A Novel, Three-Stage Intelligent Fuzzy Traffic Signal Control System

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Abstract: Traffic congestion is a serious issue for cities and urban areas, owing to the increasing usage of vehicles. This phenomenon results in several negative consequences, such as high fuel consumption and loss of time. To address this problem, several countries have implemented optimal traffic signal control systems. However, these systems have some drawbacks, such as the need for expensive hardware and maintenance difficulties. Because the sensors are buried under the road surface, the system often cannot account for the full length of the vehicular queue. This, among several issues, inhibits the full potential of the technology's effectiveness and sustainability. In addition, there is much uncertainty in traffic conditions, which points to the need for a model that includes vagueness in the control system. This study proposes a novel hierarchical structure for a three-stage fuzzy traffic control system. This new system assesses the vehicle queue, identifies heavy traffic, detects emergency cars, and adjusts the duration of traffic lights according to the traffic flow and waiting times of vehicles using fuzzy inference rules. This controller was evaluated and validated using a micro-simulation model of an isolated intersection. The obtained results revealed the increased adaptability and flexibility of the proposed system owing to its potential to differentiate a random number of traffic directions. It is also able to handle emergency vehicles and can decrease waiting times, stalling fewer cars, if there is a high traffic flow in the conflicting direction(s) and is a robust and scalable system with lower computational costs.

Keywords: three-stages; fuzzy inference system; degree of heavy traffic; short vehicle queues

1 Introduction

In urban areas, traffic control systems are a major requirement for the transportation infrastructure in day-to-day operations [1]. Traffic signal control is a mechanism used at intersections to manage conflicting movements by determining the right-of-way between conflicting traffic flows [2]. Due to the increase in vehicle usage and limited transportation infrastructure (roads), it can be difficult for people and goods to arrive at their destination on time. Traffic congestion has several impacts on cities and urban areas, such as increased pollution, extreme fuel consumption, lost time in traffic, and car accidents [3, 4]. Traffic congestion occurs when the density of vehicle flow creates a demand that is greater than the available transportation infrastructure. Enhancing the efficiency of traffic signal control systems has led to improved road safety and logistics, reduced traffic congestion, and fewer traffic accidents (severe injuries, crashes, etc.). To solve the problem encountered by traffic control systems, several new models have been introduced by researchers, and some optimal traffic controls have been used for decades in some developed countries. Since the 1960s, various approaches have been proposed to solve the problem of controlling traffic intersections and to create efficient control mechanisms [5]. One of the most commonly used traffic signal control systems is pre-timed traffic signal control, which is not based on current traffic demands and cannot handle unexpected traffic conditions. This method cannot predict traffic demands [6]. Since the 1970s, truly functional traffic control methods have emerged. These traffic-actuated control methods use inductive detectors that are buried in the pavement to observe actual traffic conditions [5]. Traffic conditions are dynamic and highly affected by time, weather, and unpredictable situations, and there are many other parameters [7]. Pretimed traffic control and actuated traffic control do not use a control policy, do not consider the parameters mentioned above, and do not utilize accumulated information to improve traffic signal control performance. Therefore, to overcome these problems traffic-adaptive control systems and many other optimal traffic control systems have been presented to improve these systems' efficiency as seen in Yau *et al*., 2017 [6].

Although several approaches have been proposed, they all have disadvantages. According to [6, 8], these control methods usually have limitations, such as activating the green signal based only on the presence of vehicles in the lanes immediately before reaching the intersections and not considering longer vehicle queues when they are out of the range of the sensors. In addition, existing optimal control systems are often unfeasible in the city environment because of the expensive hardware requirements and high computational costs. The difficulty and vagueness of existing traffic systems can be resolved by using an intelligent traffic control system [9]. Hence, to solve the existing traffic system problem, computational intelligence methods have been proposed to develop an efficient and flexible traffic control system. Currently, computational intelligence (CI) control mechanisms are widely used to develop efficient traffic control systems to solve problems faced by pre-timed, actuated, and adaptive traffic control. The CI strategy may improve road safety, road capacity, and traffic control performance; predict traffic situations; reduce the waiting times of vehicles at intersections; and control the overall dynamicity of traffic situations. The most efficient and important CI traffic control systems are fuzzy systems, neural networks, and reinforcement learning. Each of these CI control methods has strengths and weaknesses [5, 10]. To realize the objective of this study, a fuzzy control model was proposed that is more intelligible because it imitates human perception using mappings for inputs and outputs, which are linguistic terms, such as "low," "medium," "high," and "very high." There are several reasons for using the fuzzy control approach to implement the proposed approach. One advantage is the ability to model the uncertainty and ambiguity of traffic conditions, which transportation engineering experts often describe as subjective, ambiguous, or vague. Fuzzy control systems use imprecise input information, because the input of the control system may be inaccurate. Fuzzy inference rules can generate useful and accurate responses from vague input (as seen in [11]). Thus, fuzzy control approaches are better suited for modeling fluctuations in traffic conditions than other computational intelligence controllers or classical control methods. In addition, fuzzy control systems can capture the key factors in the control process without requiring complex mathematical formulas, making them an ideal choice for designing and implementing intelligent fuzzy traffic control systems that can efficiently manage increasing traffic saturation levels [12].

