IEEE Open Journal of
Intelligent Transportation Systems

Received 14 February 2023; revised 3 April 2023; accepted 6 April 2023. Date of publication 11 April 2023; date of current version 24 April 2023.

Digital Object Identifier 10.1109/OJITS.2023.3266267

Fuzzy-Based Variable Speed Limits System Under Connected Vehicle Environment: A Simulation-Based Case Study in the City of Naples

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This work was supported by the Ministero Università e Ricerca (MUR) of Italy through the PRIN 2020 "DigiT-CCAM (Digital Twins for Cooperative Connected and Automated Mobility)," under Grant E67G22000010005 (coordinator Prof. Gennaro Nicola Bifulco).

ABSTRACT This paper handles the problem of controlling speed limits on freeways in a connected traffic environment to reduce traffic congestion and improve both the operational and environmental performance of the road network. In order to achieve this objective, we present a Variable Speed Limit (VSL) system that utilizes fuzzy logic, which adjusts the speed limits that connected vehicles must comply with by leveraging traffic data such as vehicle flow, occupancy, and speed obtained from loop detectors installed along the road. To evaluate the effectiveness of the proposed Fuzzy-based VSL system and its potential benefits compared to the conventional rule-based VSL system in terms of traffic congestion and environmental impact, we conducted a simulation analysis using the microscopic traffic simulator, VISSIM. Specifically, three simulation scenarios are taken into account: *i*) *no VSL*, where the VSL system is not enabled; *ii*) *Rule-based VSL system*, where a typical a decision tree-based system is considered; *iii*) *Fuzzy-based VSL system*, where the herein proposed approach is appraised. The results demonstrate that the proposed approach enhances road efficiency by decreasing speed variation, increasing average speed and vehicle volume, and reducing fuel consumption.

INDEX TERMS Congestion management, connected vehicles, fuel consumption, traffic control, variable speed limits.

I. INTRODUCTION

VARIABLE Speed Limit (VSL) is among the most exploited Intelligent Transportation Systems (ITSs) solutions to deal with the problem of traffic congestion on freeways [1], [2]. By computing an appropriate speed limit of the mainline based on prevailing road and traffic conditions, such systems aim to mitigate traffic congestion near bottleneck areas; as a consequence, it is possible to improve both the effectiveness and safety of roads compared to adhering solely to the legal speed limit [3], [4]. The updated speed limit is calculated by a centralized unit based on traffic data (e.g., vehicle speed, flow, weather conditions, and so on) obtained through fixed-point sensors (e.g., inductive loops-detectors) located along road segments or via Vehicle-to-Infrastructure (V2I) communication [5], [6]. The benefits these systems could bring can be summarized as follows.

1) *Road safety enhancement:* Minimizing the variation in speed among vehicles traveling in the same lane reduces the likelihood of collisions [10];
2) *Mobility efficiency improvement:* the critical density shifts to higher values, thereby enabling higher flows in overcritical conditions (see Fig. 1) [8];
3) *Traffic flow breakdown prevention:* prevention of slowing down phenomena [11];
4) *Energy efficiency improvement:* alleviating traffic congestion has been proven to reduce energy consumption and pollutant emissions [12]. Examples of possible

The review of this article was arranged by Associate Editor Stefania Santini.

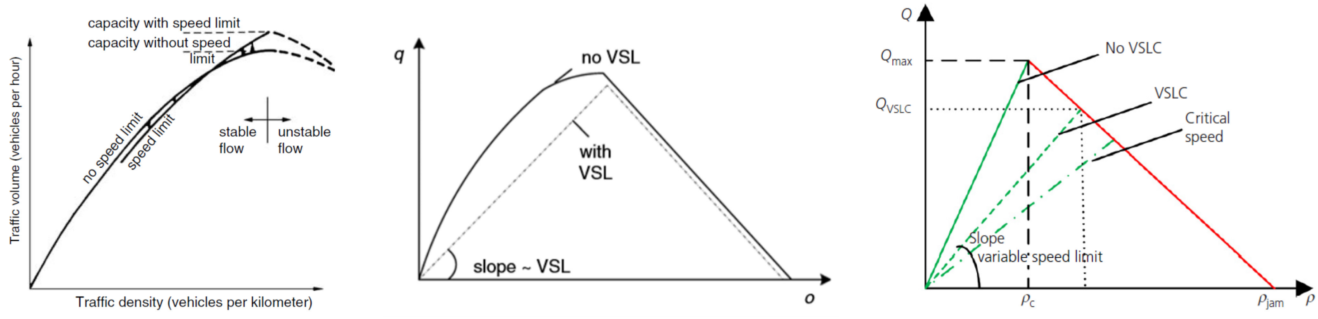

FIGURE 1. Change in Fundamental Diagram due to speed limits variation: (a) Zackor model for VSL impact [7]; (b) Papageorgiou model for VSL impact [8]; (c) Hegyi model for VSL impact [9].

VSL impacts on the Fundamental Diagram are depicted in Fig. 1.

Over the years, numerous VSL control strategies have been developed, which can be categorized into two groups: reactive rule-based approaches and proactive approaches [13], [14]. Reactive rule-based approaches modify speed limits according to predetermined rules that are established based on fixed threshold values of traffic flow, occupancy, or average speed. However, due to the non-stationary and nonlinear nature of the traffic system, such approaches present some issues in computing appropriate control outputs, leading to rather rough control actions for speed control and hence to oscillations in traffic flow. Instead, the proactive approach adjusts speed limits based on a forecast of future traffic conditions to prevent the formation of shock waves caused by traffic breakdowns. These approaches are more effective in managing traffic flow compared to reactive rule-based approaches since they are designed to be adaptable to non-stationary and nonlinear traffic conditions. However, they present some critical drawbacks such as: *i*) significant computational effort required to forecast future traffic conditions accurately; *ii*) implementation complexity; *iii*) may require a larger number of fixed-point sensors or V2I communication infrastructure to collect the necessary traffic data; *iv*) may not be effective in managing traffic in situations where unexpected events occur, such as accidents or adverse weather conditions. To face all these issues, Fuzzy Logic Control (FLC) approaches, a specialized form of reactive ruled-based methods, offer a promising solution for speed control applications. By exploiting fuzzy sets instead of crisp ones, these approaches are capable of producing smoother outputs than traditional rule-based algorithms [15], [16]. Additionally, fuzzy controllers can handle both systematic inaccuracies in information (e.g., inexact traffic model, sensor noisy measurements, or incomplete information [17]) and nonlinear, non-stationary, and stochastic behavior of traffic systems (even with unknown models). Finally, due to the absence of a mathematical model, ease of tuning, and computational simplicity, this approach is well-suited for real-world traffic applications.

