Fuzzy System-Based Solutions for Traffic Control in Freeway Networks Toward Sustainable Improvement

Mehran Amini[1,2](✉), Miklos F. Hatwagner[1,2], and Laszlo T. Koczy[1,2]

[1] Department of Information Technology, Szechenyi Istvan University, Gyor, Hungary
mehran@sze.hu
[2] Department of Telecommunications and Media Informatics, Budapest University of Technology and Economics, Budapest, Hungary

Abstract. In the scientific community, the topic of traffic control for promoting sustainable transportation in freeway networks is a relatively new field of research that is becoming increasingly relevant. Sustainability is a critical factor in the design and operation of mobility and traffic systems, which impacts the development of freeway traffic control strategies. According to sustainable notions, freeway traffic controllers should be designed to maximize road capacity, minimize vehicle travel delays, and reduce pollution emissions, accidents, and fuel consumption. The problem is full of uncertainty, there is no way to model the whole system analytically, thus a fuzzy modeling approach seems to be not only adequate but necessary. In this study, a Fuzzy Cognitive Map based model (FCM) and a connected simple Fuzzy Inference System (FIS) are presented, as the tools to analyze freeway traffic data with the goal of traffic flow modeling at a macroscopic level, in order to address congestion-related issues as the core of the sustainability improvement strategies. Besides presenting a framework of Fuzzy system-based controllers in freeway traffic, the results of this work indicated that FIS and FCM are capable of realizing traffic control strategies involving the implementation of ramp management policies, controlling vehicle movement within the freeway by mainstream control, and routing vehicles along alternative paths via the execution of suitable route guidance strategy.

Keywords: FCM · FIS · Congestion prediction · Sustainability · Freeway networks

1 Introduction

The expanding number of vehicles has exacerbated traffic congestion, resulting in longer travel times and a decrease in driver confidence in the reliability of traffic services [1]. Moreover, congestion has become a global problem that hinders developing a robust and sustainable transportation infrastructure system. This problem is mainly caused by urbanization, expansion of the number of motor vehicles and associated infrastructure,

D. Ciucci et al. (Eds.): IPMU 2022, CCIS 1602, pp. 288–305, 2022.
https://doi.org/10.1007/978-3-031-08974-9_23

and the growth of ride-share and courier services. This latter becoming even more popular because of the recent pandemic situation. Congestion has been defined based on a variety of approaches [2]. Congestion in the traffic flow state is most commonly defined as when demand for travel exceeds the capacity of a road section, e.g., the freeway. Also, congestion arises when the normal flow of traffic is disrupted by a dense concentration of vehicles, resulting in higher travel time [3]. Despite substantial advancements in information and communication technology, it appears that full utilization of such novel technologies to reduce freeway traffic congestion has not been appropriately obtained [4]. Nevertheless, the rapid growth of personal vehicles has resulted in congestion on a daily basis, both recurrent and non-recurrent, spanning thousands of kilometers worldwide. Therefore, congestions significantly restrict accessible infrastructure capacity during rush hours when needed; consequently, delays, high environmental pollution, and decreased traffic safety occur. Such effects were noted frequently in the event of non-recurring congestions caused by incidents and freeway maintenance [5].

However, many current infrastructures cannot be modified to satisfy ever-increasing traffic volume, mainly due to physical and financial limitations. In this context, the progress of planning and managing tools for traffic systems remains critical in order to maximize the efficiency of the existing freeway network without requiring significant infrastructure improvements [6]. Due to a large portion of the freeway network being incapable of meeting current mobility needs, affecting drivers in the form of congestion, worsened air pollution, and declining safety, various researches have been conducted to advance planning and control techniques for freeway traffic networks. Former researchers were primarily concerned with mitigating congestion problems, but the current global roadmaps for eco-innovation in transportation systems necessitate the fulfillment of much better policies [7]. This requires a reframing of conventional control approaches for a more sustainable perspective because then control purposes cover not only the optimal use of freeway network capacity but the minimization of emission, fuel consumption, accidents, etc. [6].

Computational Intelligence (CI) methods as nature-inspired techniques have been used to address multi-criteria issues in real-world settings [8]. Neural networks, evolutionary computation, and fuzzy systems are the main CI based approaches [9]. Although the majority of existing CI methods to address the problem of vehicle traffic routing and congestion are based on evolutionary computation [10], fuzzy inference-based techniques are also widely applied in traffic-related problems [11]. However, the abilities of the CI techniques concerning sustainable freeway traffic control are relatively neglected. Significant characteristics of sustainable road traffic control mechanisms include traffic flow, dispersion, emission, consumption, and safety models [12]. Accordingly, in this study, flow-based modeling at a macroscopic level is considered to analyze freeway traffic data by employing Fuzzy Cognitive Maps (FCM) and Fuzzy Inference System (FIS) to address congestion-related issues as the core of the sustainability improvement strategies. In addition to providing a generic framework of Fuzzy system-based controllers in freeway traffic, the extended aim of this study is to contribute to the implementation of a sustainable and responsive traffic control and management system. The main contribution of the proposed system is modeling and computing imprecise traffic data at the macroscopic level and mitigating harmful economic, social, and environmental repercussions of congestion in freeway networks.

