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An Adaptive Method for Traffic Signal Control Based on Fuzzy Logic With Webster and Modified Webster Formula Using SUMO Traffic Simulator

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ABSTRACT In the past, the Webster optimal cycle time formula was limited to calculate the optimal cycle from historical data for fixed-time traffic signal control. This paper focuses on the design of an adaptive traffic signal control based on fuzzy logic with Webster and modified Webster's formula. These formulas are used to calculate the optimal cycle time depending on the current traffic situation which applying in the next cycle. The alternation of the traffic condition between two successive cycles is monitored and handled through the fuzzy logic system to compensate the fluctuation. The obtained optimal cycle time is used to determine adaptively the effective phase green times i.e. is used to determine adaptively the maximum allowable extension limit of the green phase in the next cycle. The SUMO traffic simulator is used to compare the results of the proposed adaptive control methods with fuzzy logic-based traffic control, and fixed-time Webster and modified Webster-based traffic control methods. The proposed methods are tested on an isolated intersection. In this study, real field-collected data obtained from three, four, and five approaches intersections in Kilis/Turkey are used to test the performance of the proposed methods. In addition, to examine the efficiency of the proposed techniques at heavy demands, the arbitrary demands are generated by SUMO for a four approaches intersection. The obtained simulation results indicate that the proposed methods overperform the fixed time and fuzzy logic-based traffic control methods in terms of average vehicular delay, speed, and travel time.

INDEX TERMS Adaptive traffic control, fixed-time traffic control, fuzzy logic control, modified Webster's formula, SUMO simulator, Webster's formula.

I. INTRODUCTION

Since the beginning of the last century, traffic signal control systems have received worldwide attention due to the daily increase in the number of vehicles. This increase in the number of vehicles is noticeable in large and populated cities with limited infrastructure. This leads to the congestion phenomena that affect the social and economic life of urbanites [1]. Additionally, it causes fuel squandering and environmental pollution that occurs as a result of carbon dioxide emissions from vehicles. It is known that carbon dioxide affects the ozone layer, consequently causing climate change and disturbing the lifestyle of all living organisms. Automatic traffic signal control systems are employed to reduce the waiting time at the intersections as well as the quantity of the emitted harmful gases. Traffic signal control is a technique used in crossroads to manage conflicting movements by determining the right-of-way to certain conflicting traffic flows. The traffic flow comprises vehicles, motorcycles, bicycles, and pedestrians. In most cases, vehicles and pedestrians are considered while designing a traffic control system.

Briefly, the traffic signal control system simply determines the number of phases that need to be included in a given cycle and how long these phases should last. Mainly traffic light or traffic signal control systems can be divided into two

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basic groups: Fixed time traffic control and traffic-dependent control. In fixed-time traffic control, the signal plans are prepared depending on the historical traffic volume data. In a traffic-dependent control, the volume of traffic, speed, or occupancy rate are measured instantly in the field by using traffic detectors. Traffic-dependent control can also be divided into actuated traffic control and adaptive traffic control. In an actuated traffic control, the decision of extending the green time depends on the appearance of vehicles on the road. The adaptive traffic control is a version of actuated traffic control with an additional real-time optimization algorithm. Although the fixed-time traffic control system is simple in its implementation, its disregard for the variability and dynamic nature of traffic leads to inefficient utilization of available resources. On the other hand, due to their capability to adapt to the dynamic nature of the traffic, traffic-dependent control systems such as adaptive traffic control are more suitable for monitoring and controlling the traffic system [2].

The fundamental principle of an adaptive traffic control technique is its responsiveness to dynamic changes in traffic demand. In this technique, at least one of the adjustable traffic parameters such as the cycle length, green time splits, and phase sequences must be adjusted. The main purposes of adjusting these parameters include the reduction of average waiting time and the number of stops at the intersections.

Although several studies have been obtained on this topic, most of these methods are ignore the importance of fixed phase sequences. In the vehicle-actuated control, the controller attempts continuously to adjust green times. The phase green times are adjusted by shortening or extending until it reached the fixed predefined maximum time. This predefined fixed maximum time can affect the performance of the controller negatively. Moreover, the vehicle-actuated control can skip the phase that has no vehicle waited to serve it. Although the skip of phase seems like good behavior, however, it influences the pedestrian movements that corresponding to the skipping phase negatively as well as confusing the motorist. Besides, the most of proposed pure fuzzy logic traffic control methods are based on vehicles waiting in the queues and change both the phase lengths and the phase sequences adaptively to the traffic situation. This change in the phase sequences can lead to phase skip. To overcome this drawback, we proposed an adaptive traffic control based on fuzzy logic with Webster and modified Webster's optimal cycle time. In general, Webster's optimal cycle time formula is employed for a fixed-time traffic control method by using historical data. However, here, the formula is applied differently, in other word is used in a real-time manner. In this method, the optimal cycle time is used to determine the maximum allowable extension limit of phase adaptively cycle by cycle instead of predefined fixed maximum time. Moreover, the effective green times are distributed (for all phases without skip) proportionally to the critical lane flow as a portion of optimal cycle time at each cycle. The main advantage of the proposed methods is the simplicity of the implementation in the real world.

There are a lot of performance indices in traffic control used as an objective function for traffic optimization purposes. These indices include total and average delay time, fuel consumption, emissions, queue length, number of stops, average speed, and total and average travel time [3]. In this study, the average waiting time, average travel time, and average speed are considered as performance indices. This work aims to reduce the average waiting and travel time as well as increase the average speed. This research proposes two adaptive traffic control methods based on Webster optimal cycle time formula with fuzzy logic and modified Webster optimal cycle time formula with fuzzy logic.

The comparison between the proposed approaches, the fuzzy logic-based approach introduced in [4], and fixed time traffic control using Webster and the modified Webster method are presented at the end of this paper.

II. THE RELATED WORKS

A lot of work has been done in the field of adaptive traffic signal control. Since Webster published his famous optimal cycle for minimum delay formula in 1958, the formula has become dominant in the field of fixed time traffic control for an isolated intersection [5]. However, until now this formula is limited to calculating the optimal cycle from historical data for a fixed time traffic signal control. There are a lot of modified versions of Webster's optimal cycle for minimum delay formula [6], [7]. *Zakariya and Rabia* suggested a modified version of Webster's optimal cycle formula which is considered the fundamental brick of this work [7]. Although the Webster formula has been formulated decades ago, it is still applicable to modern systems. Nowadays, several optimization algorithms and modern control techniques are applied to optimize the traffic signal control system.