The technical literature contains various fuzzy-based control approaches (see [18], [19] and references therein), many of which involve the integration of ramp metering and VSL systems. These approaches utilize macroscopic traffic models and incorporate data on local density/speed or local speed/flow as input to describe traffic conditions within a controlled area. Additionally, existing fuzzy approaches assume that speed limits are continuous variables, which may not be applicable in real-world implementations involving human-driven vehicles, as speed limits should be limited to a discrete set of values.

In this paper, we propose a novel fuzzy logic-based VSL system for freeway traffic control in a connected vehicle environment. The system is specifically designed to alleviate traffic congestion. Our proposed control strategy offers several key advantages over existing approaches: *i*) the optimal speed limit is computed based on $60-s$ loop detector speed, occupancy, and flow data, and, since their combination fell within a particular traffic condition, it allows avoiding imprecise control actions; *ii*) the approach is more suitable for real applications since the speed limit assumes a discrete value, obtained by the ceiling of the fuzzy control output value to the closest discrete one.

As case a case study to validate the effectiveness of the proposed VSL system, an urban freeway section in the northern part of Naples is simulated employing VISSIM microscopic simulator. Furthermore, to effectively demonstrate the enhanced traffic and environmental performance achievable with the Fuzzy VSL in comparison to traditional control techniques, we compare it with a rule-based approach we previously proposed in our prior work [20]. Numerical results show how the proposed approach can guarantee improved performances in terms of traffic congestion and fuel consumption.

Finally, the paper is organized as follows. In Section II we present the literature review. Section III suggests the fuzzy-based VSL we use for the speed control of a freeway segment in the northern part of the city of Naples, Italy. Section IV describes in detail the case of study we consider while Section V discloses the obtained simulation results. Conclusions are drawn in Section VI.

II. LITERATURE REVIEW

A. FIELD-BASED STUDIES

The VSL traffic systems have been implemented in some countries, such as the United States, Canada, Australia, and Europe, leveraging rule-based control techniques.

The very first attempt goes back to the early 1970s in Germany [7], which allowed reducing speed difference among vehicles and increasing road capacity by about 5-10%. A different outcome was obtained in the Netherlands, where a VSL system was deployed on a 20-*km* long segment of the A2 motorway. The results indicated that VSL is not suitable to reduce congestion at bottlenecks since it does not increase the capacity of bottlenecks themselves [21].

Again, U.K. Highways Agency performed an evaluation study on the performances of the flow-based VSL control strategy for the M25 motorway since 1995 in [22]. The results proved a slight change in weekday journey times while off-peak journey times increased slightly w.r.t. the previous year. Instead, a before/after VSL implementation analysis performed in [8] on a European motorway proved that implemented system decreased the slope of the flow-occupancy diagram at under-critical conditions and shifted the critical occupancy to higher values in the flow-occupancy diagram w.r.t. no-VSL curve, as depicted in Fig. 1(b).

To improve safety during adverse weather conditions, the Northern Arizona University and the Arizona Department of Transportation developed a VSL system based on a fuzzy control algorithm, deployed along the I-40 corridor in rural Arizona, which used road atmospheric and road surface conditions to determine the appropriate speed limit [23]. More recently, in [24], an experimental campaign conducted on A20 near Rotterdam (Netherlands) disclosed a reduction of 20% in loss time, while the capacity at the main bottleneck increased by 4%. By exploiting the data collected from the E4 motorway in Stockholm (Sweden), [25] indicated that the advisory VSL had no significant impact on traffic conditions. Instead, by considering a segment of freeway in Barcelona (Spain), [26] proved how speed-based dynamic speed limits (DSL) could improve both road safety and environmental footprint while increasing free-flow travel times.

B. SIMULATION-BASED STUDIES

Reactive VSL approaches are designed to respond quickly to changes in traffic conditions and can be an effective way to manage traffic flow on highways and freeways.

Early reactive rule-based VSL approaches, proposed for instance in [26], [27], looked upon factors such as predefined thresholds of upstream traffic flow, occupancy, or average speed, to dynamically adjust the speed limits to mitigate traffic congestion.

The problem of simultaneously improving both traffic mobility and safety has been instead addressed in [28], [29], [30]. The results herein presented are very contrasting. Indeed, for instance, while in [28] the VSL system was able to reduce the crash rate of 25% in highly congested traffic scenarios, results in [29] show that the system is effective only for low traffic density. Again, [8] investigated the impact of flow-speed threshold on traffic efficiency, proving that, to maximize benefits, speed limits have to be imposed around the critical speed. VSL systems improvements in both throughput and travel time have been disclosed in [31], while the effects of different driver compliance rates were investigated in [32], [33]. The increasing attention to environmental issues led several authors to investigate also the impact of VSL systems on energy savings and pollutant emissions. Assuming strict enforcement of VSL, reduction in pollutant emissions and fuel consumption of 4–6% were observed in free flow conditions in [34], while Fuel Consumption-Aware Variable Speed Limit strategies (FC-VSL) that minimized greenhouse emissions were proposed in [32], [33]. Despite the benefit that traditional rule-based VSL control strategies could bring, they are very limited in effectively improving mobility performances since, due to the exploitation of crisp sets bases to define control rules, they are not able to manage the non-linear and non-stationary nature of traffic flows. In general, reactive VSL systems are suitable for managing unexpected changes in traffic flow, such as accidents or other disruptions, but present the following major weaknesses: *i*) limited effectiveness in high-density traffic; *ii*) Delayed response time, can reduce the effectiveness of the system in managing traffic flow; *iii*) Limited ability to predict future traffic conditions. To overcome this limitation, some researchers have started to develop a fuzzy-based control strategy. Along this direction, [18] proposed a fuzzy VSL controller for mainlane that, computing the optimal speed limit only based on local flow and occupancy (probability of breakdown) as input data, allows improving the efficiency performance, in terms of travel time and pollutant emissions, of the freeway system w.r.t. a classic rule-based one. Other works, such as [19], [35], [36], combine the mainline fuzzy-based VSL controller with ramp metering and show improved performances w.r.t. traditional control strategies, but without assessing the environmental impact of the proposed control strategies. Recently, Li and Wagner [37] developed a type 2 fuzzy logic-based VSL system for mixed traffic that exploits Connected and Automated Vehicles (CAVs) as an alternative data source for freeway traffic management. Results proved that when more 10% CAVs are deployed, the performance of the traffic control system can approach that of the detector-based system, while a high penetration rate of CAVs may make VSL obsolete. However, all the aforementioned works return continuous speed limit values as the output of fuzzy VSL algorithms, which is not suitable for human drivers.