This work is conducted into five sections. Section 2 introduces traffic flow models with sustainable objectives. An FIS designed for congestion level prediction and an FCM developed for traffic flow simulation after introducing the case study are presented in Sect. 3. In Sect. 4, the results of both fuzzy system-based methods are analyzed, while some conclusions are drawn in Sect. 5.

2 Traffic Flow Models with Sustainable Objectives

Sustainable mobility encompasses a wide variety of issues, from environmental protection to social and economic growth. In this perspective, road transportation is critical for economic growth and social well-being, as it is still the most widely used mode of transport for passengers and commodities. In this view, sustainable transportation aims to meet economic and social needs while also providing a sustainable and accessible service that improves availability and connections for all users. Given the intricacy of the topic, the scientific community has been investigating transportation sustainability-related issues for several decades [13]. Among these problems, reducing traffic congestion becomes the prime common objective of conventional freeway traffic control systems. As previously highlighted, the expansion of freight and passenger mobility systems has contributed to the socio-economic growth of a society. However, it has also led to the spreading of congestion and, as a result, a deterioration of the existing mobility service. Such congestion can manifest itself in various ways, from just forming bottlenecks and increasing travel times to significantly deteriorating the system and bringing vehicular traffic to a halt.

Additionally, as acknowledged by the research conducted in [14], repeated exposure to congestion results in an increase in driver irritation, as drivers view the additional time required to reach their destination as wasted time that could be used for other purposes. Identifying appropriate traffic control actions is a possible approach for expediting the procedure towards resolving congestion and, subsequently, a better sustainable mobility system. Various control measures (Fig. 1) can be employed to manage the flow of traffic on a freeway network. The primary options include ramp management, i.e., ramp metering in conjunction with traffic lights at on-ramps; mainstream control, e.g., variable speed limits, keep-lane directives, lane control, and congestion warnings; and route guiding, i.e., typically, particular indications are displayed at junctions [15].

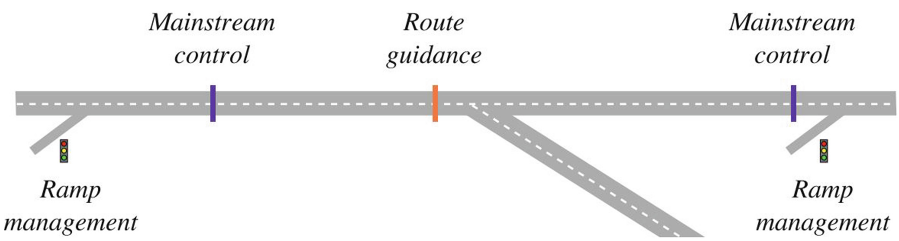

Fig. 1. Various traffic control strategies [15]

To design these control actions, an appropriate modeling approach needs to be defined, not only for describing traffic flow behaviors but also for assessing all sustainability-connected problems. Figure 2 depicts the primary modeling criteria for sustainable freeway traffic control mechanisms, among which the traffic flow-based model is discussed in further detail.

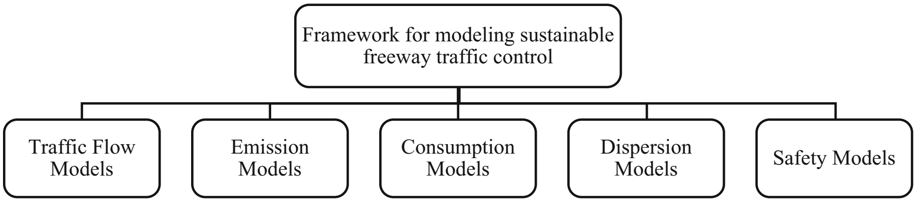

Fig. 2. Modeling framework for sustainable freeway traffic control methods [6]

Traffic flow models were developed in response to the requirement to represent the dynamic behavior of real-world traffic systems mathematically. Apart from evaluation and prediction of the system, traffic flow models can be used to define planning actions, evaluate the effects of new infrastructures or changes to current freeway layouts, and develop, simulate, and evaluate specific control mechanisms. Beginning with work by [16] in the 1950s, a diverse spectrum of traffic flow models with varying features and applications has been developed. Different criteria can be used to classify traffic models [17]. The commonest classification scheme for traffic flow representation is based on their level of detail, with macroscopic, microscopic, and mesoscopic models being the most prevalent.

The most typical and consolidated method of traffic regulation is at the macroscopic level (road-based control measures, i.e., mainstream control, ramp management). Further classification of macroscopic forms is based on the continuous or discrete character of the features representing time and space. Macroscopic discrete models are the most commonly used ones for freeway traffic control because their low degree of detail and discretization enable a low computational complexity, making them particularly well suited for real-time control systems in vast freeway traffic networks. The model's focus in this work is on discrete macroscopic characteristics, emphasizing overall vehicle behavior within hourly time intervals. In addition, instead of employing continuous variables, the related variables are discretized (both spatially and temporally), i.e., freeways are viewed as a collection of sections with fixed lengths, and time is correspondingly divided into distinct intervals [18]. Consequently, these features rely frequently on standard mathematical methodologies, which are regularly incapable of modeling the intricacy of road traffic characteristics and complex interactions among involved parameters. Moreover, these parameters are greatly affected by imprecise and uncertain qualities because of being imposed by constant dynamic behaviors of drivers; therefore, these properties and their varying levels of vagueness need to be included in mathematical reasoning.

