow prediction component. 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 by Peeta and Mahmassani (1995). As stated earlier, although the SVM prediction performance is promising, additional effort need to be devoted to applying the SVM model for online application. Thus, for the time being, in the model evaluation section below, the MS-FLC use the data in the current interval to project the future state. In this experiment ALINEA (ALINEA\Q) control algorithm is used to compare with MS-FLC, thus the control algorithms must have the same simulation and network setting as described below.

Model Evaluation

General Settings

It would be preferable to use observed data with a real network to explore the model behavior under various conditions for model evaluation. However, obtaining data from actual sites is technically complex, time consuming, and very costly. Simulated traffic, on the other hand, may be duplicated from one run to the next, making comparisons between scenarios simple. The use of a generic network for simulation-based evaluation is a viable option that allows for more flexibility in examining various traffic conditions and incident scenarios, while the criteria for evaluating the success of control algorithms can be simply and uniquely obtained. In this regard, the FLC control algorithm evaluated in this part uses a simulated study segment as shown in Fig. 6. The study segment is modelled after the validated site (section 80007774) that was previously described. The segment comprises three links: one upstream of the ramp, one downstream of the ramp, and one upstream of the incident (downstream of the ramp). The majority of measurements for local ramp control are collected in the vicinity of the incident, notably the upstream and downstream links. The lengths of the links used in this experiment are L_{upstr}=1,000m, $L_{downstr} = 500m$. The expressway's capacity is reduced as a result of the lane-blocking incident, and local ramp control is implemented to regulate traffic demand from the ramp in order to avoid or alleviate mainline congestion.

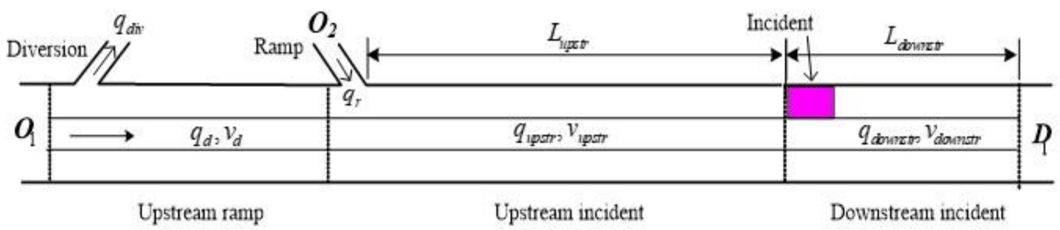

Fig. 6. Layout of the study segment

The inputs in evaluation involve two pairs of time-dependent O_1D_1 demands, 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_1 flows are 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 streets and enter the expressway through downstream ramps. The availability of diversion alternatives encourages the local traffic to utilize the parallel urban streets 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 the (;) 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 about 90 minutes, including: the first one third part is normal traffic, the second one third part is incident period, and the last one third part is normal traffic again. There are several MOEs that can be used as the evaluation criteria, including total travel time on expressway, total waiting time on the ramp, total time spent in the system, total travel distance, average speed on expressway, and mean density.

The basic parameters of the simulation: simulation time: 90 minutes, including:

- From the 1st min. to 30th min.: normal traffic
- From the 31st min. to 60th min.: incident period
- From the 61st min. to 90th min.: normal traffic
- Evaluation interval: every 10 seconds
- Evaluation period: from the 16th min. to 90th min.

To achieve a high level of representation and accuracy, the vehicle's acceleration, speed and position are updated every 0.1 second.

Three control methods can be considered: No control; *ALINEA\Q* control, and *FLC* control. *ALINEA* is the most widely used technique in the close-loop control (Papageorgiou et al. 1991). *ALINEA* determines the metering rates such that the traffic state on the expressway approaches a pre-defined condition. Developed as an enhancement of *ALINEA*, the *ALINEA\Q* (Smaragdis and Papageorgiou 2003) 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.

Since ALINEA is considered an efficient local-ramp control algorithm for monitoring the mainline traffic, in this experiment ALINEA is used to compare with FLC. ALINEA uses the measured occupancy at a loop detector downstream of the ramp, and regulates the ramp flow based on the difference between the measured occupancy and the optimal set point occupancy (Papageorgiou et al. 1991). The Eq. used to calculate the metering rate for time interval t is:

$$q_r(t) = q_r(t-1) + K_R\left[O_{opt} - O_{down}(t-1)\right] \tag{13}$$

where:

$q_r(t)$ and $q_r(t-1)$: metering rates of the current and previous intervals, respectively.

