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An Adaptive Method for an Isolated Intersection Under Mixed Traffic Conditions in Hanoi Based on ANFIS Using VISSIM-MATLAB

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ABSTRACT It is a new attempt to use an adaptive neuro-fuzzy inference system (ANFIS) as an adaptive traffic signal control method for an isolated intersection under mixed traffic conditions in Hanoi City, the capital of Vietnam. The proposed method using ANFIS can work more effectively as it gives full play to both an artificial neural network and a fuzzy logic system, hence can intelligently control the green time for each phase of the traffic signal lights according to the fluctuating traffic volume under mixed traffic conditions to improve the vehicular throughput and reduce delays. Taking a typical signalized intersection in Hanoi City as a case study is to evaluate the performance of the proposed method through a microscopic traffic simulator with an interface between VISSIM traffic simulation model and MATLAB. Simulation results of the proposed method using ANFIS indicate better performances and adaptability compared with the fixed-time control method and the fuzzy logic method.

INDEX TERMS ANFIS, mixed traffic conditions, VISSIM, MATLAB, isolated intersection.

I. INTRODUCTION

Along with the rapid expansion of the economy and speedy increase of the number of vehicles while the capacity of the road is limited in large cities in Vietnam, especially in Hanoi and Ho Chi Minh City where there have been many other problems such as disorderly urbanized city, traffic congestion, air pollution, etc. For examples in Hanoi, there were 41 locations which were congested and potentially congested in 2016. The average time of traffic congestion is from 45 minutes to 60 minutes per day. Losses due to the waste of time and increase in fuel costs were estimated about 22 trillion Vietnamese Dong (around US$ 1 billion) [1], [2]. One of the reasons leading to the above-mentioned traffic problems in the cities of Vietnam is that the traffic signal control system is not suitable. Almost signalized intersections in Hanoi, as well as other cities of Vietnam, are controlled by fixed-time traffic control systems with two or three phases. Moreover, the design specifications of traffic control systems are not detailed enough, traffic signal timing is often determined according to the personal experience of traffic engineers [1], [3].

Traffic signal control system is known as one of the most cost-effective measures to maintain the intersection capacity and ensure a smooth traffic flow, as well as to relieve traffic congestion and improve traffic conditions. Generally, traffic signal control at an isolated intersection can be divided into two main groups, including fixed-time control systems and intelligent traffic signal control systems. In fixed-time control systems, the phasing sequence is consistently fixed on a cycle time which is pre-set based on statistical traffic flow data during different periods of a day [4], [5]. They sometimes fail to deal efficiently with the high fluctuation rate of traffic demand and complex traffic conditions in real time, leading to the phenomenon of ‘‘lack’’ or ‘‘excess’’ of the green duration in a cycle time. Therefore, it is difficult to propose a stable fixed-time control system for traffic controlling with high fluctuation.

To overcome the shortcomings of fixed-time control systems which are not corresponding to the current traffic conditions, intelligent traffic signal control systems such as fuzzy logic systems (FLS), artificial neural networks (ANN), etc. have been developed in recent years. In traffic signal control

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systems, the useful information of traffic flow is collected by vehicle detectors to adjust the parameters of the traffic signal control system (e.g. phase sequence, cycle time, and green duration) in real time.

Fuzzy logic, which was first introduced by Zadeh [6], [7], has been developed widely to control traffic flow at intersections [8]–[11] because it allows describing and qualitatively modeling of complex systems with inherent uncertainties that are not easy to be solved using conventional mathematical models. In [11], a fuzzy logic with Webster and modified Webster formula was used to improve the average vehicular delay, the speed, and the travel time of vehicles at intersections, but only traffic flow with dominated cars. In [12], a fuzzy logic was used to calculate the green time of an isolated intersection with only two phases under mixed traffic conditions, but the parameters of membership functions are not optimized. Some scholars used the two-stage fuzzy logic method to improve the performance of traffic control systems [13]–[16]. The traffic signal control system using FLS has the advantage of expert reasoning and does not require an accurate mathematic model [17]. Besides, it also allows traffic flow more smoothly, a shorter waiting time of vehicles, and lower stopping percentages at an isolated intersection. However, the fuzzy rules and the membership functions of a traditional FLS are invariable. Therefore, one of the difficulties is how to define the appropriate rule base and membership functions to obtain the best efficiency.