3 Fuzzy System-Based Controllers in Transportation

As an essential part of computational intelligence, fuzzy systems use methods and techniques comparable to human observation, reasoning, and decision-making for computing under imprecise conditions. Fuzzy systems lay the groundwork for combining subjective and objective inputs to handle numerical and linguistic data. In the field of transportation engineering, these systems have been widely used. In [19], the freeway-related speed is regulated using measurements and expert knowledge data through speed advisory boards. Other researchers introduce current and potential traffic network control and management issues by surveying some commonly used computational intelligence paradigms, analyzing their applications in traffic signal control [20]. In order to seaport operations, [21] presents a fuzzy system-based method for determining an optimal investment plan. In [22], a fuzzy system-based lane-changing model that accounts for and simulates drivers' socio-demographics was developed to increase the realism of lane-changing operations in work zones.

Even though fuzzy system methods have been used for various traffic-related topics, their application for traffic control in the context of sustainable mobility on freeway networks has been overlooked. However, sustainable mobility is a relatively new area of research that is gaining increasing attention within the scientific community of traffic control experts. In continuation, a Fuzzy Inference System (FIS) and a Fuzzy Cognitive Map (FCM) that were preliminarily designed and developed in [23, 24] respectively, are employed parallelly (see Fig. 3) for traffic control with sustainable mobility purposes in freeway networks at a macroscopic level (road-based control measures, e.g., mainstream control, ramp management). In Fig. 3 a feedback loop is presented as a generic framework of a supervised vehicular traffic system by the proposed fuzzy system-based controllers. In this framework, preventive and uncontrollable inputs are two distinct forms of inputs that influence the characteristics of the system. Preventive inputs are generated from fuzzy controllers that through preassigned actuators, transmitted to the freeway network, e.g., in case of mainstream control, preventive inputs generated by FIS are the number of vehicles that need to be entered in the next segment of the freeway to avoid breaking down of the flow by predefined means such as VMSs. Meanwhile, uncontrollable inputs denote unmanipulable external issues that affect the density of the segment, such as weather-related issues or lane drop caused by accident. Within this context, performance demands are the controllers' computational-related requirements, e.g., time, rule generation, and performance measurements are the key indicators through which evaluating the applicability and efficacy of the control strategy in relation with sustainability-related objectives such as reducing congestion, emission, and travel time is possible.

3.1 The Case Study

The proposed FIS and FCM models were developed using data from the Hungarian freeway networks, wherein their users encounter complicated and dynamic congestion patterns. Apart from other factors, such as the relatively heavy road traffic resulting from Hungary's pivotal placement within Europe's transit system and corridor network [25], this is primarily as a result of an increase in the number of registered vehicles in

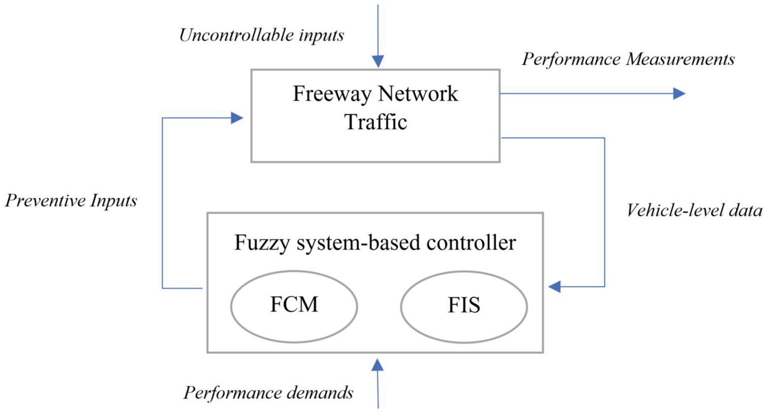

Fig. 3. A framework of Fuzzy system-based controllers in freeway traffic

Hungary, which increased by around 25% between 2010 and 2018 [26]. These issues cause complicated behavior in road traffic, including spatial and temporal changes. The dataset is derived from the Hungarian e-toll system's online transaction processing server, an electronic system maintained by the Hungarian national toll payment services for the country's whole network of freeways and primary roads. This system offers the guidance and support of freeway usage authentication, admittance, levying, and eventually collecting tolls on conventional road sections tollways.

The dataset contains the following independent variables: the freeway's name, the section's name (identifier), the number of e-toll collected over one week in each section (segment) of the 212 freeway sections (links), which latter is used as a proportional criterion of the number of vehicles, the time (per minute), the day, the section's length, and the number of lanes in each section. These links contain a total of 2446 distinct segments. Each segment is between 100 and 18,000 m long. In designing the FIS engine and input and output variables clustering ranges, the entire dataset and freeway sections are analyzed; in the developed FCM to keep the model effective and timely, a sample of 58 segments was chosen, representing the entire set of freeway sections connecting Budapest to the Austrian border.

The majority of road traffic models are designed to describe the behavior of traffic-related variables over a wide range of operations, which recognized locations playing a critical part in the dataset under investigation. This dataset can reflect real-time road traffic behavior based on location. A sample of connections between three segments *A*, *B*, and *C* is shown in Fig. 4. The provided dataset is based on time series; therefore, present traffic circumstances in upstream segments can project future road traffic flow conditions in downstream segments.