Fuzzy logic is one of the most common techniques used in traffic signal control systems. The fuzzy set theory introduced by Zadehin 1965 has become a new alternative to treating uncertain situations in various fields of a control system which includes transportation [8]. Fuzzy logic is an interpretation and transformation of expert knowledge into a practical reality [9]. Fuzzy logic traffic system for isolated signalized intersection is introduced in [4]. The system adjusts the cycle time and minimizes unused green times of phases. The method shows outperformance in terms of vehicular waiting time when compared to fixed time control. A two phases fuzzy logic-based traffic signal control for mixed traffic conditions is suggested by [10]. In this method, fuzzy logic is used to calculate the phase green time depending on the maximum queue length and the arrival rate. The suggested method compared to the fixed-time control using the VISSIM traffic simulator. In this method, only an isolated intersection with two phases is used. *CheSoh et al.* are developing a traffic model and fuzzy traffic controller for a multilane isolated intersection using MATLAB Simulink and SimEvent toolbox [11]. This traffic model is designed based on the queue theory and the control decisions determined by the queue length and the waiting time of the vehicles at the intersections. The traffic controller not only changes the traffic lighting timing but also changes the phase sequence of a traffic signal to obtain a good performance. The comparative analysis of this traffic controller and traditional vehicle-actuated control system indicates that the traffic controller is overperformed the traditional vehicle-actuated technique. In [12], a dynamic control system based on fuzzy logic was proposed. The system combines the wireless sensor network with four fuzzy logic controllers. Each fuzzy logic controller observes the movements of the vehicles and dynamically manages the corresponding phase and green time. A Zigbee-based wireless sensor network was used to monitor real-time traffic data. The simulation was performed using MATLAB software. Based on the results obtained from the simulation, the multi-controller approach achieves better results in terms of reducing vehicle-waiting times, especially in heavy traffic situations. In [13], the fuzzy logic was used to determine the maximum green time of an actuated traffic signal control for an isolated intersection. The maximum green time is determined depending on the real-time traffic flow. The AIMSUN traffic simulator was used to measure the performance of the model. The simulation result shows that this model overperforms the traditional actuated traffic control.

A two-stage fuzzy logic-based traffic light system for an isolated intersection was proposed in [14] using a technology capable of mimicking human intelligence to control traffic lights. It consists of two modules namely: Traffic Urgency Decision module (TUDM) and Extension Time Decision Module (ETDM). The obtained result shows the outperformance of the proposed system as compared to fixed time control. Another two-stage fuzzy logic-based traffic signal control is proposed in [15]. It aims to reduce the average vehicular waiting time at the isolated intersection. The simulation results based on real traffic data are obtained using SUMO microscopic simulator. Based on achieved results, the method overperforms the fixed-time traffic signal control. Further two-stage fuzzy logic-based traffic signal control is suggested in [16]. It can be considered as an optimized version of two-stage fuzzy logic-based traffic signal control. The differential evolution algorithm is used to optimize the fuzzy rules. The simulation results are obtained using MATLAB.

In addition to pure fuzzy logic, neuro-fuzzy is also widely applied in designing traffic control systems. In [17] the authors proposed a model to determine the phase sequencing of the traffic signal control based on an adaptive neuro-fuzzy inference system (ANFIS). The model was applied to an isolated intersection and the simulation was performed using MATLAB. The result of the simulation shows the effectiveness of the model as compared to the fixed phase traffic signal control. The fuzzy neural network and genetic algorithm are used in [18] to implement a traffic control system for an isolated intersection. To test the proposed system MATLAB and the Genetic Algorithm Toolbox were used and the obtained results show the outperformance of the proposed model as compare to the traditional fixed time.

There are also further researches conducted in the field of traffic signal control using different methods and optimization algorithms. These methods include Petri net, Bee colony optimization, memetic algorithm, and deep reinforcement learning algorithms. *Di Febbraro et al.* introduced a model aimed at minimizing queue lengths by optimizing the duration of each signal phase [19]. The model is based on a deterministic and stochastic Petri net. The model applies to both under-saturated and oversaturated traffic conditions. It is also a deadlock-free model. The bee colony optimization algorithm has been proposed in [20] to optimize traffic signal control for a wide urban area. The algorithm was applied to calculate the near-optimal values of cycle length, splits, and offsets of signals to minimize the total travel time. The numerical experiment was achieved to measure the performance of the model. The model outperforms the Simulated Annealing algorithm as the result of the comparison. *Sabar et al.* proposed a memetic algorithm based on genetic and local search algorithm [21]. The simulation was performed using AIMSUN microscopic simulator. The obtained results show outperformance as compared to the genetic algorithm and the traditional fixed time. The Dynamic Programming (DP) based adaptive traffic control system was designed in [22]. The proposed model is a combination of the vehicle arrival estimation model and signal optimization algorithm. This model also supports the NEMA phase structure. The VISSIM simulator was used to implement and test this model. Based on the simulation result, the proposed method overperforms the optimal fixed time and the four-phase DP. The approximate DP as one type of model-based reinforcement learning with function approximation is proposed in [23]. The method is applied to an isolated intersection with vehicles and pedestrian demands. The SUMO simulator is used to test the performance of the proposed method. To enhance the performance of the traffic control algorithm, *Juntao Gao et al*. proposed an adaptive traffic control system by applying a deep reinforcement learning algorithm with experience replay and target network mechanisms [24]. The comparison was performed based on the simulation model and the obtained results indicate the superiority of the algorithm as compared to a fixed time and the longest queue first algorithm. In [25] the four-phase isolated intersection adaptive traffic signal control based on the double DQN (DDQN) is proposed. Fixed phase sequence stable traffic signal control policy is achieved using dual agent architecture.

Aljaafreh et al. proposed three real-time adaptive algorithms for traffic light control in a single intersection, which aims to reduce the average waiting time of a vehicle at an intersection [26]. To test the performance of these algorithms a discrete event simulation model for traffic light controller was developed by using MATLAB/Simulink/ Simevents toolbox. The proposed algorithms were compared to the conventional fixed time approach.

III. BACKGROUND

A. OVERVIEW OF THE FUZZY LOGIC

The fuzzy logic is conceptually different from classical control systems. In classical (traditional) logic, any object either belongs to that cluster or not. This is the basis of digital logic. In Fuzzy Logic, there is no logic 0 and 1 as in classical logic, there is a more flexible approach that we use in daily life [27].