Improving FLS using ANN is one of the research directions that has received much attention in recent years [17], [18]. A fuzzy neural network (FNN) or neuro-fuzzy system (NFS) with the combination of ANN and FLS is widely used to capture the advantages of both learning and computational power of the ANN and the high-level human-like thinking and reasoning of FLS, i.e., acquiring fuzzy rules and the membership functions based on the learning ability of ANN [19], [20]. ANFIS (adaptive neuro fuzzy inference system) proposed by Jang [21] is a kind of ANN that is based on Takagi-Sugeno fuzzy inference system. It used learning rules of ANN to identify and tune the parameters and the structure of FLS. ANFIS has been widely applied in many fields, such as classification, forecasting, traffic signal control, and so on. A few works have been done in the field of intelligent traffic signal control based on ANFIS. For example, Soh *et al.* [22] developed an ANFIS controller for multilane intersection using queuing theory in order to ease traffic congestions at traffic intersections. The average waiting time, queue length, and delay time of their system were the lowest as compared to the traditional and fuzzy systems. Araghi *et al.* [23] used ANFIS for optimizing green times and minimizing travel delay. The performance of their method is better when compared with three other methods, including the fuzzy logic-based genetic algorithm, the fixed FLS, and the fixed-time control system. Lai *et al.* [24] used fuzzy rules to generate sample data for ANFIS training. The performance of their ANFIS technique is better than FLS and traditional methods. Udofia *et al.* [25] proposed phase sequencing for a single intersection using ANFIS. Their system adaptively and effectively selects a phase to be given the next green signal after considering the traffic situation and the nature of the intersection. Seesara and Gadit [26] developed an ANFIS model using various traffic situations, and have been found that the average delay and the waiting time of the vehicles at the intersection have been reduced in comparison with FLS and fixed-time control systems. In addition to the ANFIS model, thanks to the development of intelligent traffic control systems in urban areas, some optimal models that consider connecting vehicle to vehicle and vehicle to infrastructure have conducted to improve traffic conditions at signalized intersections [27]–[30]. However, they are also limited with mixed traffic condition.

The majority of current literature shows that most of existing works evaluate the performance of intelligent traffic control systems such as FLS, ANFIS in real-time by microscopic simulators (e.g., VISSIM [10], SUMO [11], and PARAMICS [16]) with some performances indexes (e.g. average travel time, delay time, average number of stops, and queue length) under homogeneous traffic flow.

As literature mentioned above, most studies have developed ANFIS for solving traffic signal control problems effectively, but most of them are applied to homogeneous traffic conditions in car-dominant cities, and fewer researches on mixed traffic conditions with the lack of lane disciplines like Hanoi (Vietnam) where motorcycles are used frequently (around 80% in Hanoi [1], [31]). Hence, to fill the gap of adaptive traffic signal control systems for mixed traffic flow considering predominant motorcycles, the main objective of this study is to propose an adaptive signal control method using ANFIS for an isolated intersection with reference to the mixed traffic flow in such a city of developing countries like Hanoi (Vietnam). The performance of the proposed method is compared to the traditional Webster model and FLS through a microscopic traffic simulator with an interface between VISSIM and MATLAB.

The remainder of the paper is arranged as follows. Section II presents details of the proposed method. Numerical experiments are conducted in Section III, and Section IV ends the paper with conclusion.

II. MATERIALS AND METHODS

A. PROPOSED METHOD

In mixed traffic flow with predominant motorcycles in a city of developing counties like Hanoi (Vietnam), different vehicle types (e.g., cars, motorcycles, buses, trucks) share and compete together for the same road space at intersections due to the lack of lane disciplines. In comparison with four-wheel vehicles, motorcycle queue of mixed traffic flow at signalized intersections does not follow to the FIFO (first-in-first-out) principle which is generally understood that only a single vehicle, or an infinitesimal element of traffic, can enter or exit a cross-section of a standard lane at a given time. Motorcycle riders always attempt to creep slowly to the front of the queue during queue formation or queue discharge because a standard lane may contain up to three motorcycles or more [32]. Sub (virtual)-lane of motorcycle formed to guide motorcycles at intersections, as an illustration in Fig.1 [1], [33]. The queues of vehicles at intersections are based on optimum the utilization of the road space that means vehicles may occupy any position across the road based on the space available [34]. Therefore, the collection of the traffic parameters to control traffic flow must reflect the characteristics of mixed vehicles with a huge amount of motorcycles as above-mentioned analysis.