Figure 5 shows the causal linkages and correlations between the segments. The first digit on the horizontal axis represents the day, whereas the second and third digits indicate the time (in 24-h format); actual behavior of road traffic flow through time can be seen, demonstrating how traffic flow in the upstream segment might affect the downstream segments. The calculated road traffic flow correlation among segments confirms that *A* and *B* correlate 0.03, *A* and *C* have a correlation of 0.9, and *B* and *C* have a correlation of

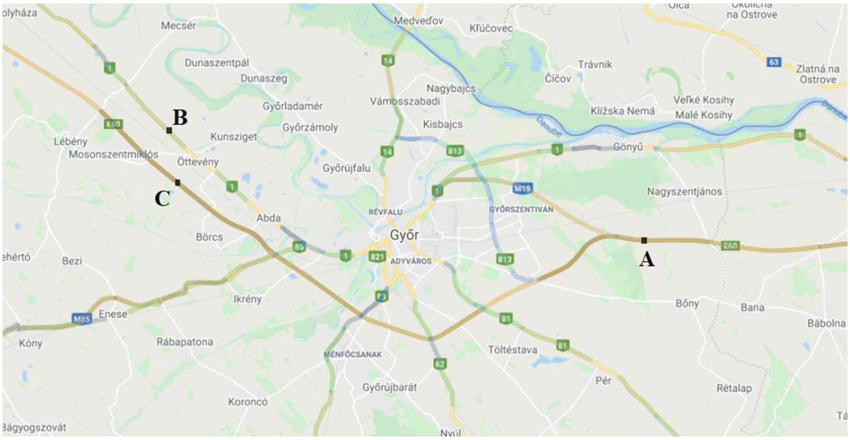

Fig. 4. An example of segments' connections

0.1; using these values, various conclusions, and correlation analyses can be performed to assess the behavior patterns and severity of traffic flow in the freeway.

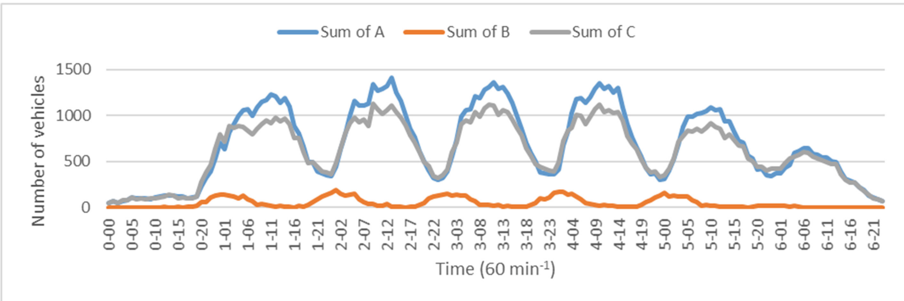

Fig. 5. Causal relations of traffic streamflow on the segments

3.2 The Fuzzy Inference System

Zadeh's original fuzzy set theory [27] has been later used to address a range of industrial and scientific concerns in various technology and science domains. The properties of fuzzy sets, coupled with their possible representation in linguistic terms, provide a computational algorithm for modeling and addressing imprecision and uncertainty-involved problems. Therefore, this work for detecting traffic congestion introduces a fuzzy inference model based on the Mamdani algorithm [28] implemented in MATLAB's Fuzzy Logic Toolbox R2021a. The developed model is designed to analyze and predict the severity of congestion in a freeway network. The model fuzzy inference system's layout in MATLAB with assigned input and output variables is presented (Fig. 6, for further details, see [23]).

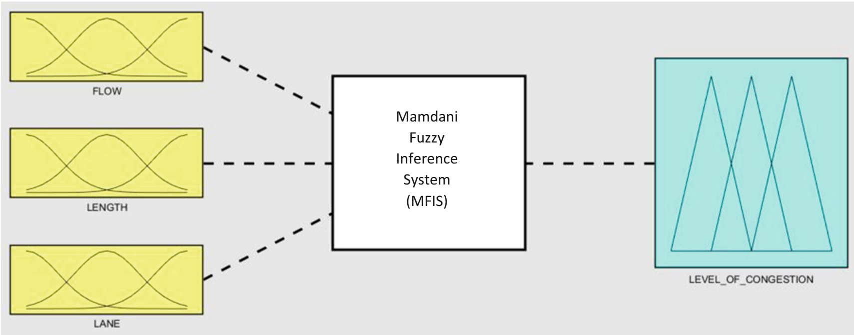

Fig. 6. Schematic representation of the proposed FIS

Specifying the model's input and output parameters is the initial step in developing a fuzzy inference model. The model will use three input parameters (length, number of lanes, and flow) and one output parameter (level of congestion). There are four primary design steps in the proposed Mamdani fuzzy inference algorithm:

1) Determining the numerical ranges for input and output linguistic variables. The following are the input variables:

- *Flow*, the number of vehicles passing through a specific segment per time unit, which time interval equals 60 min,

$$q = \frac{n}{T} = \frac{n}{\sum_{i=0}^{n} i} \tag{1}$$

  where q is the average number of vehicles *(n)* that pass a segment during a unit of time *(T)*.
- *Length* of each segment of freeway networks in kilometers.
- *Lane*, the number of lanes in each segment.