Fuzzy control systems use fuzzy sets and fuzzy rule-based inference to develop control systems in which no precise information exists and most of the previous information is available only in a qualitative form. The main idea behind the fuzzy control system is to use expert knowledge and experience to build a rule base with linguistic form. In contrast to the classical point-to-point control approach, fuzzy control systems work with range-to-point or range-to-range control [7, 13]. In the design of a controller system, the fuzzy system has evident advantages over other methods. For instance, many input and output linguistic variables can be managed concurrently, all knowledge rules in the fuzzy expert system can be applied simultaneously, and inferences can be easily mapped on a multiprocessor system. Additionally, in a fuzzy control system, if the user is not satisfied with the control action for certain combinations of system inputs, the active firing of this control action can be immediately identified and adjusted without essentially affecting the behavior of the controller for other inputs [9]. Fuzzy control approaches provide a formal methodology for representing and implementing heuristic knowledge regarding how to control a system [14]. The fuzzy controllers have four main components: the degree of matching unit, inference engine, fuzzy rule base, and defuzzification unit. The fuzzy rule base represents the knowledge of human experts and contains a fuzzy set-transformed quantification of the experts' linguistic description of how to design and operate a more efficient controller. The inference engine evaluates which control rules are relevant in the current condition and provides a decision to the control system in the best possible manner. The Degree of Matching Unit evaluates the inputs in terms of the rules and transforms them into fuzzy degrees that determine which of the individual rules must fire, and to what extent. Thus, these inputs can be interpreted in the context of the rules in the rule base. The Defuzzification module interface converts the fuzzy (vague) conclusions calculated by the inference engine into crisp inputs for the controlled process [14]. In this study, a fuzzy control method was applied to model an intelligent fuzzy traffic control system with additional features, as compared to the results of other studies.

2 Overview of Related Work

Currently, to create a conducive environment for transportation, the traffic control system is becoming a more important area to create an intelligent system that reduces the waiting time of vehicles at intersections, increases the general safety of movement, and prioritizes emergency cars. In the following section, some research work in the field of traffic signal control systems using fuzzy control system approaches is reviewed.

J. Niittymaki conducted research on the installation and field testing of a fuzzy signal controller. In that study, a fuzzy signal controller was installed at a real intersection and compared with a vehicle-actuated control system using field measurements and microscopic simulation. The obtained results prove that fuzzy control systems outperformed vehicle-actuated control systems in real signalized intersections [15].

M. E. M. Ali *et al.* used a SUMO traffic simulator to offer an adaptive technique for traffic signal control based on a fuzzy system with a Webster and modified Webster formula [16]. The proposed strategy was investigated and validated at an isolated traffic crossroads. The obtained results were compared with those of existing fuzzy-based traffic control and fixed-time traffic control systems, and the SUMO traffic simulator was employed. In terms of vehicular delay, speed, and trip time, the simulation results showed that the suggested technique outperformed the fixed-time and earlier fuzzy-based traffic control systems [1].

V. M. M. Arteaga *et al.* proposed an adaptive traffic fuzzy system controller for isolated intersections. Their approach was based on a typical fuzzy system that only required operators to know the minimum and maximum expected values for arrival flows and cycle lengths to establish IF–THEN mappings (rules). Their system was composed of two modules, a fuzzy inference system, and an adaptive mechanism. The advanced Mamdani-type [17] fuzzy inference system was designed to compute based on the reasoning that the higher the flow, the longer the cycle length. Their approach was evaluated through a microsimulation model of a real intersection using SUMO as a platform, and the proposed model results showed better results when compared to other traffic control systems [2].

S. Akhter *et al.* proposed a SUMO-based simulation framework for an intelligent traffic management system with a deep neuro-fuzzy model. The Dijkstra algorithm was used to select an optimum path from the source to the destination based on the calculated road segment weights from a deep neuro-fuzzy framework. A deep neuro-fuzzy model was implemented and simulated in a SUMO traffic simulation environment. The simulation results of the three algorithms (A*, Dijkstra, and CHwrapper [18]) showed similar performance. However, the proposed model has not yet been implemented in real-time road networks [19].

I. Tunc *et al.* presented intelligent intersection management using a fuzzy system with a proportional integrated (PI) control mechanism. Fuzzy traffic control and PI-based traffic light controllers were designed and simulated in a SUMO traffic simulation environment. The simulation was carried out only for one incoming lane from North to South and West to East, and one outgoing lane. In their simulation, the CO_2 emission outputs, and average speed values of vehicles were obtained directly from the SUMO program. The proposed approach yielded better results than the traditional methods [20].

J. Alam *et al*. proposed an intelligent traffic-light control system for isolated intersections using a Mamdani-style fuzzy system. They selected a four-way isolated junction with traffic coming from the north, south, west, and east directions. Vehicle queue and vehicle arrival were used as input variables, and the output variable was the extension of the green time. The simulation was carried out using MATLAB, and the obtained results outperformed those of the fixed-time controller and actuated traffic controller [21].

T. Mahmood *et al.* conducted research on a two-stage fuzzy adaptive traffic signal control for an isolated crossroads based on real data utilizing the SUMO platform. They implemented two-stage frameworks, with the first stage having two modules: the Next Phase Module and the Extension Time Module. The Next Phase Module chooses a candidate for the green phase from the red phases. The Extension Time Module observes the traffic situations in the green phase and produces a stop degree based on the observed results. The second stage is the Decision Module, which determines whether to change the green phase according to the outputs of the first stage of the system. The data were collected over 24 h from a genuine four-way crossing road found in urban areas in Kilis (Turkey). The simulation results revealed that the average time taken by a car to wait for transport dropped from 44 s to 17 s, with an improvement in the system performance relative to fixed-time control mechanisms [22].