Proactive VSL approaches aim to anticipate traffic congestion and adjust the speed limit in advance to prevent or mitigate potential traffic problems. These approaches typically use predictive models and real-time traffic data to determine appropriate speed limits that can prevent or alleviate congestion before it occurs. By anticipating potential traffic problems and adjusting speed limits in advance, these systems can help to ensure a more uniform flow of traffic and reduce the likelihood of accidents and delays. Most of the proactive approaches exploit the Model Predictive Control technique combined with macroscopic traffic models (see [38], [39] for a complete overview of the existing macroscopic traffic models). An early MPC-based VSL system has been proposed in [9], where the combination of the MPC with METANET model has proved a reduction in travel time of 15%. Other studies proving the effectiveness of the MPC approach in enhancing road traffic performances can be found in [11], [40]. However, since these approaches strongly depend on the robustness and reliability of the exploited traffic prediction model, its real-time application, especially in a large network, could not bring the expected results due to several different factors influencing the evolution of the traffic state [41], [42]. Another major issue is related to discrete VSL outputs variables due to the complexity burden of the Mixed Integer Nonlinear Programming (MINLP) optimization problem. While many related papers relax the MINLP problems by considering the VSLs to be continuous variables, an MPC control algorithm, considering discrete VSLs outputs, was proposed in [43], hence providing a proper trade-off between computational complexity and system performance. Recently, the emergence of Reinforcement Learning (RL) approaches provides great potential for addressing the limitations associated with state-of-art VSL control strategies since they can learn and react to several different traffic situations without knowing the explicit model of traffic dynamics (see [44] and references therein). Despite these approaches being more effective in managing traffic flow compared to reactive rule-based approaches, they present the following drawbacks: *i*) limited accuracy when few data are available; *ii*) high computational effort; *iii*) limited flexibility, since the system may not be able to respond quickly in case of unexpected events can occur, such as accidents or road closures.

C. CONTRIBUTIONS

Motivated by the above discussion, in this work we propose a novel fuzzy logic-based VSL system for freeway traffic control in a connected vehicle environment able to deal with the nonlinear, non-stationary, and stochastic behavior of traffic systems. Differently from most of the existing technical literature, the proposed approach accounts for the uncertainty in the input variables that are used for setting speed limits. This is due both to the inherent nature of the fuzzy controller, as well as to the exploitation of speed, occupancy, and flow data to estimate the actual traffic state (i.e., the traffic congestion level). This way, it is possible to enhance the accuracy of traffic state estimation and avoid imprecise control actions that could lead to oscillations in the traffic flow. Second, the computed optimal speed limit is rounded to an integer so that it can be more usable by human drivers. Most of the existing approaches apply continuous values as speed limits that, however, are not suitable for human drivers. Given that in the near future vehicles, even if equipped with assisted driving functions, will still be guided by humans, it is hence crucial to design control systems that meet the needs of drivers.

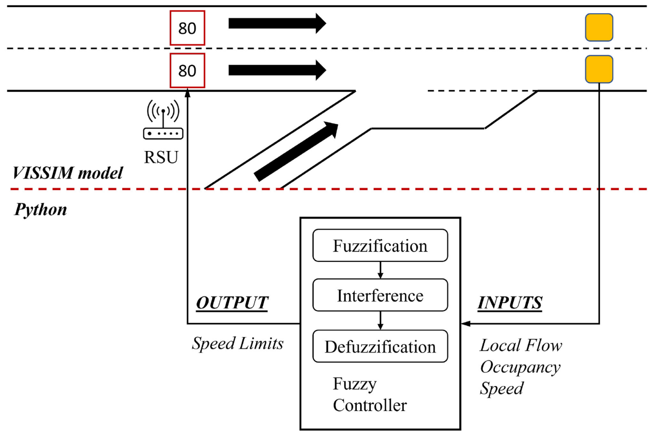

FIGURE 2. Fuzzy logic-based VSL control architecture.

III. METHODOLOGY

Here we introduce the fuzzy-based VSL system that we apply on the *Raccordo di Soccavo* urban freeway in the northern part of Naples. The proposed control strategy exploits 60-s loop-detectors traffic data, i.e., the vehicle average speed $V_m\,[km/h]$, the occupancy Occ, and traffic flow $Q\,[veh/h]$, to dynamically adapt the speed limit (see Fig. 2 for an overview of the control architecture). The road infrastructure is equipped with three Road Side Units (RSUs) able to share information (the computed speed limits) via the I2V wireless communication paradigm. The vehicle fleet is assumed to be composed of Connected Human-Driven Vehicles (CHDVs) able to receive information from the connected road infrastructure [45]. The fuzzy-based VSL system is designed according to the classical architecture of fuzzy logic systems [46] and its structure is based on three main components, namely the fuzzification interface, the inference engine, also known as decision-making logic, and the defuzzification interface. The fuzzification interface defines a mapping from a real-value space to a fuzzy space. The inference engine performs inference procedures upon the fuzzy control rules while the defuzzification interface implements a mapping from a fuzzy space to a real-valued space. Finally, to avoid sudden and frequent changes in the algorithm output, as well as guarantee its effective influence on the traffic flow, the following constraints are considered:

1) the speed limit difference between downstream and upstream links (i.e., between two consecutive links) should not exceed 20 $[km/h]$ [30];
2) the speed limit is updated, at most, every minute [3].

The pseudo-code Algorithm 1 shows the control algorithm developed in this work. In what follows we provide details on each of the components of our three-input fuzzy system.