2) Triangular and trapezoidal membership functions are used for determining the degree of matching of the input and output parameters, as they capture and express the properties of the case study's fuzzy set. Equations 2 and 3 define these triangular and trapezoidal membership functions, respectively:

$$\mu_{\Lambda}(x) = \begin{cases} 0, & x < \alpha_{min} \\ \frac{x-\alpha_{min}}{\beta-\alpha_{min}}, & x \in (\alpha_{min}, \beta) \\ \frac{\alpha_{max}-x}{\alpha_{max}-\beta}, & x \in (\beta, \alpha_{max}) \\ 0, & x > \alpha_{max} \end{cases} \tag{2}$$

$$\mu_{\Lambda}(x) = \begin{cases} 0, & x \leq \alpha_{min} \\ \frac{x-\alpha_{min}}{\beta_1-\alpha_{min}}, & x \in (\alpha_{min}, \beta_1) \\ \frac{\alpha_{max}-x}{\alpha_{max}-\beta_2}, & x \in (\beta_2, \alpha_{max}) \\ 0, & x \geq \alpha_{max} \end{cases} \tag{3}$$

3) If-then fuzzy rules determine the input-output connections. Based on the available dataset, percentile distribution of the data, and expert assessment, in the case study, a total of 75 rules were applied. To develop the inference and nonlinear surface model, these rules were implemented in the MATLAB Fuzzy Rule Editor.
4) Centroid of area as the defuzzification operator was used to detect the matching action (level of congestion) to be performed. This operator is denoted as follows:

$$Z_{COA} = \frac{\int_Z \mu_A(z) z dz}{\int_Z \mu_A(z) dz} \tag{4}$$

where z is the fuzzy system output and aggregated output membership function is given as $\mu_A(z)$.

3.3 The Fuzzy Cognitive Map

As a further development of classic cognitive maps [29], Kosko [30] established the notion of the Fuzzy Cognitive Map (FCM) in order to address limitations associated with the binary structure of the original cognitive map model. FCMs combine the idea of cognitive maps and the concept of fuzzy set initially introduced by Zadeh [27], with the additional idea of signed fuzzy effects, forming a special kind of artificial neural network or fuzzy bipolar graph. It features fuzzy nodes or concepts (components) that are used to characterize the non-binary aspects of the modeled system's concepts and their gradual intensities of causal relationships. A simple FCM is schematically illustrated in Fig. 7; linkages and interrelationships between concepts are modeled using weighted arcs.

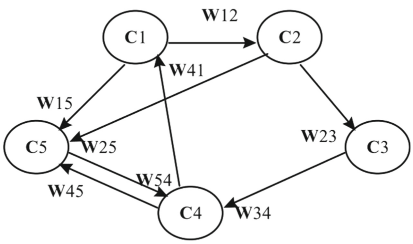

Fig. 7. A basic schematic illustration of FCM [24]

Determining activation values for the concepts related to weight assignments is critical in developing the FCM-based road traffic flow model. The presented model assigns activation values using an inference rule derived from Eqs. (5) and (6) in Table 1. Thus, the proposed integration places a premium on two critical aspects: not only may activation values be computed using the values of the connected concepts and their associated causal weights at each time step, but concepts can also reflect their past values.

Consequently, every freeway segment is signified by a concept whose value is taken as the density ρ of segment i of link m, and the weighted arcs are set to a constant value

Table 1. Involved methods and the proposed inference rule

Author/s	Equation/Method		Application
[31]	$\rho_{m,i}(t+1) = \rho_{m,i}(t) + \frac{T_s}{L_m\lambda_m}[q_{m,i-1}(t) - q_{m,i}(t)]$	(5)	Calculating the density of segment *i* in link *m* at different time frames
[32]	$A_i^{(t+1)} = f\left(\sum_{\substack{j=1 \\ i \neq j}}^{n} w_{ji}A_j^{(t)} + A_i^{(t)}\right)$	(6)	Calculating the value of concept C_i at time *t*, wherein the value of C_i may represent the calculated density in the given segment
[24]	$\rho_{m,i}^{(t+1)} = f\left(\sum_{\substack{j=1 \\ i \neq j}}^{n} \rho_{m,i,j}^{(t)} W_{ij} + \rho_{m,i,i}^{(t)}\right)$	(7)	The proposed inference rule for predicting the density of segment *i* in link *m* in $t + 1$ time step by considering the previous density value of the given segment

based on variables $L_m\lambda_m$ as an approximation of the capacity; where L_m denotes the lengths of the segments of link *m* , and λ_m denotes the quantity of the available lanes in link *m.* The concepts and the weights are initialized using the aforementioned values. Following that, the system is allowed to interact, and after each iteration, the new state vector is given newly generated values. This procedure will be repeated until the model reaches an equilibrium state by exhibiting a stabilized condition at a fixed numerical boundary (see further details in [24]).

4 Results and Discussion

In this section, further discussion on the advantages of each fuzzy system-based method is deliberated. FIS and FCM are developed in connection with traffic control strategies, i.e., mainstream control, ramp management, route guidance, in freeway networks based on the data analysis at a macroscopic level. In particular, with considering sustainable objectives such as the reduction of the traffic emission, and improving road safety.