A. Agrawal and R. Paulus proposed improving traffic and emergency vehicle clearance at congested intersections using a fuzzy-inference engine. They proposed a system for two parallel controllers that were used to select the appropriate lane for the green signal and to determine the appropriate green light time as per real-time traffic conditions. The proposed approach was assessed through a simulation, and the obtained results were compared with the pre-timed control system in changing traffic flow conditions. The simulation results showed improvement over the pre-timed control in terms of waiting time for emergencies at intersections during heavy traffic [23].

The literature clearly shows that fuzzy traffic control is more effective than existing traffic control systems. However, in most of the reviewed research papers, the existing fuzzy traffic approach does not include unusual traffic situations such as approaching one or more emergency vehicles without affecting the time of other cars at the intersection, or does not consider the waiting time of short queues of vehicles when high traffic flow loading for a long time in the conflicting direction(s).

In this study, we propose a hierarchical (three-stage) decision system structure that combines the fuzzy inference rule with one or many classic production rules based on the Mamdani-style control system. This study is a continuation of our previous study [8]. In that study, a hierarchical two-stage fuzzy control system and only four isolated intersection traffic flows from the North, South, West, and East were examined using Python. However, in this study, we extended from four isolated intersections to $3 \times 4 = 12$ lanes for all outgoing combinations. Each incoming road has three lanes in each direction; going straight through, turning right, and turning left were implemented using a graphical user interface (GUI) simulation by SUMO. The proposed approach was implemented in a modular form, and new modules could be integrated at any time without affecting the main system. Therefore, we claim that the new approach is robust and scalable, and is a much more intelligent system than the existing optimal traffic control systems.

3 Basic Models of Proposed Approach and Tools

Predefined traffic-light control is used in most parts of the world in real systems to control traffic congestion. However, it does not provide an optimal solution for fluctuating traffic conditions and a limited transport infrastructure. Schematics of the simulation are shown in Figure 1.

3.1 The Proposed Fuzzy Traffic Control System

The proposed new fuzzy traffic signal controller is composed of four modules: Prioritize Emergency Car Module (PECM), Heavy Traffic Evaluation Module (HTEM), Calculation of Waiting Time Module (CWTM), and Extension Time Decision Module (ETDM). The PECM and HTEM are the first stages of the proposed hierarchical structure of a fuzzy traffic control system. The aim of PECM is to identify and count emergency cars approaching from the current red and green light directions, giving them a weighted priority. The HTEM is responsible for calculating the intensity of heavy traffic for the red-light phase and identifying the degree of traffic flow in the red phases. CWTM is the second stage decision module that makes decisions based on the waiting time of the vehicle(s) in the current green and red phases. It is particularly effective during continuous heavy traffic in one direction(s), but only a few vehicles want to pass in conflicting directions. This module switches the green light to red light whenever necessary. ETDM is a decision module that determines the extension time of the green light phase depending on the output of the PECM, HTEM, CWTM, and the current traffic situation of the green light phase. A detailed description of these four modules is provided in Section 4. An isolated traffic intersection is selected and simulated to demonstrate the efficiency of the new controller. This simulation was characterized by four incoming directions, each with three lanes. This provides 12 different lanes together and allows cars to go straight and turn left or right (see Figure 1).

The proposed method is, however, suitable for modeling and controlling an arbitrary intersection with the arbitrary numbers of incoming and outgoing roads and lanes. In the next, one of the most common types of isolated intersection will be presented as an example, namely, four incoming roads with three different direction lanes, and four outgoing road as well. The presented method is a suitable for modeling any single intersection with arbitrary incoming and outgoing roads and lanes. In our further research we intend to conduct multiple intersection systems, where the control of the individual intersection operates in agent-like way, and thus the time complexity may be kept relatively low, by applying parallelly running algorithms.

Figure 1
Simulated Isolated Traffic Intersections

3.2 The Software Tools Used

The selection of appropriate software tools is essential to design and develop intelligent traffic control systems that manage and provide optimal solutions for unpredictable traffic conditions. Traffic simulation frameworks provide a helpful tool for conducting research, evaluating, and simulating traffic flow [24]. To implement and simulate this new model, an open-source SUMO traffic simulation using the TraCi API was chosen. This package was also used to design a graphical user interface (GUI). SUMO also includes various support tools that can handle various tasks such as route finding and importing networks from open street maps. It can be further improved and adapted to a specific goal using self-defined models and provides various features to remotely control the simulation. The fuzzy traffic controller modules were implemented using Python. Communication between the GUI and the fuzzy traffic modules is performed using the Traffic Control Interface (TraCi) tool, which is included in the SUMO simulator package. The TraCi tool provides a TCP-based client/server architecture that allows the user to control and modify SUMO simulations using an external application [25].