A. FUZZIFICATION

The Fuzzification step determines the degree to which input data belong to each fuzzy set by converting crisp input values

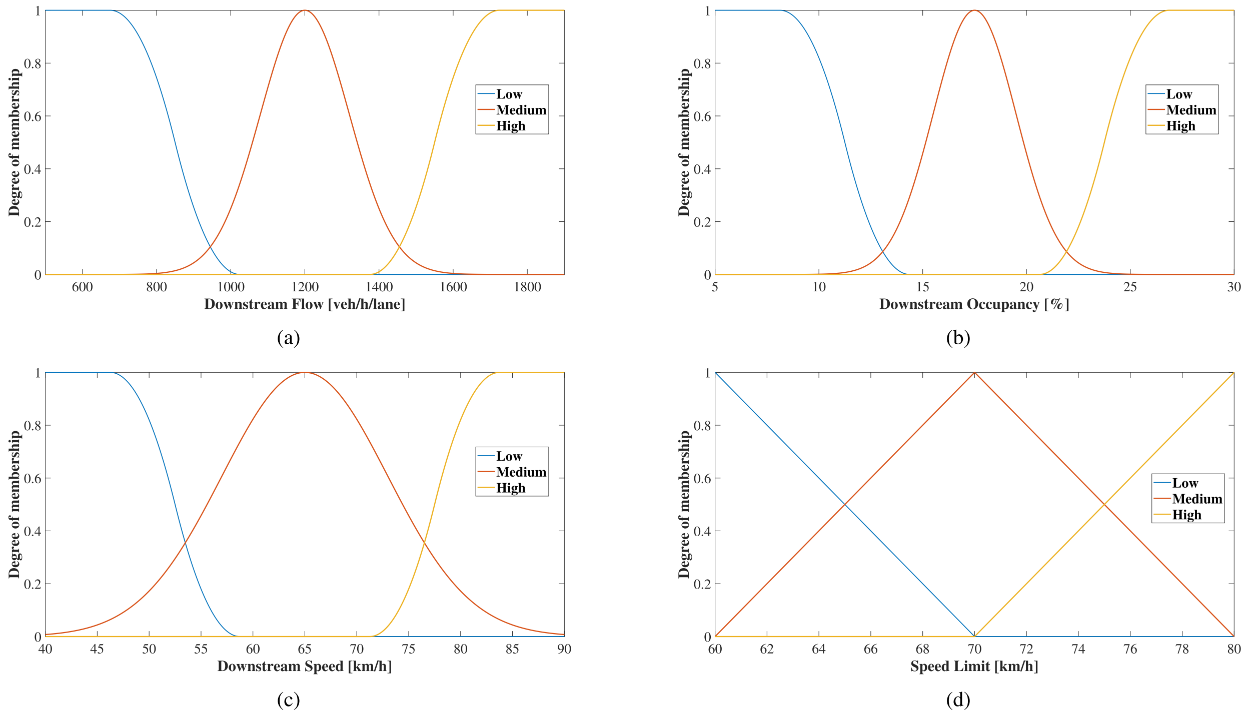

FIGURE 3. Membership functions for: (a) downstream flow [$veh/h/lane$]; (b) downstream occupancy [%]; (c) downstream speed [km/h]; (d) speed limits [km/h].

Algorithm 1: Variable Speed Limit Control

Result: VSL speed limit

Declarations

$DT = 60$ the number of discrete control intervals.

Initialization

initialized := 1;
desSpeed := 80 [km/h];
Start (evalInt).

Procedure

for *i=1,...,DT* **do**
 if *evalInt* $= 60 \cdot i$ **then**
  Collect traffic data via detectors;
  Fuzzy controller receives the local speed, occupancy, and flow data;
  Fuzzy controller computes desSpeed according to traffic data;
  Set Desired Speed := ceil(desSpeed);
  Clear detectors memory for the next interval;
  Reset (evalInt); Start (evalInt);
 end
end

to a fuzzy variable via Membership Functions (MF). The membership value for every element is a fuzzy set in [0, 1]. The fuzzy sets for each of the inputs (traffic flow, vehicle, speed, and occupancy) are established on the results of preliminary traffic data analysis for the considered freeway in the base scenario, i.e., without any VSL control strategy. The local speed, flow, and occupancy are measured downstream of an on-ramp. Based on this analysis, the downstream flow, set within the range [500; 1900] $veh/h/lane$, is described via three functions, namely: a Z-function corresponding to "*low*" set values; a Gaussian-function corresponding to "*medium*" set values; an S-function corresponding to "*high*" set values; (see Fig. 3a). The same membership functions are also considered for the average speed and occupancy inputs, which assume values in the ranges [40; 90] km/h (Fig. 3b) and [0; 30] %, respectively (Fig. 3c). Furthermore, as the output of the fuzzy algorithm, speed limits have to be converted into the fuzzy set. For this variable, three triangular sets "*low*", "*medium*", and "*high*" are considered (Fig. 3d).

B. INFERENCE

Given the mapping of the input variables into the membership function, as well as the values "*low*", "*medium*", and "*high*" of the fuzzification process, the inference system makes decisions for what action to take based on a set of fuzzy rules. These rules, essentially designed based on the system knowledge, assume the following form:

IF <antecedent1> and/or <antecedent2> and/or$\cdots$
THEN <consequent>.

All rules are evaluated in parallel by exploiting the fuzzy set theory, which describes the interpretation of the logical operations, such as the complement, intersection, and unions of sets. The consequent, based on the antecedents, assigns a fuzzy set (represented via the MF in Fig. 3d) to the control algorithm output. Therefore, each rule has a nonzero degree overlapping with other rules.

TABLE 1. Rule base for the proposed VSL control algorithm.