K_R: regulator parameter. Field experiment has shown that ALINEA has not been very sensitive to the choice of K_R, and the typical value of K_R is 70 veh/h (Papageorgiou et al. 1991).

O_{opt}: set point optimal occupancy, which is set to obtain optimal operation (Papageorgiou et al 1991).

$O_{down}(t-1)$: occupancy downstream in the previous interval.

Since the standard ALINEA algorithm targets the optimal occupancy at the immediate detector downstream of the ramp, it uses the point measurement. Therefore, in this experiment the average occupancy for the whole section from the incident location to the ramp is recommended to capture the spatial effect of the incident. The average occupancy is estimated from the average density.

$$O_{down}(t) = (L + d) \times k(t) \tag{14}$$

where *L* is the average vehicle length, *d* is the length of the detector. The average density $k(t)$ in each evaluation interval is calculated by the ratio between the number of vehicles on the link and the length of the segment.

The average vehicle length is the arithmetic mean of lengths of various vehicle types, which can be derived from the vehicle composition. Eq. (14) holds true when the vehicles have constant speeds. In congested condition this assumption is not valid, and Eq. (15) will be used instead:

$$O_{down}(t) = \frac{\sum_i (L_i + d)/v_i}{T} \tag{15}$$

where L_i is the length of vehicle type *i*; v_i is the vehicle speed; *T* is the period of measurement.

The critical occupancy O_{cr} is the occupancy associating with the maximum flow rate. It was determined from an empirical volume-occupancy relationship, established from 227 simulated records, and the resulting $O_{cr} = 26\%$ was obtained. O_{opt} is taken as 24%, slightly lower than O_{cr}.

The traffic controller of the ALINEA algorithm is designed in SIMULINK and is shown in Fig. 7.

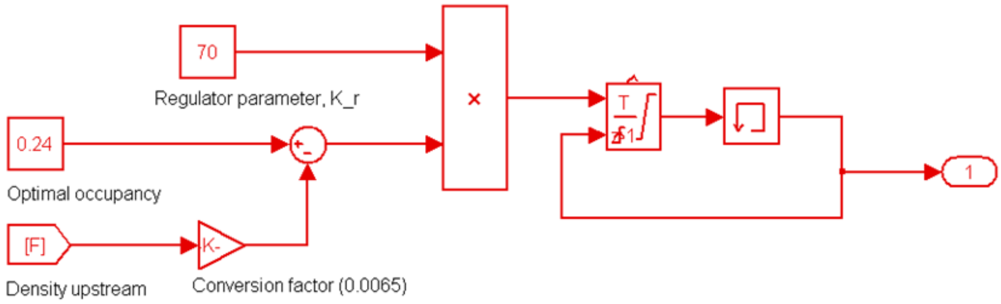

Fig. 7. ALINEA controller in SIMULINK

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 cases are investigated:

- Case 1: Medium ramp demand; and
- Case 2: High ramp demand.

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

- Case 3 with more severe capacity reduction (less remaining capacity); and

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

- Case 4 with the incident location moved upstream, to 500m downstream of the ramp.

The settings in each case are listed in Table 3.

Table 3. Settings in each case

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

Measures of effectiveness (MOEs)

The TSC uses the following measures of effectiveness as the evaluation criteria:

a) Total travel time on the expressway, TTT (veh.h)

The TTT is the sum of travel times of individual vehicles. In SIMULINK, the TTT is the sum of the number of vehicles in the expressway $N(t)$ over time in successive intervals:

$$TTT = \sum_{t=t_0}^{t=T} N(t) \times \Delta_t \tag{16}$$

The TTT is a principal evaluation criterion. The calculation of the TTT allows the comparison of the total time spent in the system. The lower the TTT indicates the positive signal, providing that higher throughput and higher speed are also obtained. Nevertheless, if the lower TTT is the result of too restrictive a control method that produces a lower throughput, this "saving" is misinterpreted. Therefore, the TTT should be evaluated in accordance with the other MOEs.