4.1 FIS in Congestion Level Prediction

Mainstream control is used to manage the traffic flow of vehicles traveling on the mainline, often by providing suitable indicators to drivers via Variable Message Signs (VMSs) or traffic lights. At a macroscopic level, these widespread control measures aim to homogenize traffic conditions, prevent the formation of recurrent congestion, and reduce the likelihood of vehicle crashes. An additional purpose is to address the emergence of non-recurring congestion problems by boosting the system's efficiency under situations of low capacity [33]. The proposed FIS aims to improve mobility and safety conditions in freeways by suggesting or imposing appropriate speed limits displayed utilizing VMSs. As seen in the preceding section, the level of congestion in each segment is determined using three types of accessible row data: the number of vehicles in a specific time unit, the number of lanes, and the length of the provided segment. All of these input data supplied approximations of the segment's relative capacity to meet recently formed demand, which could result in a change in the Level of Congestion (LOC). The collected findings demonstrate how effective the suggested FIS is at generalizing complicated nonlinear links between congestion levels and other numerical characteristics of the traffic.

The suggested FIS's interdependence between input variables and LOC may be proven by applying a fuzzy control surface in a visual insight view (Fig. 8). It demonstrates the existence of a correlation between LOC and the input variables. The most dramatic change occurs in the LOC when the length is between 4 and 6 km, and the lane count is 2 or 3 (Fig. 8 part I). Additionally, when the length variable is between approximately 1 and 6 km, an intensive reaction (approximately 50% rise) in the LOC occurs in each segment with a rising flow rate of more than 200 vehicles (Fig. 8 part II). Increasing or decreasing the number of lanes has the most significant effect on the LOC. Segments with 3 or 4 lanes will not encounter severe congestion, but raising of the flow rate by 200 vehicles in segments with fewer than two lanes can raise the LOC by more than 50% (Fig. 8 part III).

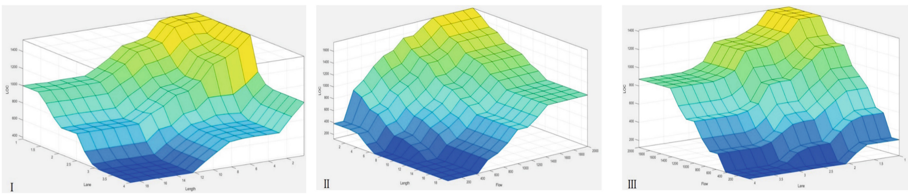

Fig. 8. Rule surface of LOC for length and lane (I), and length and flow (II), and flow and lane (III)

The developed FIS in this study can provide a prediction of congestion severity when input data is inserted. As a sample of the proposed model application from Fig. 9, it can be observed that if real-time input parameter properties are entered as follows:

Flow rate = 253, the segment has two lanes and 5.16 km length, then the LOC would be predicted as 281, which is categorized based on the assigned membership function, for the level of congestion-free.

Congestion measurement is critical for optimizing traffic management and control. The decision-making process that follows in order to create a sustainable transportation system is mainly dependent on current road traffic patterns. Hence, the method used to evaluate the severity of congestion should be realistic enough to enable decision-makers to carry out the necessary steps to alleviate congestion and to build quickly a resilient and sustainable transportation system. Therefore, transportation engineers have identified specific characteristics that are frequently required in a congestion measure [34, 35]. A practical congestion assessment ought to have mainly the following: non-technical individuals should be able to understand and interpret the outcomes of the analysis straightforwardly, give a constant range of possible values, be capable of being utilized for predictive and statistical analysis, and be universally applicable to a variety of road types. Besides all these characteristics, as opposed to conventional methods of traffic detection, the proposed mechanism has a sophisticated discipline known as approximate reasoning [36, 37] through which exact traffic connected properties (e.g., geometric features including junctions, bifurcations, off-ramps, and on-ramps) that can be assigned in both microscopic and mesoscopic types of traffic modeling are sacrificed, to reach significantly low time and computational efforts.

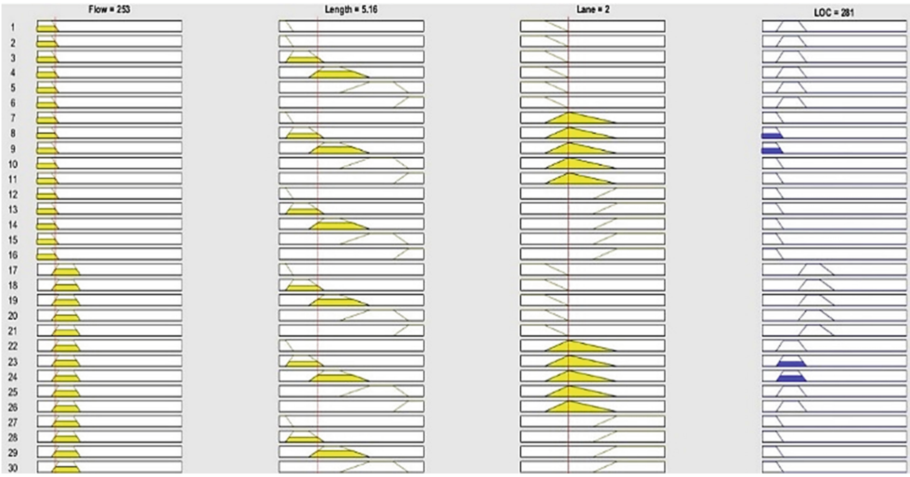

Fig. 9. A sample of the lookup diagram of the fuzzy rules, when: Flow = 253, Length = 5.16, Lane = 2, and the predicted LOC is 281

4.2 FCM in Traffic Flow Simulation

Complex road traffic flow processes are characterized by a variety of interdependent and interrelated elements. Therefore, FCM as a computational intelligence method is presented to address networks of freeways included imprecision and uncertainty. These uncertainties from the macroscopic modeling point of view are mainly connected with road traffic flow, density, and approximate capacity associated variables that can increase the probability of a breakdown and shift the free flow state of traffic to congested flow [18]. In the proposed FCM, segments of each link (freeway) are assigned as the concepts (nodes), where calculated density defines their values. In Fig. 10, a geographical representation of the selected segments is presented.