4 Implementation of the Proposed Approach

To solve the task set, we proposed a three-stage structure constructed from the four modules mentioned above, as shown in Figure 2. A cascaded multiple Mamdani-type fuzzy system composed of the aforementioned four modules was implemented in the simulation experiment. The first stage consists of two modules, namely PECM and HTEM; the second stage is CWTM, and the last stage is ETDM. For all modules, the input and output variables corresponded to the linguistic values modeled by triangular membership functions. Triangular membership functions are widely used in fuzzy-control approaches with acceptable efficiencies. Multiple investigations have shown that applying more complex membership function shapes (like Gaussian, etc.) do not lead to essential to different results whenever defuzzification or discreate values are obtained at the output. The actual parameters of the membership functions of the individual linguistic values should be adjusted to the concrete application of the system; the meaning of "heavy traffic" may be quite different in a central city area and a rural intersection. Here, the chosen parameters are the default values for the theoretical case study. The inference rules are determined and implemented. Here, the inference rules of stage-1 Modules (PECM and HTEM) are adopted by a slight modification of a previous paper [8]. A detailed explanation of how this was performed is presented in the next subsection.

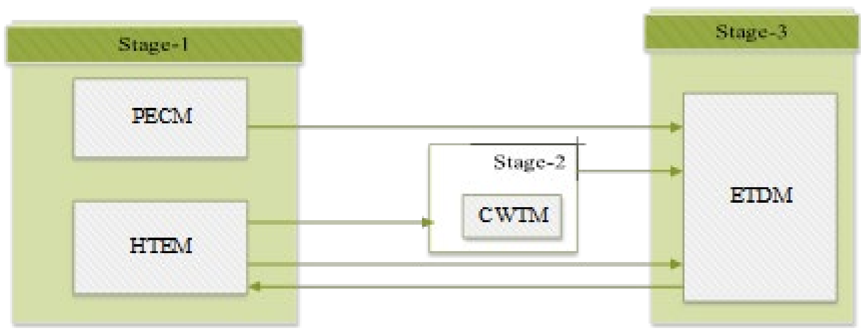

Figure 2
Architecture of three-stage fuzzy traffic control systems

4.1 The Modules of the Novel Control System

In the following paragraphs, all the four modules of the proposed control system are explained in detail.

4.1.1 Prioritize Emergence Car Module (PECM)

The role of this fuzzy control module is to detect emergency vehicles that may appear in any intersection lane and assign priority. It has two antecedents (inputs) and one consequent (output). The number of emergency cars detected from the direction of the red-light phase (E_{mr}) and green-light phase (E_{mg}) are the inputs.

Because emergency car(s) are occasional, the ranges of E_r and E_g are set to [0,3) with triangular membership functions (for example, Figure 4). The output variable is an indicator of the potential priority of the emergency vehicles (P_{em}). Both the input and output variables can assume three linguistic values. For the input variables, the linguistic values were {*none, few, many*} (see Figure 4), and the possible linguistic values of the output variable were: no emergency car (*none*), an emergency car from the red-light phase (E_{mr}), and an emergency car from the green light phase (E_{mg}). The module also actively ensures optimal traffic flow when there are no emergency cars at the intersection. If the same number of emergency cars appears simultaneously in contradictory directions, priority is given to the emergency car(s) approaching the green phase. The system also prioritizes lanes with more emergency vehicles. However, if the number of emergency vehicles arriving on the red road is significantly higher than that arriving in the conflict direction(s), the green light will immediately turn red, which makes our system more reliable and intelligent. Nine (3 × 3) fuzzy inference rules were created for this module as a sample of fuzzy rules, as shown in Figure 3. The sample of fuzzy rules of this module depicted in Figure 3 can be described using natural language; for example, rules 3 and 9 are described respectively as follows: "IF emergency cars detected from the current green phase direction is "none" (no emergency cars) AND emergency cars detected from the current red phase are "many", THEN "do" prioritize the emergency cars detected from the red phase."

"IF emergency car(s) detected from the current green phase direction are "many" AND emergency cars detected from the current red phase are also "many", THEN "keep green light" for the current green light phase until appear emergency cars pass."

```
rule1 = ctrl.Rule(Emg['none'] & Emr['none'], Pem['no'])
...
rule3 = ctrl.Rule(Emg['none'] & Emr['many'], Pem['Emr'])
...
rule9 = ctrl.Rule(Emg['many'] & Emr['many'], Pem['Emg'])
```