b) Total waiting time on the ramp, TWT (veh.h)

The TWT is the accumulated waiting time of vehicles in the ramp queue due to the control regulation. Like TTT, TWT is the sum of the number of vehicles in ramp queue Q_r over time in successive intervals:

$$TWT = \sum_{t=t_0}^{t=T} Q_r(t) \times \Delta_t \tag{17}$$

Unlike TTT, TWT is a secondary criterion an incident management strategy normally sets a higher priority for the expressway than the ramp traffic.

c) Total time spent in the system, TTS (veh.h)

The TTS is the total time all vehicles spend in the system during the simulation period, being the sum of the TTT and TWT.

$$TTS = TTT + TWT \tag{18}$$

d) Total travel distance, TTD (veh.km)

The TTD is the sum of distances travelled by individual vehicles during the simulation. In SIMULINK, the TTD is calculated as the sum of the total of travel distances upstream and downstream sections in successive intervals.

$$TTD = \sum_{t=t_0}^{t=T} \left[N_{up}(t) \times \overline{V}_{up}(t) + N_{down}(t) \times \overline{V}_{down}(t) \right] \times \Delta_t \tag{19}$$

where $N_{up}(t)$ and $N_{down}(t)$ denote the number of vehicles in upstream and downstream links during interval *t*; $\overline{V}_{up}(t)$ and $\overline{V}_{down}(t)$ are the space mean speeds during the same period.

Like TTT, TTD is a primary MOE since it indicates the level of "productivity" the expressway yields. It encompasses both the mainline throughput and average speed.

e) Average speed on expressway, MS (km/h)

The MS on the expressway is among the most important criteria since it represents the dynamics of a vehicle's motion. The average speed is calculated as the ratio of TTD and TTT.

$$MS = \frac{TTD}{TTT} \tag{20}$$

where TTD and TTT are associated with the same number of vehicles (see Block 2, Appendix D).

f) Mean density, MD (veh/km)

Like speed, MD is a primary indicator of congestion level. The mean density is the arithmetic mean of traffic densities $k(t)$ in the network in successive intervals.

$$MD = \frac{\sum_{t=0} k(t)}{N} \tag{21}$$

where N is the number of simulated intervals. Since the density is determined for upstream and downstream segments separately, the traffic density $k(t)$ in the network in an interval t is calculated as the weighted mean of densities on upstream and downstream segments:

$$k(t) = \frac{L_{upstr} \times k_{upstr}(t) + L_{downstr} \times k_{downstr}(t)}{L_{upstr} + L_{downstr}} \tag{22}$$

where L_{upstr} and $L_{downstr}$ are the lengths of upstream and downstream segments, respectively. In Section 8.4.3 the two segments respectively have the lengths of 1,000 m and 500 m, excepting for the Scenario *"High demand, Case 4"* where the incident location is assumed to move upstream, the length of the segments change, i.e L_{upstr} = 500 m and $L_{downstr}$ = 1,000 m.

Apart from the described measures, the simulation considers the maximum length of queues on the expressway $Q_{\exp}$ and on the ramp Q_r .

The TSC model was developed in SIMULINK in MATLAB. SIMULINK is a graphical programming language that offers modelling, simulation and analysing of dynamic systems under a Graphical User Interface (GUI) environment. SIMULINK facilitates easy communication between the simulation with external applications. In SIMULINK the CFM and the TC are harmonized and integrated in a close-loop control system, with the control effects (TC outputs) fed-back as inputs to the and CFM for real-time applications. Embedded in SIMULINK the simulation parameters can be easily specified and altered for various scenarios and sensitivity analysis.

Results and Analysis

Tables 4 to 7 show the values and percentile changes of the MOEs. For temporal MOEs, including total travel time (TTT), total waiting time (TWT), total time spent (TTS), a negative sign of percentile change indicates time saving. For spatial MOEs, including mean density (MD), maximum length of queues on the expressway (max Q_exp), and maximum length of queues on the ramp (max Q_ramp), a negative sign indicates improvement. For the remaining attributes, including total travel distance (TTD), and average speed (MS), a positive sign is a positive indication of the related parameter.