Rule Number	Antecedent	Consequent
1	If (Q is small or V_m is medium) and (Occ is small or Occ is medium)	Speed Limit is high
2	If (Q is small or Q is medium) and (Occ is high) and (V_m is medium)	Speed Limit is medium
3	If (Q is small or Q is medium) and (Occ is high) and (V_m is low)	Speed Limit is low
4	If (Q is high) and (V_m is high)	Speed Limit is high
5	If (Q is high) and (V_m is medium)	Speed Limit is medium
6	If (Q is high) and (V_m is low)	Speed Limit is low

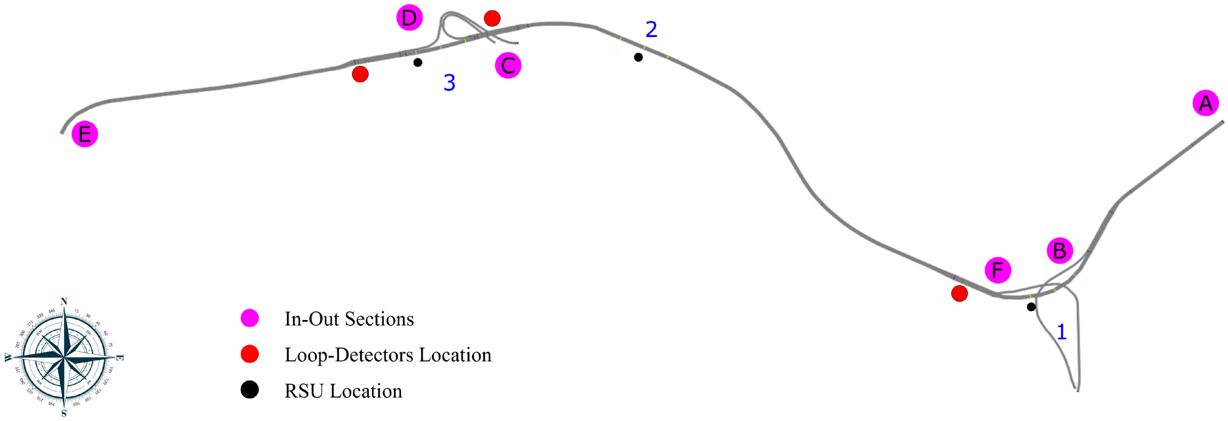

FIGURE 4. Overview of the *Raccordo di Soccavo* road stretch including the detectors-VSL signal groupings locations and in/out sections.

The aggregation method is chosen to combine the output of the interference process of all the considered rules. The fuzzy rules we propose for our VSL control system, listed in Tab. 1, are designed based on decision tree logic defined in [30]. The aim is to determine appropriate speed limits according to 60-s speed, flow, and occupancy loop detector data since their combination falls within a particular traffic condition that allows for avoiding imprecise control actions.

Rules 1 and 4, covering the case of low traffic congestion, call for high-speed limits since there is no possible occurrence of bottleneck formation. Conversely, rules 2, 3, 5, and 6 are proposed in cases of medium/heavy traffic congestion conditions, aiming at preventing the formation of downstream congestion rather than simply reacting to it. More in detail, rules 3 and 6 guarantee, under the premise that a high level of downstream occupancy indicates bottleneck formation, an effective control action that promptly reduces the displayed speed limits to lower values. All these rules aim to prevent the formation of downstream congestion, while the fuzzy sets for considered traffic variables represent a prediction of the downstream traffic behavior.

C. DEFUZZIFICATION

The defuzzification process allows the conversion of each fuzzy output variable into a crisp (non-fuzzy) form, i.e., the speed limit. As a defuzzification method, we consider the centroid one, i.e.:

$$\frac{\int xf(x)d(x)}{\int f(x)d(x)} \tag{1}$$

where x is the input value and $f(x)$ is its membership function.

To simplify the computational burden of the proposed controller, speed limits are computed according to the following discrete fuzzy centroid method:

$$\frac{\sum_{k=1}^{N} \mu(x_k)x_k}{\sum_{k=1}^{N} \mu(x_k)} \tag{2}$$

where N is the number of output classes; x_k is the input value; $\mu(x_k)$ is the membership value for point x_k.

Note that, although the output speed limits provided by (2) are continuous, in real practical scenarios they can assume limited values within the speed limit interval [60, 80] [km/h] with a discrete step of 1 [km/h] in the appraised freeway road. Based on the above consideration, the proposed fuzzy-based VSL controller returns a proper speed limit to be imposed to CHDVs, obtained by ceiling the solution of (2) to the closest discrete value [9].

IV. CASE STUDY

In this section, we present the urban freeway section in the northern part of Naples, Italy, considered for evaluating the effectiveness of the proposed fuzzy control strategy. The testing road segment is a 2-lane freeway named *"Raccordo di Soccavo"* connecting the Vomero neighborhood to the Soccavo neighborhood and with a legal speed limit V_{max} = 80 [km/h]. The road segment is depicted in Fig. 4, where the violet points represent the entrance and exit points, the red points are the detectors, and the black points are the RSUs. The main lane goes from point A (40.848802°N, 14.213324°E) to point E (40.851048°N, 14.192115°E) in the E-W direction, for a total length of 6.3 [km]. Two on-ramps (points F and D) and two off-ramps (points B and C), each of them with a three-lane section downstream and upstream, allow vehicles to enter or exit the main lane. The traffic scenario is represented in the VISSIM micro-simulator [47]. The proposed fuzzy VSL system and the application used to emulate RSUs and OBUs functioning are implemented in Python language and embedded into the micro-simulator via the Component Object Model (COM) interface. The VSL system infrastructure is represented within VISSIM by loop detectors and three VSL stations placed along each mainline lane of the considered network. Loop detectors (the red points in Fig. 4) collect local speed, flow, and occupancy every 60 [s], while three VSL stations (the black points in Fig. 4), equipped with as many RSUs, allow sharing the speed limit to CHDVs within a range of 500 [m]. Each link-detector-VSLs group is considered as an individual entity, i.e., the local fuzzy controller (proposed in Section III) assigns the "condition-based" optimal speed limit to the link computed based on traffic data collected by loop-detectors.

It is worth noting that each VSL station (and relative RSU) is represented in Fig. 4 by a black point. Once the speed limit is computed for a VSL station, the related RSU shares information about the updated signal value with all the CHDVs in its communication range. Moreover, to allow a smoother transition from higher to lower speeds for drivers who are required to slow down, the RSU share also to the vehicles information about the distance from the RSU itself at which to start the braking maneuver. The higher the speed limit variation, the higher the space required for a vehicle to reduce the speed. This space is also called *transition zone* and is set to 50 [m] for a difference of (at most) 10 [km/h], while it is set to 100 [m] for higher values of speed limit variation (up to 20 [km/h]). Furthermore, due to the morphology of the road and not compliance in traveling at low speeds, the lower bound for possible speed limit is set at 60[km/h].