Fuzzy logic is the extraction of the results values by using the help of certain mathematical functions depending on each rule, by using the experience of the people, by processing the values obtained with certain algorithms. There is a Boolean (binary value) logic in classical control methods. Fuzzy logic derives very valuable results between 0-1 by taking into account the values and expresses the magnitudes with verbal language variables such as small, very, slightly, medium, long, and normal. It allows processing with intermediate values (such as 0.7, 0.42) instead of 0-1 values. It adds the ability to generalize by carrying two-valued memberships to multi-valued [27]. Detailed coverage of fuzzy logic can be found in [28]–[30]

The principles of fuzzy logic are expressed as follows [31];

- In fuzzy logic, approximate values are used instead of certain values.
- Information for fuzzy logic is defined by very little, little, small, large linguistic expressions.
- In fuzzy logic, all values are shown with a membership degree in the range [0-1].
- Every logical statement can be converted into a fuzzy statement.
- Fuzzy logic is a suitable method for systems whose mathematical model is very complex and difficult.

Fuzzy logic has been applied to a wide area thanks to its easy and useful solution to problems that difficult and complex. In general, fuzzy logic is applied to the field of medicine such as psychology and in the field of engineering such as artificial intelligence, smart systems, robotics, and transportation systems [9], [32]–[36].

B. FIXED TIME TRAFFIC CONTROL

In this section, Webster and modified Webster's formulas that use to calculate the optimal cycle length, as well as the effective green time formula, are discussed. In general, Webster's optimal cycle length formula (in an original or modified version) is employed for a fixed time traffic control method by using the historical data [5]–[7].

Consider the intersection illustrated in Figure 1. It shows a four approaches intersection in which the north and south legs have three lanes while the east and west roads only have two lanes. According to this Figure, the ε_{sr}, ε_s and ε_l represent straight and right turn, straight and left turn flows of the three-lane approach while ε_{sr} and ε_l denote straight and right turn, left turn flows of the two-lane approach.

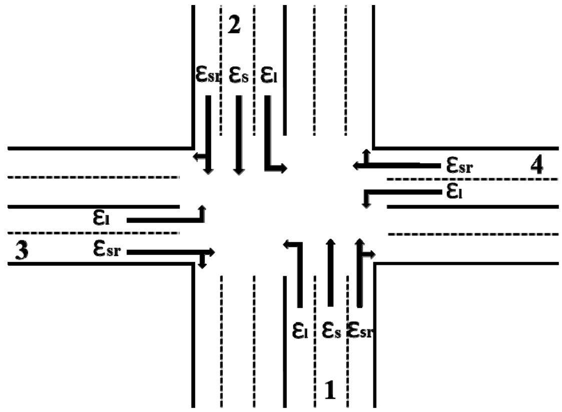

FIGURE 1. The configuration of four approaches intersection understudy.

Based on Figure 1, the critical lane flow for two and three lanes approach as in Equations 1 and 2.

$$y_i = \frac{\max(\varepsilon_s, \varepsilon_l, \varepsilon_{sr})}{S_i} \tag{1}$$

$$y_i = \frac{\max(\varepsilon_l, \varepsilon_{sr})}{S_i} \tag{2}$$

The optimal cycle length for the Webster and modified Webster methods are calculated based on Equations 3 and 4 respectively. The parameters of these equations are chosen because they are calculated by experimental methods and used in the literature especially for modified Webster [37].

$$C_o = 1.5 \cdot L + 5 \Big/ 1 - \sum_{i=1}^{n} y_i \tag{3}$$

$$C_o = 1.978 \cdot L + 5.109 \Big/ 1 - 0.9013 \cdot \sum_{i=1}^{n} y_i \tag{4}$$

where C_o represents the optimal cycle length, L denotes the total intersection losses and y_i represents the critical flow of the approach i $(i = 1, 2, 3, \text{and } 4)$.

The effective green times (G_i) are distributed proportionally to the critical flow of lanes belonging to the phase and determined using (5). The optimal cycle length is the sum of all effective green times plus the total lost time. Due to this, we subtract the total lost time from the optimal cycle length, then the remaining time can be distributed as green time among the phases of the cycle.

$$G_i = \frac{y_i}{\sum_{i=1}^{n} y_i} \cdot (C_o - L) \tag{5}$$

IV. THE PROPOSED ADAPTIVE ALGORITHM

The operating principles of the proposed adaptive traffic signal control system can be summarized in Algorithm 1.

The approach is based on fuzzy logic and optimal cycle using Webster's and modified Webster's formulas. These formulas are represented in Equations 3 and 4.

A. THE CALCULATION OF THE CYCLE LENGTH

The basic principle is that at the end of each cycle the optimal cycle time is calculated by Equation 3 in Webster's case and Equation 4 for modified Webster. In this work, the flow rates

Algorithm 1 Fuzzy Logic and Webster-Based Adaptive Traffic Signal Control

1: Initialize cycle length and all phases based on minimum values
2: Start by first phase (Phase1).
3: for M = 1 **to** END **do**
4: Read from sensors.
5: if the remaining current phase time < 15 seconds
6: Apply a fuzzy logic system for adjusting phase time in an online manner.
7: if the remaining current phase time <= 0 **or** maximum phase extension >= G_i(n) * 1.3
8: Terminate the current phase and move to the next phase
9: end if
10: if cycle finish
11: Considering all intersection roads, calculate critical lane flows based on sensors data using Equations 1-2 and 6-8.
12: Calculate C_o using Equation 3 in Webster case or Equation 4 in modified Webster case.
13: Calculate phase green split time using Equations 9-12
14: end if
15: end for

at each intersection approach are measured at the end of cycle time.

The flow rate is the number of vehicles passing a fixed point during a time. Assume that N_s, N_{sr}, and N_l are vehicles passing straight, straight and right-turn, and left-turn lanes as illustrated in Figure1. The time in which the vehicles passing lanes is simply equal to the optimal cycle (C_o). The flow rates are converted to hourly flow rates using Equations 6-8. Then the critical lane flows are calculated by Equations 1 and 2.

$$\varepsilon_s = \frac{N_s \cdot 3600}{C_o} \tag{6}$$

$$\varepsilon_l = \frac{N_l \cdot 3600}{C_o} \tag{7}$$

$$\varepsilon_{sr} = \frac{N_{sr} \cdot 3600}{C_o} \tag{8}$$

Lastly, the optimal cycle time is determined using Equation 3 or 4.