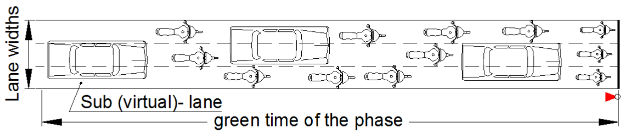

FIGURE 1. The mixed traffic model at traffic signals.

There are now the traffic parameters collected by detectors (e.g., Inductive loop, microwave radar, ultrasonic, and video image processing) which are used in the adaptive signal control systems, including the vehicle arrival, time-occupancy rate, area occupancy rate, queue length (in meters or number of vehicles), waiting time and so on. Of which, area occupancy rate (%) and queue length (in meters) are the most suitable parameters for the adaptive signal control systems under mixed traffic conditions. The queue length can be measured directly every second by video image processing. Hence, the maximum queue length (in meters) is selected as the first input data of the adaptive signal control systems of this paper. Besides, the vehicle arrival, which describes the number of vehicles on movements in the approach area of intersections, also is selected as the second input data. The vehicle arrival is converted to the passenger car unit (PCU) to deal with a mixed traffic flow of all types of vehicles (e.g., cars, motorcycles, buses, trucks).

Based on the selected input data, we present an adaptive control method using ANFIS model to adjust green duration at isolated intersection under mixed traffic conditions. ANFIS model of proposed method utilizes both ANN, which is a very fast process, and first-order Takagi - Sugeno model of FLS with the capability of human reasoning [35] to implement a demand responsive traffic signal control. In this paper, ANFIS is used to modify the rule base and adaptively learns to reach the optimal parameters for the membership functions (MFs) of dataset in fuzzy interface system (FIS) which is a key unit of FLS having decision making as its primary work. The structure of the proposed method as shown in Figure 2.

In the structure of the proposed method, the input data firstly is collected by the detectors which are installed in microscopic traffic simulator with an interface between VISSIM and MATLAB. And then, the input data is fed to a FIS module to determine phase urgency degree of the phases used to calculate the next green duration of the phases. Finally, the next green duration is given to the signal lights

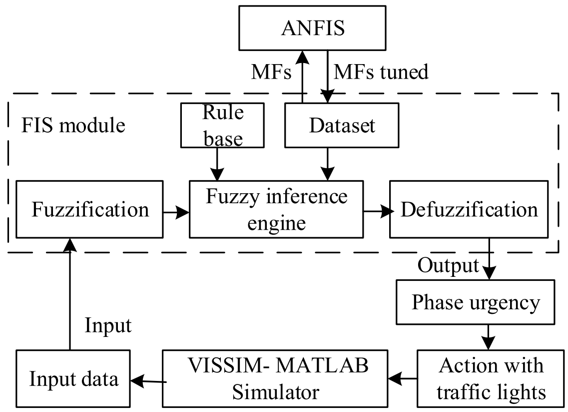

FIGURE 2. The structure of the proposed method using ANFIS.

to control traffic flow in the simulated environment using VISSIM and MATLAB.

The FIS module of proposed method is established based on the fuzzification unit, rule base, inference engine (i.e., decision-making module), and defuzzification unit (see Figure 2). The main functions of the units of FIS are as follows:

- Fuzzification unit converts the crisp quantities into fuzzy quantities.
- The rule base contains fuzzy rules of "IF-THEN" and is implemented by the inference mechanism.
- The dataset defines the MFs of fuzzy quantities used in fuzzy rules. The MFs are tuned by ANFIS model.
- The inference engine is a unit of transforming input data into output data.
- Defuzzification unit is an operator of converting the fuzzy quantities to crisp quantities using first-order Takagi-Sugeno model.