The origin-destination (O/D) matrix emulates a typical AM-peak hour of mobility demand on a typical Neapolitan freeway. The traffic flow entering the test road network from the ramps (see Fig. 4) is given as $q_{tot,in} = q_{F,1,in} + q_{D,1,in}$, being $q_{F,1,in} = 1150$ [$veh/h/lane$] the in-flow of the first on-ramp, while $q_{D,1,in} = 1300$ [$veh/h/lane$] the in-flow of the second on-ramp. Moreover, a traffic flow $q_{up} = 3400$ [veh/h] is generated at the beginning of the testing area, representing the flow upstream of the monitored section. Regarding the traffic flow on the off-ramps, it is set equal to $q_{B,out} = 0.15 \cdot q_{up}$ for the first off-ramp (point B in Fig. 4), while for the second one, it is set equal to $q_{C,out} = 0.30 \cdot (0.85 \cdot q_{up} + q_{F,1,in})$ (point in Fig. 4).

CHDVs are equipped with devices that emulate OBUs functioning. That is, by exploiting a Python script and the COM, they are equipped with an external application that acts like an OBU. Specifically, once in the communication range of an RSU, such vehicles receive a message from an RSU containing the updated speed limit and, then, adapt their longitudinal motion according to the Wiedemann 99 car-following model. To obtain more realistic traffic simulations, we consider several different types of drivers within the traffic flow, namely: slow, normal, and aggressive. For the latter type of driver, we also define a 5% probability of a temporary lack of attention of 2 seconds. The specific features and the penetration rate of each type of driver are listed in Table 3. Note that, in this work, we assumed a 100% driver's compliance with speed limits.

Finally, to evaluate the benefit of the proposed control logic regarding fuel consumption, we leverage the Virginia Tech Comprehensive Power-Based Fuel Consumption Model-1 (VT-CPFM-1) [48]. In what follows we detail the used model for the fuel consumption estimation.

TABLE 2. Vehicle parameters.

Parameter	Description	Value
m	vehicle mass	1235 [kg]
a(t)	vehicle acceleration	[m/s^2]
ρ	air density at sea level	1.2256 [kg/m^3]
η_d	driveline efficiency	0.92
C_d	aerodynamic drag coefficient	0.28
A_f	vehicle frontal area	2.118 [m^2]
H	altitude	0.105 [km]
C_h	altitude factor	0.991075
g	gravitational acceleration	9.81 [m/s^2]
θ	road grade	[rad]
C_r	rolling resistance parameter	1.75
c_1	rolling resistance parameter	0.0328
c_2	rolling resistance parameter	4.575
α_0	fuel consumption rate at idle	0.0004025 [l/s]
α_1	fuel vehicle-specific model constant	$7.2216e^{-05}$
α_2	fuel vehicle-specific model constant	$1e^{-06}$

TABLE 3. Drivers acceleration and rate within the traffic flow.

Type of Driver	a_{max} [m/s^2]	Rate [%]
Slow Driver	1.8	15
Normal Driver	2.5	65
Aggressive Driver	3.2	20

A. FUEL CONSUMPTION MODEL

The VT-CPFM-1 is a second-order model with a positive second-order parameter used to estimate vehicle fuel consumption [48]. The second-order model provides a good compromise between model accuracy and applicability. The instantaneous fuel consumption $FC(t)$ is modeled as follows:

$$FC(t) = \begin{cases} \alpha_0 + \alpha_1 P(t) + \alpha_2 P(t)^2 & \text{if } P(t) \geq 0, \\ \alpha_0 & \text{if } P(t) < 0, \end{cases} \tag{3}$$

where $P(t)$ [kW] is the instantaneous vehicle power; α_0 [l/s] is the fuel consumption rate at idling conditions; α_1 and α_2 are vehicle-specific model coefficient.

Note that consumption-model constants are calibrated by exploiting the VT-CPFM tool.

TABLE 4. Mobility performance indexes.

Simulation Scenario	Average Speed [km/h]		Average Delay [s]		Average Stops [-]	
	mean	std	mean	std	mean	std
No VSL	52.50	5.48	42.30	14.17	1.28	0.70
Rule-based VSL	52.42	5.43	39.46	13.48	1.16	0.66
	-0.14%	-0.79%	-6.73%	-4.93%	-9.33%	-5.69%
Fuzzy-based VSL	53.19	5.46	36.57	13.85	1.08	0.64
	+1.31%	-0.37%	-13.55%	-2.26%	-15.77%	-7.77%

According to [6], [49], the vehicle power is computed as

$$P(t) = \frac{R(t) + 1.04 \cdot m \cdot a(t)}{3600 \cdot \eta_d} \cdot v(t) \tag{4}$$

where $R(t)$ $[N]$ is the total resistance force; m $[kg]$ is the vehicle mass; $a(t)$ $[m/s^2]$ is the vehicle acceleration at time t; η_d is the driveline efficiency; $v(t)$ $[km/h]$ is the vehicle speed at time t.

The total resistance force $R(t)$ is calculated as follows [50]:

$$\begin{aligned} R(t) = {} & \frac{\rho}{25.92} \cdot C_d \cdot C_h \cdot A_f \cdot v(t)^2 + g \cdot m \cdot sin(\theta) + \\ & + g \cdot m \cdot cos(\theta) \cdot \frac{C_r}{1000} \cdot (c_1 v(t) + c_2), \end{aligned} \tag{5}$$

where ρ $[kg/m^3]$ is the density of the air at sea level; C_D is the aerodynamic drag coefficient; $C_h = 1 - 0.085 \cdot H$ is a correction factor for altitude, being H $[km]$ the altitude; A_f $[m^2]$ is the vehicle frontal area; g $[m/s^2]$ is the gravitational acceleration; θ $[rad]$ is the road grade; C_r, c_1 and c_2 are the rolling resistance parameters that vary as a function of the road surface type, road condition, and vehicle tire type.

In our scenario, we assume that vehicle parameters as listed in Tab. 2 refer to generic EURO 4 gasoline car [51]. Hence, vehicle-specific consumption model constants $\alpha_0, \alpha_1, \alpha_2$ are calibrated accordingly. Moreover, it is worth noting that, since each specific driver type in Tab. 3 is characterized by a specific maximum acceleration, they will show different consumption performances [52]. Specifically, the higher is a_{max}, the higher could be the delivered power $P(t)$ computed as in Eq. (5) and, hence, the higher could be the fuel consumption $FC(t)$ computed as in Eq. (3).