B. THE CALCULATION OF THE EFFECTIVE GREEN TIME

Based on Webster's model, the calculation of effective green time is performed depending on the critical flow of lanes belonging to the phase at each intersection approach. In this work, the predetermined minimum green time is located for each phase. Consequently, only the remaining of total effective green cycle time $C_e(n)$ is available to be distributed to m phases in cycle n as in Equation 9.

$$C_e(n) = C_o(n) - L - m \cdot g_m \tag{9}$$

g_m is the predetermined minimum green time available to phase m.

The critical flow ratio $\alpha i(n)$ of phase i within cycle n can be calculated using Equation 10.

$$\sigma_i(n) = \frac{y_i}{\sum_{i=1}^{n} y_i} \tag{10}$$

The extra effective green time that is added to the minimum green time is calculated based on Equation 11.

$$g_i(n) = \alpha_i(n) \cdot C_e(n) \tag{11}$$

The calculation of the total effective green time allocated for each phase is performed based on Equation 12.

$$G_i(n) = g_i(n) + g_m \tag{12}$$

These values are used adaptively to determine the maximum allowable extension limit of green time in the next cycle (cycle n+1).

C. THE ADJUSTMENT OF THE GREEN TIME

As mentioned above, the optimal cycle is calculated based on the flow measured during the previous cycle (cycle n) and used in the next cycle (cycle n+1). During the successive cycles, the traffic situation can change slightly and can be lead to a mismatch between the calculated and optimal cycle. Fuzzy logic is applied continuously at each cycle to overcome this mismatch. Figure 2 shows the flowchart of the proposed algorithm. The Mamdani fuzzy logic model with centroid defuzzification method provided by skfuzzy of SciKit toolbox package of python [38] is used to construct the fuzzy system by establishing relations between the inputs and outputs of the fuzzy system using if-then rules.

The proposed fuzzy logic is intended to adjust the phase green time during execution. The monitoring of the green phase under execution from the starting of the long phase time will be computationally expensive. To avoid this the proposed fuzzy logic system is constrained to start the monitoring of the executing phase time value reducing below15 seconds. Which is used as the input value of the remaining time of the current green phase. This value is selected due to the fact of the adjustment needed between two successive cycles is happen within a short time. The proposed fuzzy logic has three inputs, namely RQL (Remaining Queue Length), PR (Passing Rate), RT_CGP (Remaining Time of Current Green Phase), and one output denoted by EorS (Extend or Shortened).

The RQL is the Remaining Queue Length for the lane group of the current green phase. It contains four membership functions named zero, short, medium, and long that range from 0 to 30 vehicles as illustrated in Figure 3.

The Passing Rate (PR) is an input that denotes the passing rate of the green phase as shown in Figure 4. It has four membership functions named zero, low, medium, and high that range from 0 to 4 vehicles/second.

The third input denotes the Remaining Time of the Current Green Phase (RT_CGP). It contains three membership

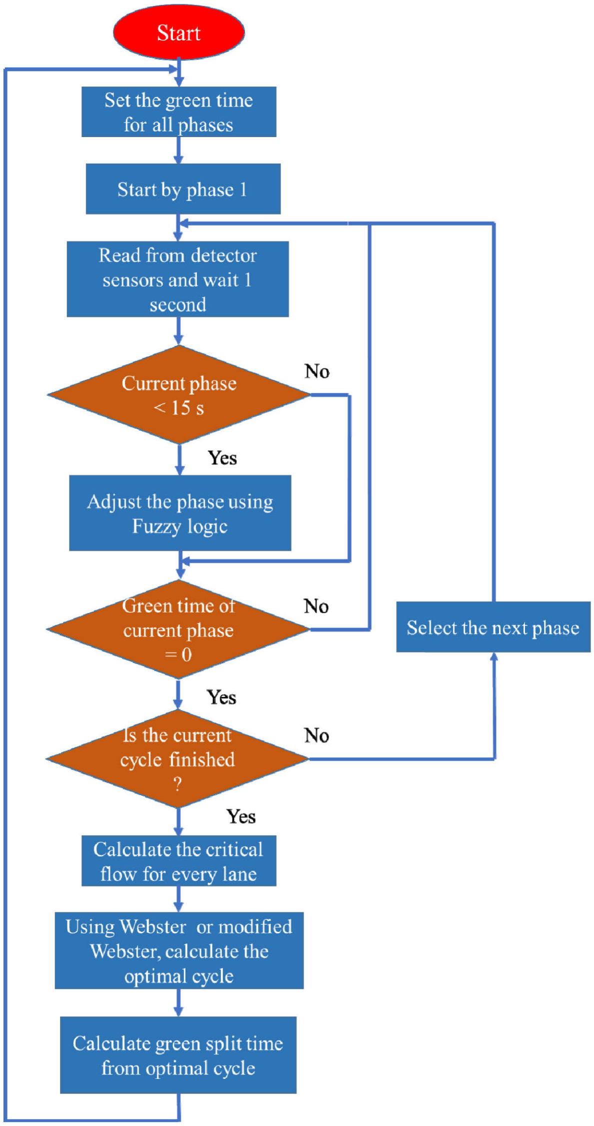

FIGURE 2. The flowchart of the proposed algorithm.

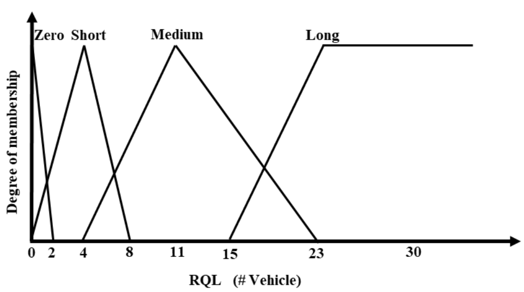

FIGURE 3. The input fuzzy membership of the remaining queue length.

functions named short, medium, and long that range from 0 to15 seconds as explained in Figure 5.

The output EorS of the fuzzy logic is used to extend, shorten or preserve the remaining time of the current green phase. It contains five membership functions called negative medium (NM), negative short (NS), zero, positive short (PS), and positive medium (PM) that range from −3 to +3 vehicles.

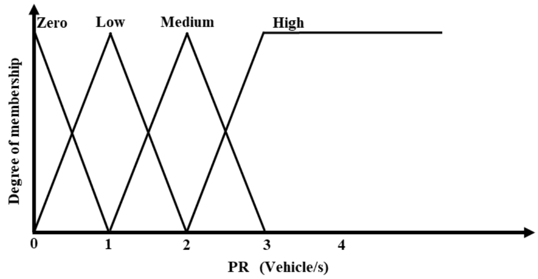

FIGURE 4. The input fuzzy membership of the passing rate.