Figure 3
Sample of fuzzy rules for PECM, Module I

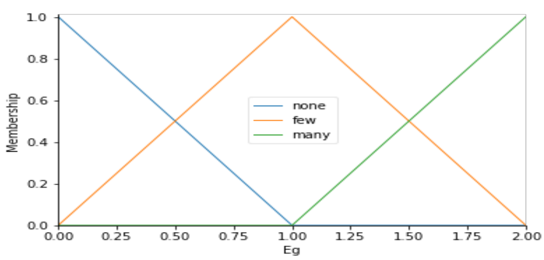

Figure 4
Input membership functions for E_{mg}

4.1.2 Heavy Traffic Evaluation Module (HTEM)

This module is one of the first stages of the proposed system for identifying the level of heavy traffic in the red-light phase. It has two antecedent variables, namely, the vehicle queue length of the red-light phase (Q_r) and the waiting time of cars in the red light (W_{tr}), and one consequent variable, which is the degree of heavy traffic (D_{ht}). For all variables, there are five linguistic values; therefore, five membership functions are given for Q_r and D_{ht}. For simplification, the domains Q_r and D_{ht} are given equally [0,60). These linguistic values are {*zero, small, medium, large, and very large*}. The range of W_{tr} is [0,300) and its linguistic values are defined as {*zero, short, medium, long, very long*}. Triangular membership functions were used, as shown in Figures 6, 9, and 11. Based on the linguistic values of the input variables,{5×5=25} inference rules are stated for this module. A subset of the fuzzy inference rules of HTEM is shown in Figure 5. For instance, "IF(Q_r is {*medium*} AND W_{tr} is {*medium*}, and THEN D_{ht} is {*medium*}". This rule can be explained using natural language, as the " IF vehicle of queues of the red phase is *medium* and the waiting time of vehicles is also *medium* THEN the degree of heavy traffic in the current red-light phase is *medium*".

```
rule10 = ctrl.Rule(Qr['zero'] & Wtr['zero'], Dht['zero'])
...
rule22 = ctrl.Rule(Qr['medium'] & Wtr['medium'], Dht['medium'])
...
rule26 = ctrl.Rule(Qr['large'] & Wtr['short'], Dht['medium'])
```

Figure 5
Sample of fuzzy rule base for HTEM, Module I

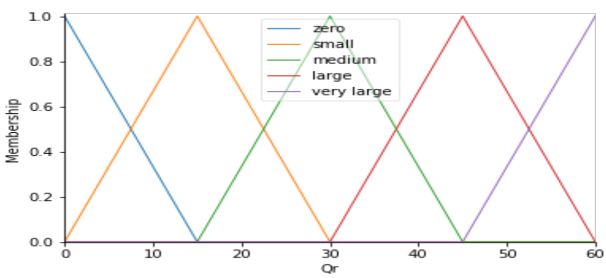

Figure 6
Membership functions for Q_r

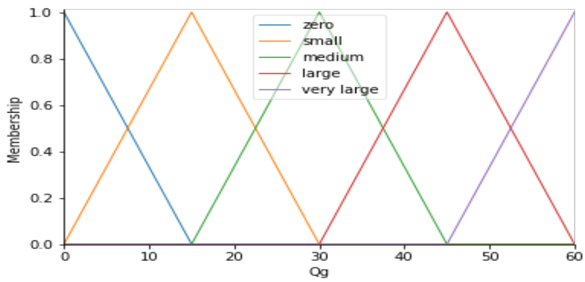

Figure 7
Membership functions for Q_g

4.1.3 The Calculating Waiting Time Module (CWTM)

This module represents the second stage of the proposed cascaded system hierarchy. The main function of this module is to calculate the waiting time of the short queues of vehicles. Therefore, because high traffic can continue in one direction for a long time, vehicles travelling in the opposite direction may have to wait for a long time to receive a green light. The CWTM is used to solve this problem by calculating the total waiting time of the individual car(s) and switching to a green light in the conflicting direction when this time exceeds a (fuzzy) limit. It has four inputs and one output variable. The inputs are the waiting time of car in the red light (W_{tr}) and the waiting time of car in the green light phase (W_{tg}), the degree of heavy traffic in the red phase (D_{ht}), and the current traffic conditions of the green light phase (Q_g). The output is the decision to switch off or maintain the green-light phase (S_{wr}). The input variables W_{tr} and W_{tg} have five linguistic values to which five membership functions are assigned: {*zero, short, medium, long, and very long*} (for example, Figures 9). In the case of D_{ht} and Q_g inputs, two linguistic values were selected because the main aim of this module is to make a decision when sudden high traffic flow is loaded in one direction(s) continuously, while some individual car(s) coming from the conflicting direction are stuck waiting for a green light. Therefore, the linguistic values used for the inference rules were used to alleviate such occurrences. Accordingly, the input variable D_{ht} was the output of the HTEM, and only two of the five linguistic values{zero, small} were used (see Figure 11). Similarly, Q_g also has only two out of five linguistic values, namely, {*large*, *very large*} (see Figure 7). The output variable also has two linguistic values: (keeping the green light) {*keepg*} and (switching to the red phase if necessary) {*switchr*}. Therefore, 5 × 5 × 2 × 2 =100 inference rules were developed for this module; some examples are shown in Figure 8. One of the rule samples can be described as follows: "IF degree of heavy traffic in the red phase is *small (*may be one or two car(s) required to pass) OR vehicle queues of the current green phase are very *large* AND the waiting time of short vehicle queues in the red phase is *very long* AND the waiting time of vehicle queues in the conflicting direction(s) (current green phase) is *very long*, THEN *keep the green light* until very large vehicle queues are reduced from the current green phase."

```
rule35 = ctrl.Rule(Dht['zero'] | Qg['large'] & Wtr['zero'] & Wtg['zero'],Swr['keepg'])
...
rule55 = ctrl.Rule(Dht['zero'] | Qg['large'] & Wtr['short'] & Wtg['zero'],Swr['switchr'])
...
rule134 = ctrl.Rule(Dht['small']| Qg['very large'] & Wtr['very long'] & Wtg['very long'],Swr['keepg'])
```