V. RESULTS

To prove the effectiveness of the proposed fuzzy-based VSL control logic in improving traffic congestion and reducing fuel consumption, we consider three different simulation scenarios: *i*) *no VSL*, where the VSL system is not enabled; *ii*) *Rule-based VSL system*, where the rule-based VSL in [20] is considered; *iii*) *Fuzzy-based VSL system*, where the proposed control approach is appraised. The former scenario is chosen as a baseline to compare the performances achievable via both the rule-based and fuzzy-based VSL control algorithms. The total simulation time is (3900) $[s]$. More specifically, we consider a warm-up time of 300 $[s]$ at the beginning of the simulation. Then, traffic data are collected for the remaining 3600 $[s]$. Intending to reduce stochastic effects of traffic assignment, we performed 300 simulations runs for each scenario considering the following simulation settings: *i*) initial random seed = 40; *ii*) seed increment = 3; *iii*) number of runs = 10; *iv*) step time (resolution) = 10.

TABLE 5. Average fuel consumption on 100 km.

Simulation Scenario	Average Fuel Consumption [l/100km]			
	mean	diff [%]	std	diff [%]
No VSL	8.26	-	0.55	-
Ruled-based VSL	7.84	-5.14%	0.52	-5.51%
Fuzzy-based VSL	7.47	-9.66%	0.5	-9.09%

To quantify and compare the performances achievable for the road network with and without the VSL system, we take into account both mobility and consumption Key Performance Indicators (KPIs) [45]. Specifically, as mobility KPI we consider: *i*) average Speed $[km/h]$; *ii*) average Delay $[s]$, i.e., the time lost by the driver traveling at a speed lower than the desired one; *iii*) the average number of stops per vehicle. As an environmental KPI, we consider the Average Fuel Consumption $[l/100km]$.

Simulation results are summarized in Tab. 4, where it is possible to appreciate how the proposed fuzzy-based VSL control strategy improves the mobility of the considered freeway network, as well as the vehicles fuel consumption w.r.t. both the base scenario and rule-based VSL system. Specifically, the fuzzy control algorithm allows increasing average speed along the road, which implies a reduction in travel time in both no-VSL and logic-based VSL control scenarios. A slight homogenization of the traffic flow is guaranteed by a reduction in speed difference among vehicles (i.e., -0.37% w.r.t. base scenario), which is, however, lower w.r.t. logic-based VSL scenario. Moreover, the proposed controller also allows reducing both the Average Delay (i.e., -13.55% w.r.t. base scenario) and the Average Number of Stops (i.e., -15.77% w.r.t. base scenario). This implies an improvement in road travel conditions since conflicts among vehicles are strongly reduced, i.e., reduction of *stop&go* and acceleration/deceleration maneuvers. Fig. 5 explicitly shows the variation in median value and distribution of all the aforementioned quantities. In addition, a specific speed distribution analysis for each control section is disclosed in Fig. 6, where the difference in controller performances is highlighted. Specifically, while in Sections I and II, the proposed fuzzy control strategy allows strongly increasing the median speed in all other simulation scenarios, in

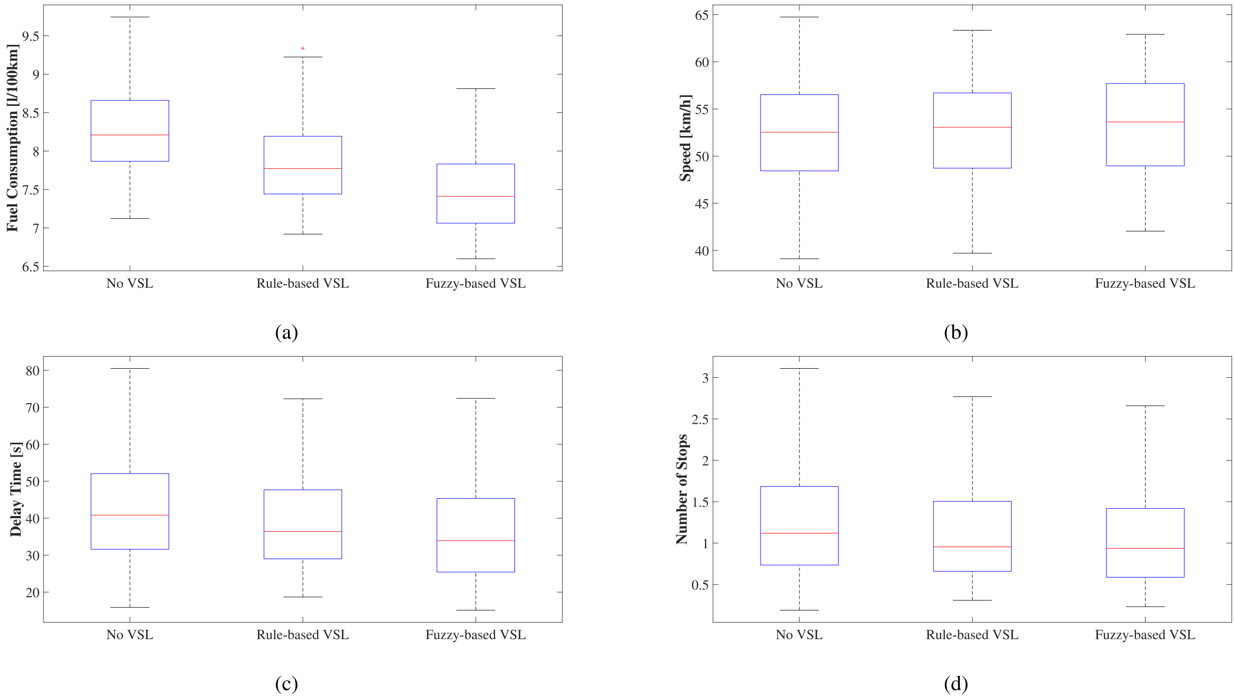

FIGURE 5. **Freeway network performance comparison for the appraised simulation scenarios. Boxplots of: (a) fuel consumption [$l/100km$]; (b) vehicles speed [km/h]; (c) delay time [s]; (d) number of stops per vehicle.**