Case 1: Medium Ramp Demand

Table 4 lists the results from Case 1. The table shows that in general under both *ALINEA* and *FLC* significant benefits were achieved. *ALINEA* gained a *TTT* saving of 13.13%, an increase in *MS* of 15.12%, and a reduction in *MD* of 13.12%, compared to *No control*. The algorithm also enjoyed a substantial reduction in *max Q_exp* of 32.28%. Nevertheless, *ALINEA* suffered considerable long *TWT* of 9.54 veh.h, and an excessive ramp queue *(max Q_ramp)* of approximately 46 vehicles.

Table 4. *MOEs* for Case 1

MOE	Unit	No Control	ALINEA		FLC		ALINEA\Q vs FLC
		value	*value*	*% change*	*value*	*% change*	*% change*
TTT	veh.h	55.62	48.32	-13.13	48.36	-13.06	-0.08
TWT	veh.h	0	9.54	---	6.56	---	31.24
TTS	veh.h	55.62	57.86	4.03	54.91	-1.28	5.10
TTD	veh.km	2541.43	2541.43	0	2541.43	0	0.00
MS	km/h	45.69	52.6	15.12	52.56	15.02	0.08
MD	veh/km	29.55	25.67	-13.12	25.69	-13.05	-0.08
max Q_exp	veh	112.47	76.05	-32.28	77.62	-30.99	-2.06
max Q_ramp	veh	0	46.54	--	20.55	---	55.84

The *FLC* obtained a compatible level of benefits: the improvements in the *TTT*, *MS,* and *MD* were 13.06%, 15.02%, and 13.05%, respectively. As compared to *ALINEA*, the *TWT* and *max Q_ramp* under *FLC* were less severe, which leads to a saving in *TTS* of 1.28% compared to a loss of 4.03% under *ALINEA*. The *TTDs* were the same since the traffic states were similar across three control methods at the beginning and at the end of the evaluation period (there was no queue on the mainline and on the ramp at these time points).

Case 2: High Ramp Demand

To explore how the control algorithm work under critical conditions, the experiment was carried out with high demands on both expressway and ramp in Case 2. The results from Case 1 (Table 2) show that the standard *ALINEA* gained substantial benefits to the mainline, where the key *MOEs* such as *TTT, MS, MD* and *max Q_exp* were improved considerably. To some extent, *ALINEA* even slightly outperformed *FLC* control with respect to the mainline conditions. Nevertheless, the *ALINEA* algorithm shows that the method merely targets benefits for the mainline without considering the status of the ramp traffic. Under heavy ramp demands, the mechanism used in the standard *ALINEA* would likely induce intolerable traffic conditions on the ramp. In practice, the principle of traffic control should be such that smooth expressway travel can be achieved, while maintaining a reasonable ramp traffic status. In incident management in particular, the control objectives should target efficient incident responses to the mainline traffic without incurring excessive ramp queue length. Therefore, the *ALINEA\Q* is used in Case 2 instead.

Table 5 summarizes the results of the simulation for Case 2. The table shows that both *ALINEA\Q* and *FLC* control methods achieved considerable improvements: *ALINEA\Q* gained a *TTT* saving of 13.92%, an increase in the *MS* of 15.61%, and a decrease in the *MD* of 13.50%. In particular, *ALINEA\Q* handled the ramp queue better than *FLC* and slightly better than the standard *ALINEA* under Case 1 (Table 4).

Table 5. *MOEs* for Case 2

MOE	Unit	No Control	ALINEA\Q		FLC		ALINEA\Q vs FLC
		value	*value*	*% change*	*value*	*% change*	*% change*
TTT	veh.h	70.31	60.52	-13.92	55.14	-21.58	8.89
TWT	veh.h	12.91	22.62	75.24	24.71	91.4	-9.24
TTS	veh.h	83.22	83.15	-0.09	79.85	-4.05	3.97
TTD	veh.km	2728.41	2715.12	-0.49	2719.53	-0.33	-0.16
MS	km/h	38.8	44.86	15.61	49.32	27.1	-9.94
MD	veh/km	37.42	32.36	-13.5	29.44	-16.7	9.02
max Q_exp	veh	153.87	135.22	-12.12	92.73	-39.73	31.42
max Q_ramp	veh	33.4	45	34.73	50	49.7	-11.11

The *FLC* control alternative, with an exception of the ramp-related attributes, gained higher benefits than *ALINEA\Q*. The improvements in *TTT, MS,* and *MD* were 21.58%, 27.1%, and 16.7%, respectively. In particular, *FLC* also gained a reduction in the *TTS* of 4.05%.