To implement the adaptive control method using ANFIS, we make some assumptions as follows:

- A typically isolated intersection of four approaches is considered with traffic arriving from north, west, east and south directions, and turning vehicles are considered.
- East-west direction is considered as the main road with heavy traffic moves.
- The traffic flow of intersections is controlled by 2 or 3 phases because this is the common form in Vietnam. The phase sequence in one cycle time is fixed.
- Input data is assumed to be given by detectors (e.g. video image processing) accurately.
- The intersection is assumed with low pedestrian traffic.

B. CREATION OF FIS MODULE

The proposed method has two inputs and one output. The input variables consist of the maximum queue length (QL) and vehicle arrival (V), which are collected from traffic detectors during the previous cycles, to determine the next green time required for the phases. Here, the queue length is defined as the distance in meters from the stop line over which vehicles are queuing. Then maximum queue length at the onset of green light time is the longest tail of queue irrespective of the lane of each phase in every time interval. It is an important parameter that reflects the performance of the mixed traffic flow in Hanoi City. The vehicle arrival is the total amount of vehicles on movements in the approach area of intersections corresponding to a phase. It reflects the traffic intensity of a phase, and is converted to passenger car unit corresponding to a standard lane and in one minute. The phase urgency degree (U) is used as the output data of FIS. It reflects the urgency of a phase as well as its green duration requirement.

Supposedly, for this work, the linguistic variables of input data are very short (VS), short (S), medium (M), long (L), and very long (VL) for maximum queue length (denoted by QL); similarly, very small (VS), small (S), medium (M), large (L), and extremely large (EL) for vehicle arrival (denoted by V).

The maximum queue length is in range of 0 to 150 m, and described by Gaussian fuzzy sets with a standard deviation of 6.67 (except for 12.88 of very short) and the constant of Gaussian MFs of very short (VS), short (S), medium (M), long (L), and very long (VL) are of 0m, 50m, 70m, 90m, and 110m, respectively (see Figure 3). Similarly, for the vehicle arrival (denoted by V) its range is from 0 to 50 and is described by Gaussian fuzzy sets with a standard deviation of 2.25 and the constant for Gaussian MFs of very short (VS), short (S), medium (M), long (L), and very long (VL) are 0, 7.5, 15, 22.5 and 30 pcu/min/ln, respectively (see Figure 4).

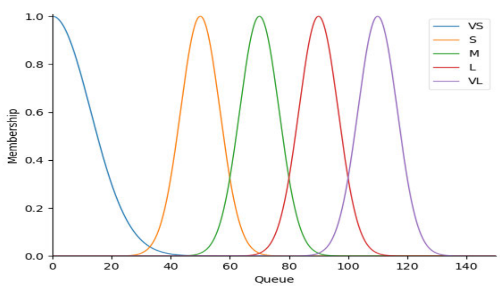

FIGURE 3. Preliminary MFs of maximum queue length.

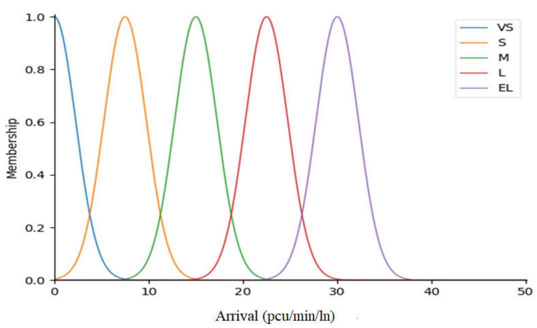

FIGURE 4. Preliminary MFs of vehicle arrival.

The linguistic variable of output data is also divided into 5 ranges, including very low (VL), low (L), medium (M), high (H), very high (VH). Their MFs is established based on Takagi-Sugeno FLS. A typical rule in the Takagi-Sugeno form as shown below:

$$R_j : \text{If } (x_1 \text{ is } A_{j1}) \quad \text{and } (x_2 \text{ is } A_{j2}) \\ \text{then } (f_{TSj} = p_{j1}x_1 + p_{j2}x_2 + p_{j0}) \tag{1}$$

where, R_j is j-th rule ($j = 1, 2, \ldots, m$); x_i ($i = 1, 2$) is the linguistic variable of input data, i.e., corresponding the linguistic variable of maximum queue length (QL) and the linguistic variable of vehicle arrival (V), respectively; A_{ji} is the fuzzy subset in corresponding input variable space; f_{TSj} is output variable deduced by Takagi-Sugeno FLS acted on the j-th rule; $p_{jk}(k = 0, 1, 2)$ is the linear parameter; m is number of the rules.