The maximum and the minimum length for the extension are selected to provide smooth change within the remaining time of the current green phase. Figure 6 illustrates the output of the proposed fuzzy system.

To avoid the infinite extension of the green phase, the maximum extension is limited up to 130 % of the estimated phase green time in this study. This value can be an estimation based on the maximum possible deviation in the flow rates between successive cycles.

The proposed fuzzy logic system comprises forty-eight fuzzy rules. Some of these rules are shown in Table 1 below.

TABLE 1. Some rules example of the fuzzy logic.

Rule No	The rule
Rule1	If RQL is *Zero* and RT_GP is *Short* and PR is *Zero* then, EorS is *NM*
Rule2	If RQL is *Zero* and RT_GP is *Short* and PR is *low* then, EorS is *NM*
Rule3	If RQL is *Zero* and RT_GP is *Short* and PR is *Medium* then, EorS is *NM*
Rule4	If RQL is *Zero* and RT_GP is *Short* and PR is *High* then, EorS is *NM*
Rule5	If RQL is *Zero* and RT_GP is *Medium* and PR is *Zero* then, EorS is *NM*
Rule6	If RQL is *Zero* and RT_GP is *Medium* and PR is *low* then, EorS is *NM*
Rule7	If RQL is *Zero* and RT_GP is *Medium* and PR is *Medium* then, EorS is *NM*
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Rule46	If RQL is *Long* and RT_GP is *Long* and PR is *Zero* then, EorS is *zero*
Rule47	If RQL is *Long* and RT_GP is *Long* and PR is *low* then, EorS is *PS*
Rule48	If RQL is *Long* and RT_GP is *Long* and PR is *Medium* then, EorS is *PM*

V. FUZZY LOGIC BASED ADAPTIVE TRAFFIC SIGNAL CONTROL

In this section, we briefly present the fuzzy logic-based traffic control method proposed in [4] that used as a benchmark

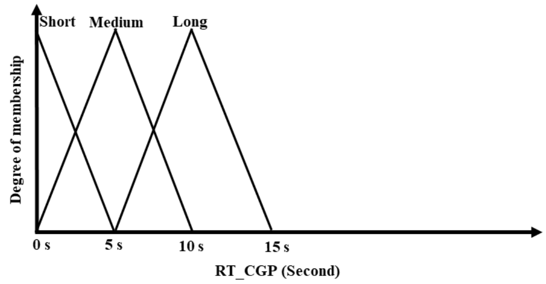

FIGURE 5. The input fuzzy membership of the remaining time of the current green phase.

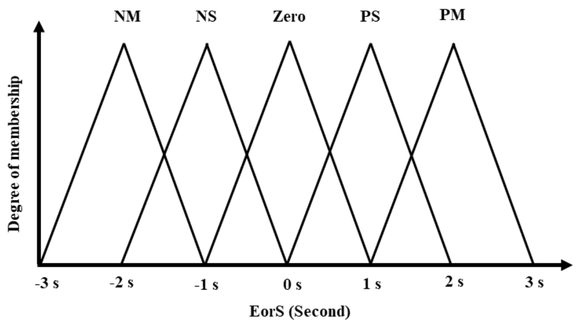

FIGURE 6. The output fuzzy membership of the extending or shortening.

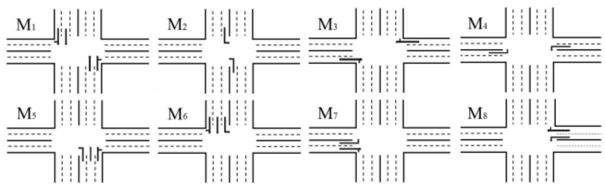

FIGURE 7. The configurable movements of the four approaches intersection.

for comparison. This method is chosen because it is one of the typical fuzzy logic-based methods comparable to our proposed method, which cyclically changes the phase without jumping any phase during the cycle.

The method uses the traffic situation level and phases sequence level as inputs. The phase sequence level is determined based on the possible movement scenarios illustrated in Figure 7.

After the sequence of phases is determined, the phases are executed in an anti-clockwise sequence.

The fuzzy logic system implemented using the MATLAB fuzzy logic tool and comprises eight inputs and sixteen outputs for more detail refer to [4].

VI. SIMULATOR OVERVIEW

There are various traffic simulator packages available nowadays. Some of these packages are intended for commercial purposes while some of them are open-source. Among the commercial traffic simulator software packages are AIMSUN, VISSIM, ARCHISIM, and CORSIM. Open source traffic simulators include MATSim, TRANSIMS, MITSIMLab, and SUMO [39].

SUMO (Simulation of Urban Mobility) is an open-source, microscopic traffic simulation software developed by the German aerospace institute in 2001. It is a powerful simulation tool for dynamic time simulation. SUMO is capable of simulating the individual behaviors of the vehicles on the networked road based on the different theories on vehicle behavior such as car-following theory [40], [41]. It is used in a variety of applications such as route selection, dynamic navigation, vehicular communication, evaluation of traffic surveillance systems, and traffic light algorithm development [42]. There are several other microscopic traffic simulation tools like AIMSUN, VISSIM, CORSIM, SimTraffic, PARAMICS, and MITSIMLab, which are suitable for simulating the traffic on the arterial and freeway network. However, the SUMO simulator is preferred by many researchers because it is the one of most advanced and well-documented open-source traffic simulators with an online support system [39], [43].

VII. DESCRIPTION OF THE CASE STUDY

To perform the comparison between proposed methods with existing methods, three intersections with different architectures are selected as illustrated in Figures 1, 2 and, 3. They are isolated intersections located in Kilis/Turkey. These intersections were selected because of the availability of real data. The proposed algorithms are tested using field-collected real data and randomly generated fixed flows.

The field-collected real traffic data are obtained by digital image processing through the fisheye camera. Mosaş Group Company owns this system; it has the capability of tracking the target, counting the entered and arrived vehicles and classify the vehicles based on their dimension. The data include information such as date and time, the number of vehicles passed the intersection with their directions and the departure time, and the class of vehicles (passenger car, buses, and trucks). This information is used to generate the traffic demands in the simulator. The collection of traffic data is performed second by second, however, the aggregated data kept in the sever (SQL table) database every five minutes. These real traffic data are collected at the intersections on April 11, 2018. This study has made use of the real data consisting of 18 hours and 25 minutes of traffic data (from 00:00 to 18:25) at the three approaches intersection. For the four approaches intersection, real traffic data of 24 hours duration has been used while 10 hours and 45 minutes of traffic data has been employed for the five approaches intersection. The data collected from the four approaches intersection have included the peak and off-peak hour because it is a 24-hour data. Figure 4 illustrates a sample of the field-collected real data of traffic demands for both cars and trucks.