Case 3: More Severe Capacity Reduction

Results from Case 1 and Case 2 show that there exist excessive long queues on the mainline. In Table 5 in particular, the expressway queues under *No control, ALINEA\Q,* and *FLC* were 153.87, 135.22, and 92.73 vehicles, respectively. This is partially attributed to the implicit assumption that the ramp closes only when the mainline queue reaches the ramp. If the incident occurs far from the ramp, this passive type of ramp closure will tolerate a very severe mainline condition. It should be noted that if a long queue exists on the mainline, additional discharge from the ramp may not benefit the ramp traffic but aggravate the mainline conditions, thus a longer time will be required for the mainline traffic to dissipate. To minimize extreme congestion, an active action of ramp closure should be conducted from a control standpoint. Therefore, in Case 3 under *ALINEA\Q* and *FLC* the ramp closure is set when the mainline queue reaches 50% of the length of the upstream-incident segment, while this feature of operation is not available under *No control.*

Table 6 lists the results from Case 3. The incident is assumed to create a more severe capacity reduction (remaining capacity within 30-40%). The table shows that benefits of *ALINEA\Q* and *FLC* obtained for the mainline in this Case were, in general, higher than the previous Cases. Compared to *No control*, *ALINEA\Q* gained a *TTT* saving of 22.14%, an increase in the *MS* of 26.82%, a reduction in the *MD* of 23.44%, and a cut down in the *max Q_exp* of 41.86%. The *FLC* benefits were even more profound with improvements in *TTT, MS, MD,* and *max Q_exp* of 23.13%, 27.98%, 23.11%, and 42.61%, respectively. The improvements of *ALINEA\Q* and *FLC* were certainly due to a strong regulation of the ramp traffic with active response to the mainline conditions. The results under *No control* also indicate that without strong control intervention, the system performances may deteriorate seriously. Despite that, with the early ramp closure subjected to the mainline queue, it is certain that *ALINEA\Q* and *FLC* impose more *TWT,* and more vehicles have to be diverted from entering the ramp.

Table 6. *MOEs* for Case 3

MOE	Unit	No Control	ALINEA\Q		FLC		ALINEA\Q vs FLC
		value	*value*	*% change*	*value*	*% change*	*% change*
TTT	veh.h	71	55.28	-22.14	54.57	-23.13	1.28
TWT	veh.h	20.28	25.75	26.99	23.9	17.86	7.18
TTS	veh.h	91.28	81.04	-11.22	78.47	-14.03	3.17
TTD	veh.km	2543.77	2511.95	-1.25	2502.36	-1.63	0.38
MS	km/h	35.83	45.44	26.82	45.85	27.98	-0.90
MD	veh/km	37.89	29.01	-23.44	29.14	-23.11	-0.45
max Q_exp	veh	181.85	105.72	-41.86	104.37	-42.61	1.28
max Q_ramp	veh	60	60	0	60	0	0.00

Case 4: Incidence Location Changed

Case 4 is associated with the mainline demand in the range of 1,000-1,100 veh/h/lane, the ramp demand in the range of $400 \pm 10\%$ veh/h, and the remaining capacity C^* between 30-40%. The incident occurred at 500 m downstream of the ramp, which is closer than those in Cases 1 to 3. Table 7 summarizes the results from the simulation, which shows that the benefits from both *ALINEA\Q* and *FLC* were less profound than the previous Cases: *ALINEA\Q* gained a *TTT* saving of 6.49%, an increase in the *MS* of 5.6%, a reduction in the *MD* of 6.72%, and a reduction in the *max Q_exp* of 13.97%. The improvements in *TTT, MS, MD,* and *max_q_exp* under *FLC* were 11.34%, 11.88%, 13.13%, and 19.69%, respectively, that are remarkably higher than *ALINEA\Q*. Nevertheless, *ALINEA\Q* and *FLC* incurred 22.27% and 10.19% more of *TWT* than *No control*, respectively. In particular, the two control algorithms yielded 1.25% and 0.81% of the total mileage *TTD* less than *No control*. This is probably due to the fact that the when the ramp queue reaches the ramp's physical storage capacity, vehicles that arrive at the ramp will not proceed to join the queue, but be diverted to the parallel street.