The values for both input variables of QL and V are assigned based on 25 fuzzy rules in Table 1 (i.e., $m = 25$). For example, if (V is "VS") and (QL is "VS") then (f_{TS} is "VL").

TABLE 1. Rule base.

Vehicle arrival (V)	Maximum queue length (QL)				
	VS	S	M	L	VL
VS	VL	VL	VL	L	L
S	VL	L	L	M	M
M	VL	L	M	M	H
L	L	M	M	H	VH
VL	L	M	H	VH	VH

The output of Takagi-Sugeno FLS can be computed by:

$$f_{TS} = \frac{\sum_{j=1}^{m} f_{TSj} w_j}{\sum_{j=1}^{m} w_j} \tag{2}$$

where, f_{TS} is the output of Takagi-Sugeno FLS; f_{TSj} is defined in Equation 1; w_j is the weight of j-th rule that can be calculated by:

$$w_j = \prod_{i=1}^{2} \mu_{A_{ji}}(x_i) \tag{3}$$

where, $\mu_{A_{ji}}(x_i)$ is the membership degree of x_i on the fuzzy subset A_{ji}.

C. PARAMETER ADJUSTMENT OF MEMBERSHIP FUNCTIONS IN FIS MODULE USING ANFIS

ANFIS model is an adaptive network that utilizes fuzzy reasoning based on Takagi-Sugeno FLS for decision making [21]. For simplicity, we assume that the examined ANFIS has two inputs and one output. The first-order Takagi-Sugeno fuzzy model with the following "IF-THEN" rules is taken into account:

$$\text{Rule 1 } (R_1) : \text{If } (x_1 \text{ is } A_1) \quad \text{and } (x_2 \text{ is } B_1) \\ \text{then } (f_1 = p_{11}x_1 + p_{12}x_2 + p_{10})$$
$$\text{Rule 2 } (R_2) : \text{If } (x_1 \text{ is } A_2) \quad \text{and } (x_2 \text{ is } B_2) \\ \text{then } (f_2 = p_{21}x_1 + p_{22}x_2 + p_{20})$$

where $[A_1, A_2]$ and $[B_1, B_2]$ are the MFs of each input x_1 and x_2, while p_{1k} and p_{2k} $(k = 0, 1, 2)$ are linear parameters for decision making calculation. As shown in Figure 5, ANFIS architecture has five layers which has function for each layer, as follows:

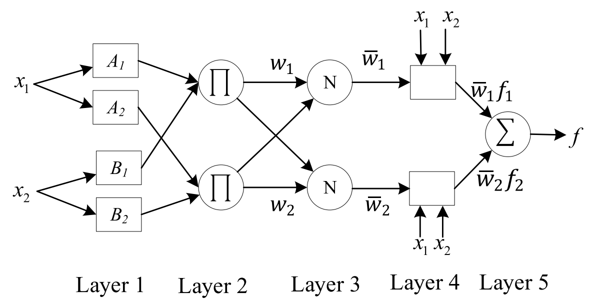

FIGURE 5. ANFIS architecture.

The first layer provides the mapping of the input variables x_1 and x_2 to membership function adaptively based ANFIS training. This transition is done using a membership function. The outputs of this layer ($O_i^{(1)}$) are the fuzzy membership degree of the inputs, which are given by:

$$\begin{cases} O_i^{(1)} = \mu_{A_i}(x_1), & i = 1, 2 \\ O_i^{(1)} = \mu_{B_{i-2}}(x_2), & i = 3, 4 \end{cases} \tag{4}$$

where $\mu_{A_i}(x_1)$ and $\mu_{B_{i-2}}(x_2)$ can adopt any fuzzy membership function. For instance, if the Gaussian function is employed, $\mu_{A_i}(x_i)$ is given by:

$$\mu_{A_i}(x_1) = \exp\left[-\frac{(x_1 - c_i)^2}{\sigma_i^2}\right], \quad i = 1, 2 \tag{5}$$

where c_i and σ_i are the variables of the MFs. As the values of these variables' changes, the Gaussian function varies accordingly, thus exhibiting various forms of membership functions on linguistic label. Variables in this layer are referred to as premise variables. The second layer contains multiplying function. Every node in this layer is a circle node labeled ($\prod$), whose output represents a firing strength from fuzzy conjunction of the input. The "AND" operator is applied to get one output that represents the results of the antecedent for a fuzzy rule. The node generates the output ($O_i^{(2)}$) by the multiplication of the input, and it can be represented as:

$$O_i^{(2)} = \mu_{A_i}(x_1) \times \mu_{B_i}(x_2), \quad i = 1, 2 \tag{6}$$

Every node in third layer is a circle node labeled (N), indicating that they play a normalization role to the firing strengths from second layer. The outputs of this layer ($O_i^{(3)}$) are called normalized firing strengths and can be represented as:

$$O_i^{(3)} = \bar{w}_i = \frac{w_i}{\sum_{i=1}^{2} w_i}, \quad i = 1, 2 \tag{7}$$

The fourth layer performs multiplication of the output from third layer using a function of Takagi-Sugeno fuzzy rule, as formulated by:

$$O_i^{(4)} = \bar{w}_i f_i = \bar{w}_i(p_{i2}x_1 + p_{i2}x_2 + p_{io}), \quad i = 1, 2 \tag{8}$$

All the calculation will be summed in fifth layer. There is only one single fixed node labeled (Σ), which computes the overall output by summing all incoming signals. The overall output of the model (f) is given by:

$$f = \sum \bar{w}_i f_i = \frac{\sum w_i f_i}{\sum w_i}, \quad i = 1, 2 \tag{9}$$

ANFIS functions by employing neural learning rules to classify and tune the membership functions of FIS. Tuning or training procedure for ANFIS is achieved based on batch learning technique using input-output training dataset which can be obtained from the local authority of transportation and real-time traffic condition of the field case studies or other proposed methods. In Vietnam, the dataset is difficult to obtain for traffic local authorities and the field. Besides, in this paper, there are no real-time traffic data for the training of the ANFIS model. Hence, in this paper, the dataset is generated from the fuzzy rules listed in Table 1 and tree diagram [22], [24]. This dataset consists of a total of 3750 input-output sample data. Each sample data has two inputs data which are maximum queue length (QL) and vehicle arrival (V), respectively, and one output data which is phase urgency degree (U). The values of the maximum queue length and the vehicle arrival are in the range of [0, 150] meters and [0, 50] pcu/min/ln, respectively. The fuzzy set of the output variable is in the range of [0, 1]. The sample data for the first fuzzy rule that is rule 1 in proposed method is obtained as shown by the tree diagram in Figure 6.

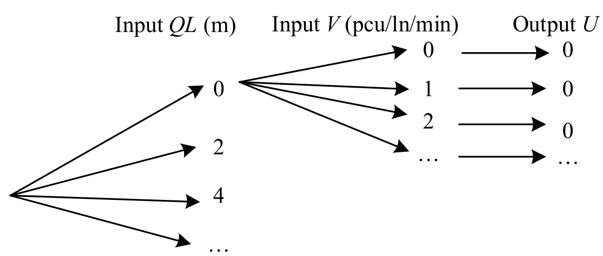

FIGURE 6. Tree diagram for training dataset.

The dataset is divided into three parts. In which, one part is fed to the ANFIS as the training set, accounting for 70% of the dataset. The second part is used as the checking set, accounting for 20% of the dataset, and the final part is used as a testing set, accounting for 10% of the dataset. The ANFIS is trained using the hybrid optimization method with an error tolerance of 0.02 and the epoch of 2500 through the "Neuro-fuzzy design" tool of MATLAB. By this method, the membership function parameters are trained to emulate the training data. ANFIS architecture trained is shown in Figure 7. The error of the training process is shown in Figure 8.