Figure 8
Sample of fuzzy rule base for CWTM, Module II

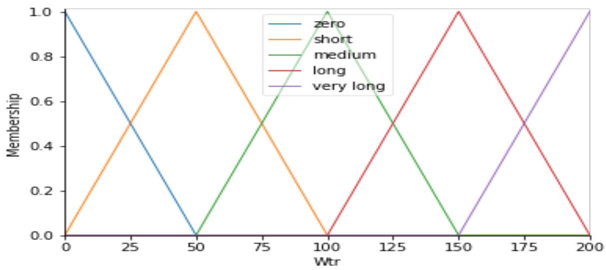

Figure 9
Membership function for W_{tr}

4.1.4 Extension Time Decision Module (ETDM)

This is the third stage of the hierarchical (three-stage) fuzzy traffic control system. This module decides whether to extend the green light or switch to the red phase. The outputs of the PECM, HETM, and CWTM are used as input variables for this module. The current green-light phase traffic situation is also considered as the fourth input variable for decision-making, which is denoted by Q_g. *The* Q_g range is [0,60) and its membership functions are shown in Figure 7. The linguistic values of the other input and output fuzzy variables are shown in Figures 10, 11, and 12. A set of $3 \times 5 \times 2 \times 5=150$ fuzzy inference rules were implemented to perform appropriate actions based on the linguistic values of the input. The Fuzzy rule base of this module was created using Python in the same fashion as illustrated in Figures 3, 5, and 8.

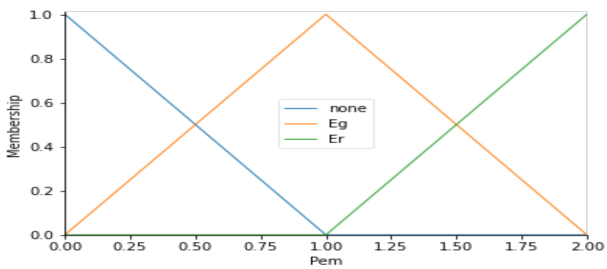

Figure 10
Membership function for P_{em}

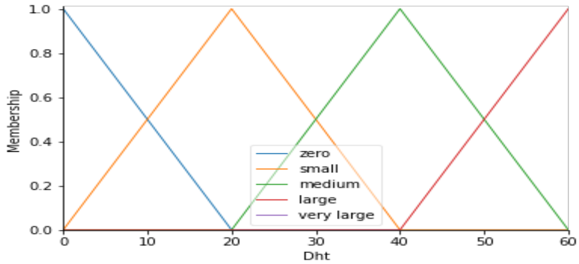

Figure 11
Membership function for D_{ht}

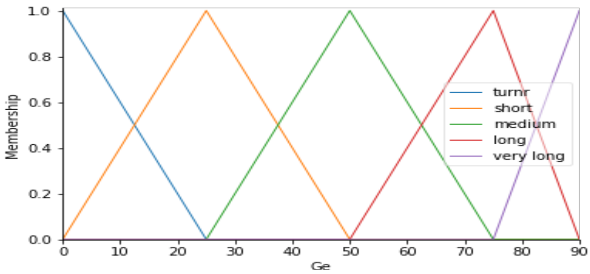

Figure 12
Membership function for G_e (extension time of green light)

5 Simulation and Discussion

The intelligent fuzzy traffic control system (IFTCS), including its four modules, was created using the scikit-fuzzy system library package in Python and integrated with the SUMO graphical user interface traffic simulator using TraCi. The simulated vehicular data were adjusted for SUMO using a text editor, and 12 routes were defined, together with incoming and outgoing lanes (see Figure 1). Various vehicle types were created (emergency cars, trucks, etc.), along with information on the number of vehicles and the probability of their trips for each route, as shown in the segment code in Figure 13.

```
...
<flow id="bus-route12" number="50" begin="0" probability="0.2" type="danfo">
      <route edges="D1 H1 F2 B2" />
   </flow>
   <flow id="truck-route12" number="10" begin="0" probability="0.01" type="truck">
      <route edges="D1 H1 F2 B2"/>
   </flow>
   <flow id="emergency-route12" number="5" begin="0" probability="0.03" type="emergency">
      <route edges="D1 H1 F2 B2"/>
   </flow>
...
```

Figure 13
Segment code of vehicular data created using SUMO

To measure the effectiveness of the proposed system, indicators such as the average waiting time of the vehicle at the intersection, number of stopped vehicles caused by the red light, and average extension of the green light duration were used. To evaluate the performance of the developed system, the results were compared to the graphical user interface of a pre-timed (fixed) traffic control (PTC) system that was implemented and simulated in the same fashion and in the same software (SUMO and Python) without a fuzzy system module. The PTC used for comparison was implemented based on traditional and non-intelligent algorithms. Both systems count the number of vehicles in both the green-light and red-light phases while distinguishing emergency vehicles from all others. Similarly, both calculate the waiting times of the vehicles in the red and green phases. For proper comparison, two experimental simulation scenarios were conducted using SUMO, which operates in one second. Scenario-1 was an 8,000-step run simulation, whereas Scenario-2 consisted of 32,000 steps. Four cases of experimental simulations were conducted for both scenarios, each categorized based on the distribution of the vehicle arrivals. These cases were as follows. (a) In Case 1, the number of vehicle arrivals in the East to West or West to East directions increased (i.e., high traffic conditions in specific directions). There are six routes in this case: east-to-west, east-to-south, east-to-north, west-to-east, west-to-north, and west-to-south. However, there were a low number of vehicles arriving from conflicting directions (i.e., low traffic conditions in conflicting directions). (b) Case 2 involved an increasing number of vehicle arrivals in the north–south and south–north directions. This case also includes the North to East, North to West, South to North, South to West, and South to East directions. However, a few vehicles exist in contradictory directions. (c) Case 3 had an equal distribution of vehicle arrivals in all 12 directions in terms of both the number of vehicles and their probability. (d) Case 4 had an arbitrary distribution of the number of vehicle arrivals and their probabilities for all the 12 routes. For these simulations, only five types of vehicles were used: one emergency car(s) and four non-emergency vehicle types. In Cases 1 and 2, the probability of each car type was the same, and only the number of vehicles was increased or decreased. For instance, the probability of emergency cars was 0.03 for both Cases 1 and 2, and the total probability of non-emergency vehicles was 0.62 for all routes (directions). Both Scenarios were simulated for all cases.