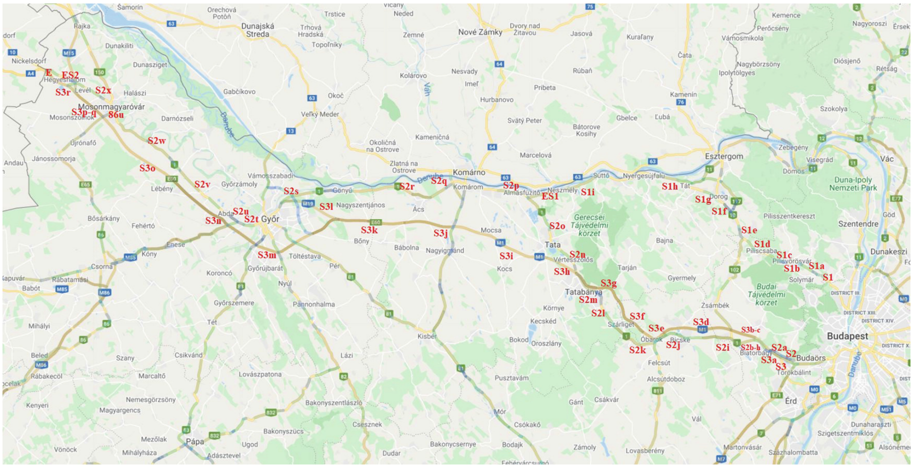

Fig. 10. Geographical locations of the selected segments

In Fig. 11, the FCM is illustrated with initialized weights and concepts. FCM begins to analyze the performance of the process. In every running step of the FCM, the state of concepts is computed on the basis of Eq. 7 in Table 1. Greater activation values in the concepts (segments) are indicated by larger nodes in the modeled FCM; they represent greater density and show stronger activation values that cause a greater impact on the network. Three alternative freeways that can be chosen from Budapest to the Austrian border are illustrated by *S1*, *S2*, and *S3* and their 58 nodes in the network. *S1* includes nine segments that end at segment *ES1* and combines with one of the *S2* segments; *S3*,

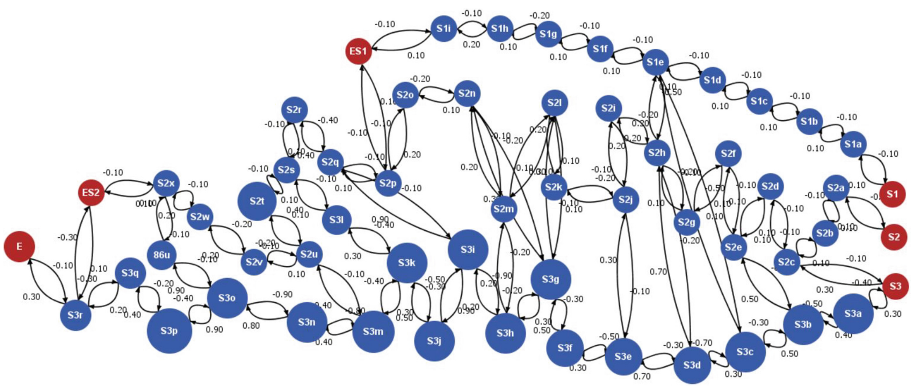

Fig. 11. FCM model of the road traffic flow

as the most chosen route, also has close interaction with the segments in *S2*, which both end at segment *E* as the last Hungarian segment before entering Austrian territory.

To see how alteration in variables properties (i.e., change in the number of lanes or altering in the flow rate) affect system behavior, the FCM traffic flow simulation of the initial states is shown in Table 2 wherein the road segments are defined by nodes, e.g., *S3a*, *S3b*,… and the calculated values indicate the segments' density. This model offers multiple contributions through which the most common traffic control approaches, such as ramp management and route guiding, can be implemented. Accordingly, as one of the common causes of severe LOC, i.e., based on Fig. 8 part III, a lane-drop scenario is simulated in a two-lane segment (*S3h*). However, one of the lanes is reduced, the density declined just marginally, obviously indicating that the remaining lane's density rose considerably and reached severe LOC. In comparison to the initial states, changing in the density values among connected segments, i.e., *S3g* and *S3i* can be seen in Table 3, wherein the density of *S3i* is dropped by 11% and subsequently slight decrease in *S3j*, while in the upstream side *S3g* and *S3f* are escalated by 16% and 8% respectively.