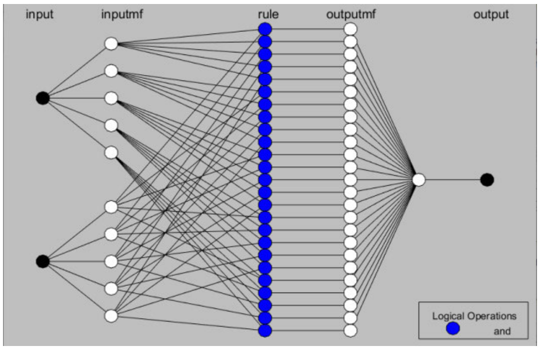

FIGURE 7. ANFIS architecture trained.

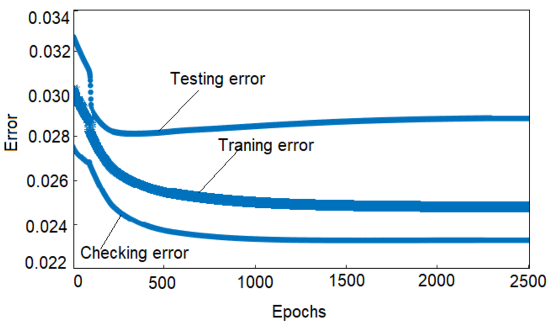

FIGURE 8. The error of training process.

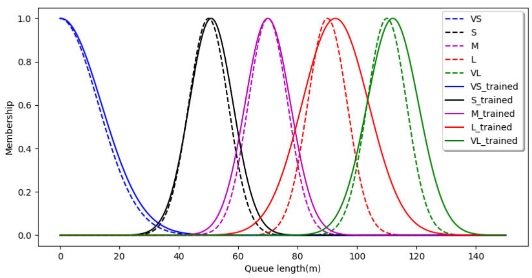

FIGURE 9. Membership functions trained of maximum queue length.

The results in the network training diagram in Figure 8 show that the training curve goes down, the checking curve has a downward direction, the special point is that these two curves are variable and are located relatively close to each other. The RMSEs (root mean squared errors) on the training sample, the checking sample and the test sample are 0.0248, 0.0233 and 0.0287, respectively, the difference between them is negligible. This shows that the dataset established is consistent with the research objectives. The results of the membership functions after adjustment are shown in Figure 9 and Figure 10.

D. DETERMINATION OF GREEN TIME

The output data of FIS module is phase urgency degree of the phases (U) used to calculate the next green duration of the phases. According to linear interpolation, we can get

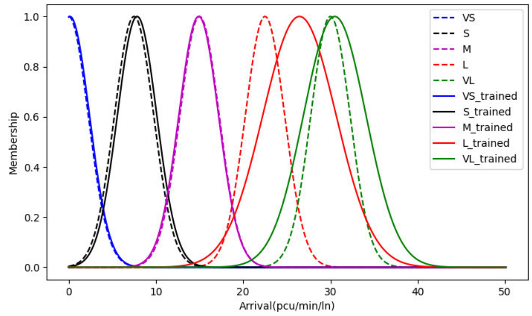

FIGURE 10. Membership functions trained of vehicle arrival.

the relationship among the green duration and minimum and maximum green time as follows:

$$g_i = g_{\min,i} + U_i(g_{\max,i} - g_{\min,i}) \tag{10}$$

where g_i is the green time of the i-th phase in the next cycle; $g_{\min,i}$, $g_{\max,i}$ are the minimum and the maximum green time of the i-th phase, respectively; U_i is the urgency degree of the i-th phase. According to the actual experiences, the green duration of an approach cannot be too short, for avoiding vehicles and pedestrians not passing intersection in time, and it also cannot be too long because it can make red time in other approach too long, annoying drivers in this approach. The minimum green time for each phase is 15.0 seconds [36]. The maximum green duration of each phase is determined by calculating the effective green time at fixed-time control system (i.e., Webster model [37]) in peak hour. The optimal cycle time for the Webster model are calculated based on Equation 11:

$$C_0 = \frac{1.5L + 5}{1 - \sum_{i=1}^{n} y_i} \tag{11}$$

where C_0 represents the optimal cycle time; L denotes the total intersection losses and y_i represents the critical flow ratio of the phase $i (i = 1, 2, \ldots, n)$, $y_i = \frac{q_i}{s_i}$, q_i is traffic volume of the critical lane in phase i(PCU/h); s_i is saturation flow of that critical lane (PCU/h), and the value of saturation flow (s_i) in this study obtains from [16].