Table 1
Performance of the Proposed System Compared with PTC for Scenario 1

Case	Average waiting time of non-emergency vehicles for PTC	Average waiting time of non-emergency vehicles for IFTCS	Improvement (%)	Average waiting time of emergency cars for PTC	Average waiting time of emergency cars for IFTCS	Improvement (%)
1	477024.1	208529.1	56.3	15118.7	10946	27.6
2	472267.8	185550.6	60.8	15838.3	6897.8	56.4
3	614290.0	395811.9	35.6	18109.4	11733.3	35.2
4	547395.2	292848.3	46.5	13178.8	7105.7	46.1

Table 2
Performance of Proposed System Compared with PTC for Scenario 2

Case	Average waiting time of non-emergency vehicles for PTC	Average waiting time of non-emergency vehicles for IFTCS	Improvement (%)	Average waiting time of emergency cars of PTC	Average waiting time of emergency cars of IFTCS	Improvement (%)
1	1422055.3	291081.3	79.5	15118.7	10946	27.6
2	1342283.0	259974.3	80.6	118198.8	6897.8	94.2
3	14608725.0	609783.8	95.8	18163.4	11733.3	35.4
4	1181666.0	450159.4	61.9	13576.7	7124.0	47.5

Table 3
The number of cars that stopped in the heavy scenario was caused by the red phase

Scenario	Cases	TCP	IFTCS	Improvement (%)
1	1	105775.00	74573.00	29.5
	2	105431.00	70694.00	32.9
	3	138810.00	108444.00	21.9
	4	128781.00	96730.00	24.9
2	1	309581.00	139950.00	54.8
	2	302089.00	134393.00	55.5
	3	269689.00	165947.00	38.5
	4	277301.00	160002.00	42.3

As shown in Tables 1 and 2, the proposed fuzzy traffic control system outperformed the pre-timed traffic control system in both scenarios and situations. In Scenario 1, in Case 1, the average waiting times for non-emergency vehicles decreased by 56.3% compared to PTC, and the average waiting times for emergency cars were reduced by 27.6%. In Scenario 1 (Case 2), the average waiting time for non-emergency vehicles was reduced by 60.8%, which was nearly the same as Case 1's average waiting time for non-emergency vehicles. However, the average waiting time for emergency cars was reduced by 56.4%, which was better than Case 1's average waiting time for emergency cars. Furthermore, when the number of simulation steps or the intensity of heavy traffic increases, the average waiting times of non-emergency vehicles are reduced by 79.5% and 80.6% for Cases 1 and 2, respectively, which are more comparable (Table 2). However, the average waiting time for the emergency car(s) in Scenario 2 (Case 2) was reduced by 94.2, whereas that of Case 1 was the same as that in Scenario 1 (27.6%). The rationale behind Case 2 is more advantageous in terms of prioritizing emergency car(s) in both scenarios 1 and 2 and needs further investigation. However, in both Scenarios and in all Cases, the proposed system prioritized emergency car(s) without significantly affecting the time of non-emergency vehicles at intersections. Here, the proposed approach has more flexibility and driver-friendly features that prioritize emergency car(s) without essentially affecting other vehicles. Similarly, as shown in Table 3, the intensity of heavy traffic (number of stopped vehicles) was calculated, and the proposed fuzzy traffic control reduced the amount of heavy traffic flow stopping in the red phase in all cases compared to the traditional traffic signal control system (see Table 3). Another intelligent feature of this system is that it provides a more equitable distribution of waiting times in the case of a heavy traffic load in a conflicting direction for a long time. To assess the performance of the new three-stage fuzzy traffic control system relative to the two-stage fuzzy traffic control system with regard to the equitable distribution of the green time duration in situations where long vehicle queues are consistently present in only one direction for extended periods, whereas only short vehicle queues are necessary to pass through the conflicting direction. A two-stage fuzzy traffic signal control system was developed without a CWTM module, as presented in [8] and depicted in Figure 14. To execute this experimental simulation, the data were organized based on linguistic values that demonstrated heavy traffic during the current green-light phase, which signifies that Q_g falls within the range of {*large, very large*} and W_{tg} ranges from {*zero, short*}. In contrast, during the current red phase, the light traffic conditions (characterized by short vehicle queues) necessary to satisfy the Q_r linguistic values are situated within the range of {*zero, small*}, whereas the range of W_{tr} linguistic values spans {*long, very long*}. Finally, a comparison was made in terms of the average extension of the green light duration for shorter queues facing heavy traffic from conflicting directions (s). The result proved to be more equitable towards short queues, as shown in Tables 4 and 5. Both control systems were evaluated using the same data, with the absence of emergency cars and heavy traffic loads in the current green light phase. As shown in Table 6 and Figure 15, the three-stage fuzzy system outperformed the two-stage system in terms of the average extension of the green-light duration to provide an equitable green-light time for short vehicle queues.