Table 7. *MOEs* for Case 4

MOE	Unit	No Control	ALINEA\Q		FLC		ALINEA\Q vs FLC
		value	*value*	*% change*	*value*	*% change*	*% change*
TTT	veh.h	57.41	53.68	-6.49	50.89	-11.34	5.20
TWT	veh.h	23.05	28.18	22.27	25.4	10.19	9.87
TTS	veh.h	80.45	81.86	1.75	76.29	-5.18	6.80
TTD	veh.km	2509.66	2478.26	-1.25	2489.29	-0.81	-0.45
MS	km/h	43.72	46.16	5.6	48.91	11.88	-5.96
MD	veh/km	30.72	28.65	-6.72	26.68	-13.13	6.88
max Q_exp	veh	127.19	109.42	-13.97	102.14	-19.69	6.65
max Q_ramp	veh	60	60	0	60	0	0.00

Through the evaluation in comparison with the *No-control* scenario and *ALINEA (ALINEA\Q)* ramp control algorithm, it can be concluded that the proposed MS-FLC with the FLC controller showed substantial benefits. Particularly, under high traffic demand and severe capacity reduction, the FLC brings higher travel time savings as well as improvements of traffic conditions on both the mainline and ramp. Not only does the FLC outperform ALINEA\Q in managing ramp traffic, it also outperforms ALINEA\Q in managing the mainline flow under critical incident congestion. However, it is noted that the benefits of control interventions (*ALINEA* and *FLC*) depend on the magnitude of traffic demand and incident situation. In general, under high traffic demand and critical incident conditions, more significant gains can be realized than under favorable conditions. This comparison is likewise based on a simplified segment with a one-lane ramp. The assumption that the lane has a storage capacity of 60 vehicles should be modified accordingly, and the benefits (savings in travel times, distances, and so on) should be adjusted accordingly.

Sensitivity Analysis

The findings of the simulation experiment in varied traffic demand (low, medium, high) and incident scenarios are presented in the previous section (capacity reduction, incident location). Nonetheless, the scenarios were coupled with predetermined hypothetical network designs (a 1.5-kilometer network length (upstream section = 1.0 km, downstream section = 0.5 km) and a 60-vehicle ramp storage capacity), and a 90-minute simulation time. These network and simulation settings have a substantial impact on model performance, and it is unclear whether the control methods' comparative performance will remain valid if the input parameters change.

A sensitivity analysis is conducted to explore the effects of changes in these parameters on the comparative performance of the control approaches and to enhance confidence in the models' performance in an uncertain environment. Because these parameters are unrelated, the sensitivity analysis is carried out separately for each one, so that one parameter is altered while the others remain constant in each run.

The simulation parameters are changed as follow:

a) Network length: The simulated mainline consists of the upstream and downstream sections of the incident. Since the impacts of the incident can mostly be observed upstream, this analysis investigates how the change with a change in the length of the upstream section. Four scenarios are extended to the length of the upstream section increased from 1.0 km to 1.5, 2.0, 2.5, and 3.0 km, respectively. The length of the downstream section in the four scenarios remains at 0.5 km.

b) Ramp storage capacity: the ramp storage capacity of 60 vehicles in the simulation is now changed to 20, 40, 80 and 100 vehicles, respectively.

c) Simulation time: The previous simulation investigated the model performances for the simulation time of 30 minutes for each of the pre-incident, incident, and post-incident periods (named hereafter as scenario "30-30-30"). To explore how the improvement in the mean speed changes with simulation time, the simulation time is extended to two scenarios 30-60-30 and 30-60-60 minutes, respectively.

Since the use of all MOEs in this analysis would be very confusing, the mean traffic speed could be the best MOE in this sensitivity analysis given that the mean speed is a key parameter that reflects the operational condition on the mainline. The relative change in the mean speed of the control methods over "No control" is used and is calculated as:

$$\Delta^{\mathrm{i}}_{\mathrm{MS}} = 100 \times \frac{MS_i - MS_{No}}{MS_{No}} (\%) \tag{16}$$

where *i* denotes either *ALINEA\Q* or *FLC* method, MS_i denotes the mean speed under the control method *i*, and MS_{No} denotes the mean speed under "No control".