For evaluation of the proposed algorithm in the congested condition (due to the real field-collected data not include the saturation state), we generate the three different traffic demands each for one hour. These demands are given as detailed in the next section. It is generated only for the four

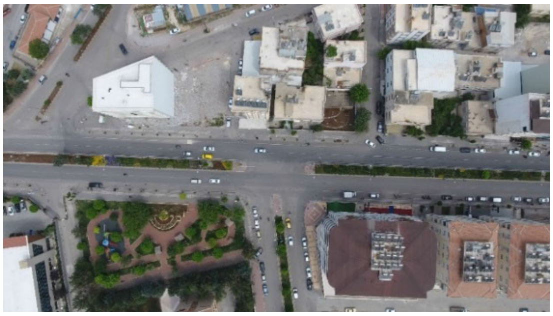

FIGURE 8. The structure of three legs isolated intersection understudy.

FIGURE 9. The structure of four legs isolated intersection understudy.

FIGURE 10. The structure of five legs isolated intersection understudy.

approaches intersection for simplicity. The configuration, network, and route files of this study are open-sourced in [44].

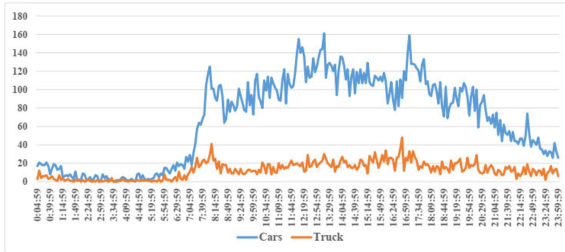

FIGURE 11. The measured traffic demand for a period from 00:00:00 to 23:59:59.

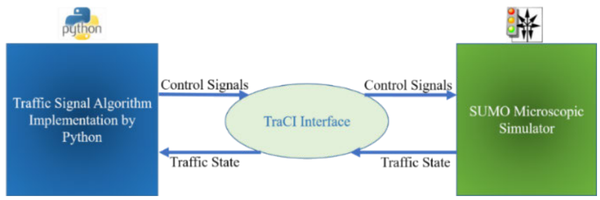

FIGURE 12. The configuration of SUMO and Python through TraCI.

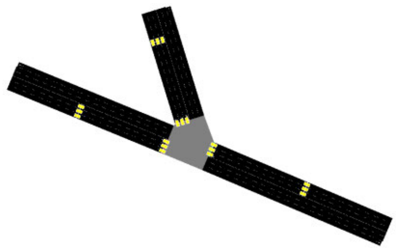

FIGURE 13. The built simulation model of three approaches intersection.

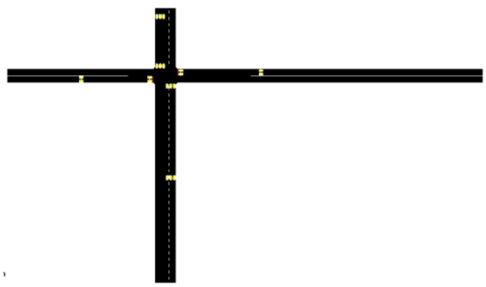

FIGURE 14. The built simulation model of four approaches intersection.

VIII. THE SIMULATION STEPS

The python programming language together with the SUMO simulator has been employed to implement the proposed algorithms. The python script is used to control the SUMO through the TraCI interface. The configuration of SUMO and Python is depicted in Figure 12. The SUMO simulator acts as a server while the python script act as a client in a server-client manner.

The simulation model is constructed for the selected intersections by using SUMO. This is depicted in Figures 13 through 15. It is a SUMO model GUI version of Figures 8 through 10 respectively. In this simulation, the inductive loop detectors are used to provide state feedback for the algorithms.

The SUMO simulator allows the user to generate traffic demands in different ways. Among these, it can be adding a predefined flow or generate demand randomly by using a dedicated python module. These two methods are used in this research. The simulation is performed for both real field-collected data and the arbitrary generated traffic demands. Arbitrary-generated demands produced based on the fixed number of vehicles each have a random departure time within the predefined interval. The steps taken to perform the simulation are described as follows.

These traffic data are collected from the real fields and stored in the database. For the real field-collected data, the parts of the data that belong to the intersections at the specific study area are selected from the SQL table. The maximum hourly critical lane volumes extracted from the data are presented in Table 4, 9, and 10 for four, three, and five approaches intersections respectively.

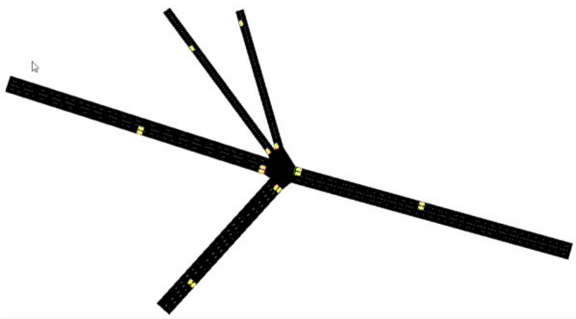

FIGURE 15. The built simulation model of five approaches intersection.

```
<vehicle id="5.0" depart="7.91" color="red">
    <route edges="1 33"/>
</vehicle>
<vehicle id="3.0" depart="9.74" color="red">
    <route edges="1 22"/>
</vehicle>
<vehicle id="14.0" depart="10.31" color="magenta">
    <route edges="3 11"/>
</vehicle>
<vehicle id="15.0" depart="12.79" color="red">
    <route edges="3 22"/>
</vehicle>
<vehicle id="15.1" depart="18.01" color="red">
    <route edges="3 22"/>
</vehicle>
```

FIGURE 16. Route file that can be used by SUMO simulator.

TABLE 2. The assignment of the phase to the movements.

Phase	1	2	3	4
Movements	M_1	M_2	M_3	M_4

TABLE 3. The critical lane volumes of the real data and arbitrary generated traffic demands.

Case No	Critical lane volume of phase 1	Critical lane volume of phase 2	Critical lane volume of phase 3	Critical lane volume of phase 4	The sum of Critical lane volumes
Case 1	525	352	465	245	1587
Case 2	392	295	461	193	1341
Case 3	163	222	213	218	816
Combined cases	525	352	465	245	1587
The real data	202	70	587	286	1145

The traffic demands are defined in the xml SUMO route file using the data Figure 16 illustrates the example of the route file. SUMO simulator uses this file during run time.