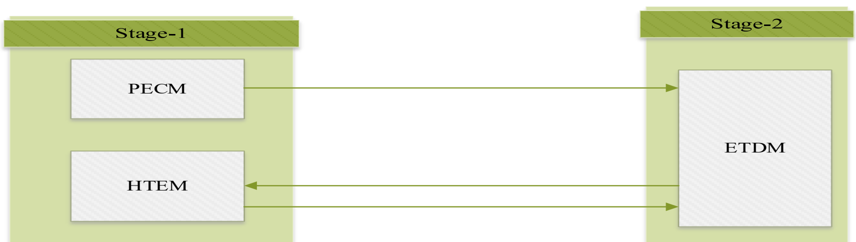

Figure 14
Architecture of two-stage fuzzy traffic-control systems [8]

Table 4
Three-stage fuzzy traffic control (no emergency vehicles)

Antecedents						Consequent
Q_r	Q_g	E_r	E_g	W_{tr}	W_{tg}	G_e
10	25	0	0	130	50	22.13
20	80	0	0	225	75	29.23

5	100	0	0	250	25	29.23
2	200	0	0	250	45	31.16
1	150	0	0	115	55	28.88

Table 5

Two-stage fuzzy traffic control without CWTM (no emergency vehicles)

Antecedents					Consequent
Q_r	Q_g	E_r	E_g	W_{tr}	G_e
10	25	0	0	130	22.50
20	80	0	0	225	54.83
5	100	0	0	250	55.15
2	200	0	0	250	55.47
1	150	0	0	115	54.00

Table 6

Average extension green time of the cars in shorter queues

Number of simulations	Extension Time for green light for three-stage (second)	Extension Time for green light two-stage without CWTM (second)
1	22.13	22.5
2	29.23	54.83
3	29.23	55.15
4	31.16	55.47
5	28.88	54
Average	28.39	48.39
Improvement (%)	41.3%	

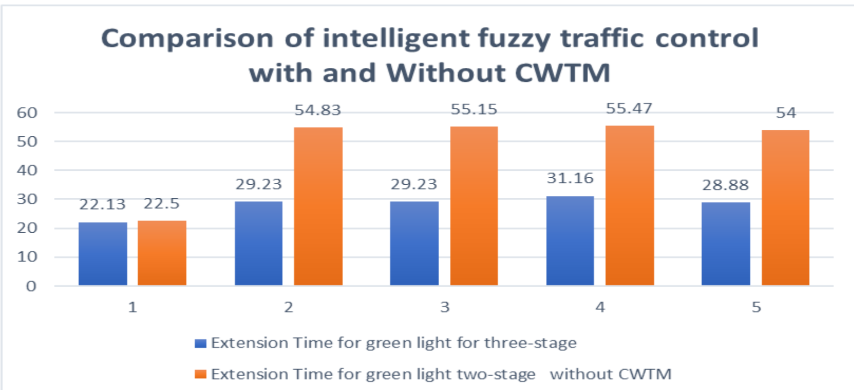

Figure 15

Average extension green time for shorter vehicle queue

Another advantage of the newly proposed system is that it is capable of switching or extending the green light phase in the case of two or more emergency cars appearing simultaneously. Regarding the technical requirements for the setup, the Mamdani-style fuzzy system structure simplifies scalability and maintenance because it is easy to expand various modules without affecting the main system. Therefore, scalability and robustness are other benefits of our method compared with other optimal traffic control systems.

Conclusions and Future Work

With the rapid increase in vehicle usage and limitations in the transportation infrastructure, the development of traffic control systems is critical. Over the past few decades, the number of traffic accidents has surged globally owing to a constant increase in traffic jams. A novel approach to a hierarchically cascaded fuzzy traffic control system was proposed to overcome the problems encountered by the existing pre-timed and optimal traffic control systems. The new GUI software implements an intelligent system that reduces traffic congestion and at the same time, it prioritizes emergency cars without significantly affecting other vehicles in the same intersection. The proposed fuzzy traffic control system not only reduces delays at intersections but also enhances their overall efficiency and safety. The proposed system solves this problem, calculates the waiting time of the red phases, compares it with the current green-light phases, and then switches the green light to the red phase as necessary. This aspect improves driver friendliness, as it offers green lights toward stalled drivers when encountering heavy traffic from conflicting directions.

Simulation experiments were conducted using a microscopic traffic simulator (SUMO), and the results clearly demonstrate that the new approach is more advanced and has more intelligent behavior than the current traffic control system. A Pre-timed Traffic Control system (PTC) was also simulated in the same manner as the proposed systems, and a comparison was made between the PTC and the new approach in terms of the average waiting times for vehicles, average waiting times for emergency cars, and number of vehicles stopped by the red phase. The simulation results show that the proposed approach outperformed PTC in all scenarios.

Future experiments may focus on expanding the isolated traffic intersection to two or more connected intersections or applying a more efficient inference engine, such as a fuzzy rule interpolation algorithm that can manage various traffic parameters. Similarly, it is possible to integrate fuzzy inference rules with deep neural networks and reinforcement learning, enabling the system to predict future traffic conditions and interact with the environment, to make better decisions.

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L. T. Kóczy is also a Professor Emeritus at the Budapest University of Technology and Economics.

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