The sensitivity analysis is performed for the Case 3 "High expressway and ramp demands, severe capacity reduction (C*=30-40%). Table 8 show the Δ_{MS} versus the length of upstream section. The Table indicates that both ALINEA\Q and FLC are highly sensitive to the length of the upstream section, and the superiorities of the control methods over No control deteriorate as the network length increases. For a relatively short simulated network (the length of the upstream section = 1.0-1.5 km), a small change in the network length may lead to a large change in Δ_{MS}, but for a relatively long simulated network (the length of the upstream section = 2.5-3.0 km) the change in Δ_{MS} against a change in the network length is smaller. A possible reason under this phenomenon could be due to the fact that for a given traffic demand and incident parameters, when the upstream section is shorter, the traffic condition is more critical. By contrast, when the network length is large the traffic condition is less severe, and the effectiveness of the control is lower.

Table 8. Δ_{MS} versus the length of upstream section

Control method	Length of upstream section (km)				
	1.00	1.50	2.00	2.50	3.00
ALINEA\Q	26.82	14.62	10.84	8.84	7.42
MS-FLC	27.98	20.84	16.68	14.16	12.45

Table 9 shows that in both control methods the Δ_{MS} varies slightly in the range 23-29%, and the values of Δ_{MS} increase as the ramp storage capacity increases. A possible reason could be that when the ramp storage capacity increases, the ramp can accommodate more vehicles, hence fewer vehicles have to divert from the ramp. Consequently, given a long ramp and regardless of the control method, more vehicles can be metered into the mainline. In both cases, it is obvious that the MS-FLC consistently outperforms the ALINEA\Q control algorithm.

Table 9. Δ_{MS} versus the ramp storage capacity

Control method	Ramp storage capacity (veh.)			
	20	40	60	80
ALINEA\Q	23.19	24.26	26.82	27.45
MS-FLC	25.74	26.96	27.98	28.77

Table 10 summarizes the Δ_{MS} for the three simulation time scenarios. The figure indicates that in both control methods, the benefits in the mean speed are highest in the simulation 30-60-30 (31.93% and 37.47% for ALINEA\Q and FLC respectively), followed by the simulation 30-60-60. The evaluation times for the three scenarios are 75/90, 105/120, and 135/150 minutes respectively (excluding 15-minute warm-up period), and the ratios of the incident and non-incident period in the evaluation period are 30/45 (0.67), 60/45 (1.33), and 60/75 (0.80), respectively. This indicates that when the ratio of the incident and non-incident period is higher, the improvement in the mean speed of the control algorithms over No control increases. This coincides with the findings in cases a) and b) that the effectiveness of control is higher in the more critical mainline conditions.

Table 10. Δ_{MS} versus the simulation period

Control method	Simulation period (min.)		
	30-30-30	30-60-30	30-60-60
ALINEA\Q	24.90	31.93	26.40
FLC	27.47	37.47	32.14

Discussions: feasibility and limitations

The study of results from the simulation scenarios shows that the benefits of control intervention (*ALINEA* and *FLC*) depend on the magnitude of traffic demand and incident situation. Broadly speaking, more significant benefits can be achieved under high traffic demands and critical incident conditions than under favourable conditions. The study of results from the sensitivity analysis provides further understanding on how the control performances change with changes in the input parameters, specifically:

- The benefits of control intervention are highly sensitive to the length of the network, in particular to the length of the upstream section. In general, the superiorities of the control methods over *No control* deteriorate as the network length increases.
- The superiorities of the control methods are less sensitive to the ramp storage capacity, in comparison to the network length. In general, the benefits of the control methods increase as the ramp storage capacity increases.
- The level of out-performance of the control algorithms is subject to the temporal structure of the simulation: when the ratio of the incident and non-incident period increases, the benefits over "No control" increase.

It should be noted that the aforementioned findings are obtained from the model evaluation that was performed on a simplified network with an onramp, upstream and downstream incident segments, and a segment upstream of the ramp, under the local control as stated in the research scope. Although the model properties were further explored through sensitivity analysis with variations in the network length and simulation parameters, they are not verified for a more complicated network such as a corridor-wide control.