For the arbitrary generated traffic demands. We generate different demands in three cases and we measured the hourly critical lane volumes. The method used here is based on the method used in [45] without considering pedestrian's demands. These demands are only applied to the four approaches intersection. The critical lane volumes for the combined cases are equal to the maximum case (case1). Table 3 represents the critical lane volumes of the cases including the real field-collected data.

Table 2 shows the assignment of phases for four approaches intersection based on the movement illustrated in Figure 7.

The hourly maximum critical lane volume of arbitrary generated demands and the real field-collected data for four approaches intersection.

TABLE 4. The optimal cycle and the distribution of effective green times for Webster.

Case No	G_1	G_2	G_3	G_4	C_o	$\sum_{i=1}^{4} y_i$
Case 1	60	41	53	28	194	0.881667
Case 2	23	17	27	11	90	0.745
Case 3	6	8	8	8	42	0.453333
Combined case	60	41	53	28	194	0.881667
real data	9	3	27	13	64	0.636111

TABLE 5. The optimal cycle and the distribution of effective green times for modified Webster.

Case No	G_1	G_2	G_3	G_4	C_o	$\sum_{i=1}^{4} y_i$
Case 1	42	28	38	20	140	0.881667
Case 2	22	17	26	11	88	0.745
Case 3	7	10	10	10	49	0.453333
Combined case	42	28	38	20	140	0.881667
real data	10	3	29	14	68	0.636111

TABLE 6. The hourly maximum critical lane volume of the real field-collected data.

Critical lane volume of phase 1	Critical lane volume of phase 2	Critical lane volume of phase 3	The sum of Critical lane volumes
523	163	276	962

TABLE 7. The hourly maximum critical lane volume of the real field-collected data.

Critical lane volume of phase 1	Critical lane volume of phase 2	Critical lane volume of phase 3	Critical lane volume of phase 4	Critical lane volume of phase 5	The sum of Critical lane volumes
324	282	264	14	152	1036

We calculated the optimal cycle time and the effective phase green time for both Webster's and modified Webster's using the given critical lane volume.

The calculated optimal cycle time and effective green times for Webster's optimal cycle formula for four approaches intersection under arbitrary generated demands and the real field-collected data are given in Table 4.

The calculated optimal cycle time and effective green times for modified Webster's optimal cycle formula for four approaches intersection under arbitrary generated demands and the real field-collected data are given in Table 5.

The hourly maximum critical lane volume of the real field-collected data for three approaches intersection are given in Table 6.

The hourly maximum critical lane volume of the real field-collected data for five approaches intersection are given in Table 7.

The calculated optimal cycle time and effective green times for Webster's and modified Webster's optimal cycle formula for three approaches intersection are given in Table 8.

TABLE 8. The optimal cycle and the distribution of effective green times for Webster and modified Webster.

The method	G_1	G_2	G_3	C_o	$\sum_{i=1}^{3} y_i$
Webster's optimal formula	17	5	9	40	0.53444
Modified Webster's optimal formula	20	6	10	45	0.53444

TABLE 9. The optimal cycle and the distribution of effective green times for Webster and modified Webster.

The method	G_1	G_2	G_3	G_4	G_5	C_o	$\sum_{i=1}^{5} y_i$
Webster's optimal formula	15	13	12	3	7	65	0.575556
Modified Webster's optimal formula	18	15	14	3	8	73	0.575556

The calculated optimal cycle time and effective green times for Webster's and modified Webster's optimal cycle formula for five approaches intersection are given in Table 9.

The major assumptions taken into account to perform the simulation are:

- The predefined minimum values of 24 s, 32 s, and 40 s have been used for the three approaches, four approaches, and five approaches intersections respectively.
- The maximum cycle length of 100 s is used for all the intersections. The purpose of using the maximum and minimum values; is to eliminate the under and over-estimation of cycle length in case a low or an oversaturated flow occurs.
- All phases have equally lost time and equal to 3 seconds.
- The 1800 Vehicle/lane/hour is assumed as saturation flow (the value considered in [6, 45, 46]).
- Inductive loop detectors were used to measure the traffic flow on the roads.
- The modified Krauß-model that is the SUMO default car-following model is used.
- The minimum gaps of 2.5 m are used.
- SUMO default lane change model is used.
- The max speed of 50 km/hour is used for the passenger cars and 30 lm/hour is used for trucks.
- The max speed of 50 km/hour is used for the passenger cars and 30 lm/hour is used for trucks.

IX. THE SIMULATION STEPS

Due to the difficulty of measuring the performance of the proposed algorithms in the real field intersection, we preferred to test the algorithms using simulation options through real and arbitrary generated traffic demands. In this work, the simulation was conducted based on the data and the steps presented in sections VII and VIII. Two adaptive techniques, namely the fuzzy logic with Webster's formula and the fuzzy logic with modified Webster's formula, have been proposed. The proposed algorithms are compared to the fixed-time Webster's, fixed-time modified Webster's formula, and adaptive fuzzy logic-based traffic control using the SUMO simulator. They are simulated under the same conditions. The average waiting time, average travel time, and average speed are used as indices of performance at the intersection. The obtained simulation results are divided into three parts.

TABLE 10. The comparison of adaptive and other methods in terms of average waiting time for arbitrary data.

Control method / The case	Webster's formula (s)	Modified Webster's formula (s)	Adaptive fuzzy logic with Webster's formula (s)	Adaptive fuzzy logic with modified Webster's formula (s)	Adaptive fuzzy logic (s) based
Case 1	76.49	87.74	59.04	54.88	61.45
Case 2	42.90	42.06	45.29	44.41	44.57
Case 3	18.18	18.04	18.20	19.06	24.51
Combined case	80.77	66.78	40.83	44.39	46.96

In the first part, the results obtained from the arbitrary generated demands are represented. Table 10 illustrates the average waiting time for four different cases. In the most congested situation (case 1), the proposed adaptive fuzzy logic with Webster's optimal cycle formula-based adaptive algorithm shows better performance while the worst performance is obtained from the modified Webster-based fixed-time traffic control.

In medium and low congested situations (case 2 and case 3), all methods expose approximately the same performance excepting the adaptive fuzzy logic-based method that gave a slightly high average waiting time. Such results come from the fact that in those conditions, the traffic volume is fixed, thus the optimal cycle calculated by all methods has the same effect. In the combined case (combined from case 1, case 2, and case 3) that mimics the variation in traffic volumes can happen in real life. Since the traffic volume is not fixed in this case, the adaptive algorithms including adaptive fuzzy logic based over perform the fixed-time Webster's and modified Webster's methods. Among the adaptive methods, the proposed adaptive fuzzy logic with Webster's optimal cycle formula algorithm overperforms the other methods.