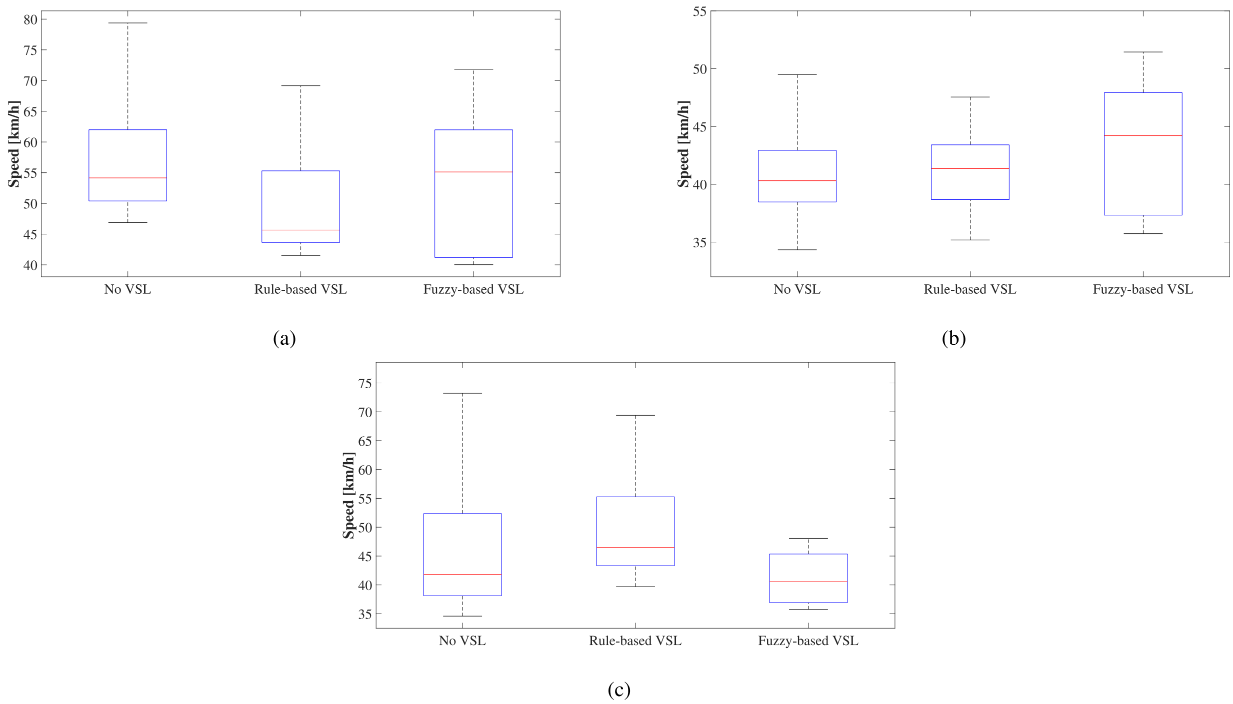

FIGURE 6. **Boxplots of speed for the appraised simulation scenarios at each detector station (from E to W direction): (a) station 1; (b) station 2; (c) station 3.**

Section III it provides a reduction of the degree of dispersion of speeds w.r.t. both base scenario and rule-based scenario. Globally, the proposed fuzzy control strategy allows for improving speed homogenization among all control stations.

Finally, we remark on how the harmonization and the homogenization of traffic flow, as well as the reduction of traffic conflicts among vehicles, also lead to environmental benefits. Indeed, the dynamic adaptation of speed limits according to actual traffic status ensures a reduction of Average Fuel Consumption [$l/100km$] up to -9.66% w.r.t. base scenario and of -4.52% w.r.t. rule-based VSL system (see also Fig. 5a).

VI. CONCLUSION

This paper addressed the traffic congestion problem for the 6.3 *km* long *Raccordo di Soccavo* urban freeway in the city of Naples, considering a connected road environment.

To deal with it, we have proposed a novel fuzzy-based VSL control system to enhance both operational and environmental performances of the road network w.r.t classical rule-based VSL controllers. Differently from existing fuzzy approaches, the proposed control strategy computes the optimal speed limit based on flow, speed, and occupancy data collected by 60-*s* loop-detectors to avoid imprecise control actions. Moreover, to make speed limits acceptable to drivers as in current real-world applications, the suggested speed limit is obtained by the ceiling of the optimal output of the proposed controller to the closest discrete value.

The effectiveness of the proposed control strategy has been numerically evaluated by exploiting VISSIM micro-simulator and the VT-CPFM-1 model for the fuel consumption estimation. Vehicles are assumed to be manually driven but equipped with OBUs able to receive information from RSUs via I2V communication. To take into account the stochastic nature of the traffic flow, 300 AM-peak hour simulations have been carried out for the three appraised simulation scenarios (*No VSL system*, *rule-based VSL system* and *fuzzy-based VSL system*) in the case of 100% drivers compliance level.

Numerical results have proven how the proposed fuzzy-based VSL system outperforms the other approaches. More specifically, it allows harmonizing the traffic flow by increasing the average speed and reducing the average delay (-13.55% w.r.t. base scenario) and the average number of Stops (-15.77% w.r.t. base scenario). Moreover, a slight homogenization of the traffic flow is achieved (-0.37% in speed differences among vehicles w.r.t. base scenario). This implies an improvement in road travel conditions since conflicts among vehicles are strongly reduced. This lead to some environmental benefits. Indeed, the dynamic adaptation of speed limits ensures a reduction of the average fuel consumption up to -9.66% w.r.t. base scenario and of -4.52% w.r.t. rule-based VSL system. Hence, the proposed fuzzy control strategy outperforms other considered approaches by dealing better with the non-linear, non-stationary, and stochastic behavior of traffic systems.

Future works could include: *i*) the generalization of the proposed approach to generic road stretches; *ii*) the exploitation of different optimization methods, such as Genetic Algorithm (GA), to automatically tune the fuzzy set parameters; *iii*) the extension of our analysis by considering different levels of driver compliance, as well as the presence of both connected/non-connected vehicles and human-driven/automated vehicles [53].

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Open Access funding provided by 'Università degli Studi di Napoli "Federico II"' within the CRUI CARE Agreement