Table 2. Initial simulation result of the traffic flow density in the chosen network

Step	S3	S3a	S3b	S3c	S3d	S3e	S3f	S3g	S3h	S3i	S3j	S3k	S3l	S3m	S3n
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50
2	0.67	0.71	0.73	0.65	0.71	0.74	0.73	0.74	0.64	0.68	0.80	0.70	0.76	0.66	0.67
3	0.67	0.72	0.76	0.63	0.72	0.77	0.76	0.78	0.63	0.68	0.85	0.72	0.79	0.66	0.66
4	0.67	0.72	0.77	0.63	0.72	0.78	0.77	0.79	0.63	0.67	0.85	0.73	0.80	0.67	0.65
5	0.67	0.72	0.77	0.62	0.72	0.78	0.77	0.79	0.63	0.66	0.85	0.73	0.80	0.67	0.65
6	0.67	0.72	0.77	0.62	0.72	0.78	0.77	0.79	0.63	0.66	0.85	0.73	0.80	0.67	0.65
7	0.67	0.72	0.77	0.62	0.72	0.78	0.77	0.79	0.63	0.66	0.85	0.73	0.80	0.67	0.65

Table 3. Traffic flow density in one lane reduction scenario

Step	S3	S3a	S3b	S3c	S3d	S3e	S3f	S3g	S3h	S3i	S3j	S3k	S3l	S3m	S3n
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
2	0.67	0.71	0.73	0.65	0.71	0.74	0.74	0.74	0.62	0.68	0.80	0.70	0.76	0.66	0.67
3	0.67	0.72	0.76	0.63	0.72	0.77	0.78	0.78	0.61	0.68	0.85	0.72	0.79	0.66	0.66
4	0.67	0.72	0.77	0.63	0.72	0.77	0.79	0.79	0.61	0.67	0.83	0.73	0.80	0.67	0.65
5	0.67	0.72	0.77	0.62	0.72	0.79	0.84	0.84	0.61	0.64	0.83	0.73	0.80	0.67	0.65
6	0.67	0.72	0.77	0.62	0.72	0.79	0.84	0.94	0.63	0.62	0.82	0.73	0.80	0.67	0.65
7	0.67	0.72	0.77	0.62	0.72	0.79	0.84	0.94	0.63	0.59	0.82	0.73	0.80	0.67	0.65

The simulations demonstrated the FCM's capabilities as a feasible computational intelligence method, not only at the macroscopic modeling level to investigate the overall behavior of road traffic flow but also to capture the involved features in terms of examining and monitoring meaningful alterations within freeway networks. These characteristics offer valuable information and can contribute to beneficial results related to the traffic control strategies with sustainable objectives, such as prediction and surveillance of the road traffic flow state in complex networks for reducing traffic emissions and improving road safety; the estimation of the influence of new road constructions or comparing the impacts of various development scenarios for planning purposes; predicting the effects of road capacity alteration, e.g., in maintenance purposes; and detecting dynamic congestion patterns and prone error locations for optimizing ramp management and route guidance toward eco-routing [10].

Additionally, as opposed to the obsolete traffic control with fixed strategies that were derived from historical data, current methods, regardless of their unique characteristics, are capable of functioning online based on real-time qualities originating from the road network. The presented FIS and FCM are also able to provide analyses and predictions to feed these traffic control strategies, e.g., mainstream control, ramp management, and route guidance. Moreover, in the classification of the traffic controllers, the local strategies are in the basis of localized data generated by sensors located near the related actuators, while in the global control mechanism, the collected segments data is not considered independently but as an input to analyze the entire freeways network state [15]. Therefore, in the illustrated framework (see Fig. 3), FIS can be proposed as a local traffic controller that can be applied to mainstream control mechanisms and FCM as a global one that is able to compute the dynamics of the whole system in favor of ramp metering and route guiding.

5 Conclusion

The concept of incorporating sustainability considerations into the design of a traffic controller is relatively recent and emerged within the scientific community of traffic control engineers. Moreover, the rapid advancement of road traffic flow modeling necessitates special attention on evaluating the capabilities of various computational intelligence techniques in this field. Therefore, this work proposed FIS and FCM as two computational intelligence methods in analyzing freeway traffic data concerning traffic flow modeling at the macroscopic level for addressing congestion-related issues as the core of the sustainability improvement strategies. While there is no certainty that congestion can be eliminated altogether due to the world's expanding population, these methods are presented to alleviate congestion to a reasonable degree.

This research approach introduced new applications of FIS and FCM to modeling complex freeway networks, with a particular emphasis on practical vehicular traffic congestion control strategies, such as ramp management, mainstream control, and route guidance, with the primary goal of increasing freeway safety and emission reduction. Additionally, by using these methodologies as the primary reason for developing and managing transportation systems, sustainability-related objectives can be improved. It is possible that the FIS and FCM models cannot capture all of the contributions of a macroscopic traffic flow control strategy, according to the problem's complexity, and as such the derived findings may vary from the real state of the freeway traffic. Any estimation technique, however, will inherently include a trade-off between model performance and operating time. In this perspective, methods based on fuzzy systems offer significant advantages in traffic control measures. Additionally, the study's dataset does not include all segments that potentially influence road traffic behavior, but only those that include the e-toll network. It is important to note that by incorporating additional mapping and data, the resolution of the representation of freeway networks can be significantly increased, resulting in more accurate but also more complex FCM models with refined simulation results. Therefore, as a next phase in the research, it would be highly important to take into account the entire involved segments in the freeway networks with a particular emphasis on bottleneck locations, as well as combining FCM with other algorithms such as Dijkstra to develop a real-time route guidance generation method.

Acknowledgements. The authors gratefully acknowledge Gergely Mikulai and Hungarian national toll payment services for their work on providing the original dataset. László T. Kóczy is supported by NKFIH K124055 grants.

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