Tables 11 and 12 illustrate results obtained for the average travel time and average speed. These results reflect the similar performance of methods as in the results obtained from the average waiting time.

In the second part, the results obtained from real field-collected data are represented. Tables 13, 14, and 15 represent the average waiting time, average travel time, and average speed respectively. These results obtained from four approaches intersection and the comparison between proposed methods, fixed-time Webster's and modified Webster's formula-based methods, and adaptive fuzzy logic are performed.

In this situation, the proposed fuzzy logic with Webster's optimal cycle formula-based adaptive algorithm overperforms the other methods. These results reflect the similar performance of methods as in the results obtained from

TABLE 11. The comparison of adaptive and other methods in terms of average travel time for arbitrary data.

The case \ Control method	Webster's formula (s)	Modified Webster's formula (s)	Adaptive fuzzy logic with Webster's formula (s)	Adaptive fuzzy logic with modified Webster's formula (s)	Adaptive fuzzy logic based (s)
Case 1	113.86	129.03	91.34	96.27	100.26
Case 2	78.13	77.23	79.92	80.99	81.00
Case 3	52.35	51.89	53.50	52.46	58.53
Combined case	118.48	104.02	76.44	80.34	83.79

TABLE 12. The comparison of adaptive and other methods in terms of average speed for arbitrary data.

The case \ Control method	Webster's formula (km/h)	Modified Webster's formula (km/h)	Adaptive fuzzy logic with Webster's formula (km/h)	Adaptive fuzzy logic with modified Webster's formula (km/h)	Adaptive fuzzy logic based (km/h)
Case 1	17.26	14.86	16.84	16.47	14.97
Case 2	19.62	19.81	18.96	19.08	17.96
Case 3	24.89	25.19	24.63	25.04	23.43
Combined case	17.19	17.31	19.65	19.33	18.15

TABLE 13. The comparison of adaptive and other methods in terms of average waiting time for real field data.

The case \ Control method	Webster's formula (s)	Modified Webster's formula (s)	Adaptive fuzzy logic with Webster's formula (s)	Adaptive fuzzy logic with modified Webster's formula (s)	Adaptive fuzzy logic based (s)
Real field data	30.66	41.84	17.88 s	19.76	29.82

TABLE 14. The comparison of adaptive and other methods in terms of average travel time for real field data.

The case \ Control method	Webster's formula (s)	Modified Webster's formula (s)	Adaptive fuzzy logic with Webster's formula (s)	Adaptive fuzzy logic with modified Webster's formula (s)	Adaptive fuzzy logic based (s)
Real field data	66.05	78.06	53.46	55.96	65.85

the arbitrary generated demands. The fixed-time modified Webster's formula-based method exposes the worst result.

In the third part, the simulation performed using real field-collected data for three and five approaches intersections. The proposed methods compared with fixed-time Webster's and modified Webster's formula-based traffic control methods. Based on these results, the fuzzy logic with modified Webster's optimal cycle formula-based adaptive algorithm overperforms the other methods in terms

TABLE 15. The comparison of adaptive and other methods in terms of average speed for real field data.

The case \ Control method	Webster's formula (km/h)	Modified Webster's formula (km/h)	Adaptive fuzzy logic with Webster's formula (km/h)	Adaptive fuzzy logic with modified Webster's formula (km/h)	Adaptive fuzzy logic based (km/h)
Real field data	24.96	24.91	25.55	24.57	22.47

TABLE 16. The comparison of adaptive and fixed-time in terms of average waiting time for real field data.

The case \ Control method	Webster's formula (s)	Modified Webster's formula (s)	Adaptive fuzzy logic with Webster's formula (s)	Adaptive fuzzy logic with modified Webster's formula (s)
Three approaches intersection	10.65	10.98	8.60	7.02
Five approaches intersection	33.02	30.56	38.45	28.42

TABLE 17. The comparison of adaptive and fixed-time in terms of average travel time for real field data.

The case \ Control method	Webster's formula (s)	Modified Webster's formula (s)	Adaptive fuzzy logic with Webster's formula (s)	Adaptive fuzzy logic with modified Webster's formula (s)
Three approaches intersection	32.39	32.62	31.81	29.15
Five approaches intersection	64.61	61.22	73.60	61.16

TABLE 18. The comparison of adaptive and fixed-time in terms of average speed for real field data.

The case \ Control Method	Webster's formula (km/h)	Modified Webster's formula (km/h)	Adaptive fuzzy logic with Webster's formula (km/h)	Adaptive fuzzy logic with modified Webster's formula (km/h)
Three approaches intersection	31.55	31.46	29.43	31.91
Five approaches intersection	29.99	30.47	23.56	27.33

of the average waiting time, and average travel time as in Tables 16, and 17.

Table 18 illustrates the. Both Webster's, and modified Webster's optimal cycle formula-based adaptive algorithms present the low performance in terms of the average speed in the case of the five approaches intersection. Such results come from the fact that due to the increased number of phases as well as the proposed methods try to switches between phases relatively in short times comparing to the fixed-time methods, which caused repeatedly vehicles to stop before passing the intersection then reduce the average speed at the intersection.

X. CONCLUSION AND RECOMMENDATION

In this paper, the simulations of the two proposed adaptive traffic signal control algorithms, the adaptive fuzzy logic and the fixed-time Webster's and modified Webster's formula-based traffic signal control for the three different intersections have been provided. The simulations have been performed using the SUMO simulator based on the arbitrary generated demands as well as the real fields collected data. In the case of four approaches intersection, the two proposed adaptive traffic signal control algorithms have demonstrated a performance enhancement in terms of average waiting time, average travel time, and average speed as compared to other methods. However, it is pointed out that our proposed methods show the drawback in terms of the average speed in the case of five approaches intersection due to the switching cost of the five-phase intersection. Based on the obtained results, the proposed methods perform better, when the traffic demands are highly varying with time. The proposed adaptive fuzzy logic with Webster's formula is recommended due to its superior compared with modified Webster's formula based-method. Finally, our methods can be applied to real field isolated intersections to improve the intersection performance by extension to more complex scenarios through considering more calibration of data.

To enhance the performance of the proposed methods furthermore, we recommend that the tuning of the fuzzy logic memberships using a neural network or a genetic algorithm must perform.

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