It should also be noted that there are no clear cuts between the terms *low*, *medium*, and *high* demands. They are loosely defined based on traffic demand in association with the reduced capacity. The question "to what range each of the demand categories covers" has not been verified numerically. An inspection of daily traffic volume profiles in the PIE's database revealed that *low-medium* demand level is usually associated with nighttime, while *medium-high* and *high* demands can mostly be observed in the daytime. Therefore, the MS-FLC has opportunities for practical applications in most of the time domain (daytime) when control intervention should be in operation.

Notwithstanding the important operational advantages, the MS-FLC has a number of limitations:

- The MS-FLC is complex and operationally expensive. It employs a considerable number of input parameters, thus extensive observations and measurements from the network are required.
- The essence of the fuzzy MS-FLC is the fuzzy rule base that formulates rules following fuzzy logic concept. In fuzzy logic, the input parameters are represented by fuzzy terms that are normally ill defined. In some cases, the partition of fuzzy sets must rely purely on personal judgements or common sense reasoning without having reference data to justify them based on solid technical grounds.
- The MS-FLC only enhances its performance if the rule base is well formulated with appropriate membership function design and input-output mapping. Otherwise, the system performance can deteriorate seriously.
- In calibrating parameters of membership functions of the fuzzy rule base, certain level of knowledge and expertise is required. The process of learning fuzzy rules requires a long time and the derivation of the membership functions can be tedious.
- In general, in the design of control system, stability analysis is one of the fundamental concerns. As an FLC, the MS-FLC is a highly non-linear system with complex stability behaviour. However, there exists no systematic methodology with respect to the stability analysis of the MS-FLC, to the best of the authors' knowledge.

Conclusion and Future Works

A multi-stage Fuzzy Logic Controller (MS-FLC) has been developed for traffic control under incidents on expressways. It aims at assisting traffic operators in decision making on non-recurring congestion management in a systematic manner. The decision-making process for traffic control during incidents on expressways include three tasks: (i) evaluation of incident traffic conditions, (ii) prediction of congestion tendency during the incident, and (iii) recommendation of local control strategies and control actions to alleviate the congestion. Following this logic, a multi-stage composite structure is proposed. The MS-FLC is divided into three stages, each of which corresponds to one of the three tasks listed above, with rules being executed sequentially from one stage to the next. The MS-FLC performance is evaluated by comparing with no control scenario and ALINEA\Q, a popular local ramp control algorithm. Principal performance evaluation criteria include travel time, waiting time on-ramp, total travel distance, mean speed, mean density, and queue length. The experiment evaluated the control algorithms under various traffic demand levels and incident scenarios. The experiment results show that in general MS-FLC outperforms ALINEA\Q with respect to global objectives. In particular, while the ALINEA\Q algorithm gives control preferences to the mainline, the MS-FLC algorithm gains a better balance between the mainline and the ramp.

In summary, the findings from this research allow the following conclusions to be drawn:

- The MS-FLC provides a systematic procedure in deriving control actions. Through the systematic assessment of prevailing traffic conditions in advance of control actions, the MS-FLC ensures that salient-influencing factors can be considered for proper control actions.
- For incident management, many types of data and information need to be gathered and analyzed, which may overload the traffic control operators. The MS-FLC resolves this challenging problem by its data-handling capability and knowledge representation to deliver simplified linguistic expression that is easy to understand by the operators.
- Flexibility of the performance: unlike ALINEA (ALINEA\Q) whose control algorithm does not consider incident situation, MS-FLC is specifically designed for incident management. Issues such as capacity reduction and queue management are addressed. However, MS-FLC can also be applied for recurring congestion management since the problem-solving strategy for both types of congestion aims at demand-capacity balance on the mainline and the ramp.

The findings of this study have the extended potential for future research on application development of an adaptive MS-FLC. First, a MS-FLC with an adaptation component where parameters can be calibrated and rules can be modified on-line is worth exploring; second, effort should be extended to integrating the SVM short-term traffic prediction component for MS-FLC online operation; and third, future research should be devoted to development of the rule base and calibration of the MS-FLC model, as applicable for corridor-wide control.

Data Availability Statement

Some or all data, models, or code used during the study were provided by a third party. Direct requests for these materials may be made to the provider as indicated in the Acknowledgements.

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