The effective green times (g_{ei}) of the i-th phase which is calculated based on the Webster model as the maximum green time of the i-th phase, is distributed proportionally to the critical flow ratio of phase and determined using Equation 12. The optimal cycle time is the sum of all effective green times plus the total lost time. So, the total effective green time is the subtraction of the optimal cycle time and total lost time, then this time can be distributed for effective green time of the phases.

$$g_{ei} = \frac{(C_0 - L)y_i}{\sum_{i=1}^{n} y_i} \tag{12}$$

E. ESTABLISHMENT OF MICROSCOPIC SIMULATION USING VISSIM AND MATLAB

Due to the difficulty of measuring the performance of the proposed method in the field, we prefer to test the proposed method using a micro-simulation model using VISSIM and MATLAB. The interface diagram between VISSIM and MATLAB is as shown in Figure 11. VISSIM developed by PTV can simulate multimodal traffic flows using the psychophysical model of driver's behavior developed by Wiedemann, and consider each individual vehicle such as cars, buses, trucks, motorcycles, pedestrians, and bicycles [3], [38]. So far, some scholars have been calibrated VISSIM to match mixed traffic conditions [1], [39], [40]. Besides, VISSIM can connect to other tools such as MATLAB through a connection port to make intelligent controls, such as FLS, ANFIS, and so on.

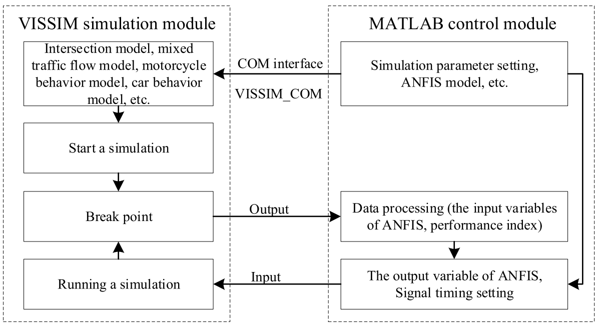

FIGURE 11. Framework of VISSIM-MATLAB simulator.

To simulate the proposed method and other methods under mixed traffic conditions using VISSIM-MATLAB simulator, the most parameters of motorcycle behavior are calibrated based on previous studies in the context of Vietnamese transport [1], [3], [39], [41], [42]. All parameters for the driving behavior of four-wheeler vehicles are taken as the default values in VISSIM. The vehicle speed is calibrated based on a field survey. All traffic simulations are performed for a 15-minute interval, excluding a warm-up period of 3 minutes to prevent initial loading effects.

Average travel delay (seconds per vehicle) is selected as the main performance index which is computed by using the data of vehicle trajectories obtained from simulation model. Besides, the average travel time, the maximum queue length, and the throughput also are used to test the proposed method.

F. IMPLEMENTATION STEPS OF PROPOSED METHOD

This study is conducted through the following steps:

- Establishment of the proposed method using ANFIS for mixed traffic flow is set up.
- Real traffic data is collected in the morning peak hour via video shooting and manual at an isolated intersection. Traffic data consist of traffic volume, maximum queue length in meter, travel time of vehicles, and vehicle speed. Traffic volume is determined by manual in the laboratory through replaying the video recorded in the field. Maximum queue length is determined manually in field. Travel time of vehicles is determined by two testing motorcycles. Vehicle speed in the approaches of an intersection has been collected using radar guns which is used to establish and calibrate simulation models in VISSIM-MATLAB environment.
- All vehicles have been converted to passenger car units to standardize the effect of vehicles on the intersection as well as to determine green duration based on the Webster model. The size differences within the cars themselves can be ignored, but the area covered by a bus or motorcycle at the intersection is very different from the cars. For this, each vehicle is considered to be a car corresponding to traffic conditions of Hanoi City. Minibus (less than 25 seats) are taken equivalent as the 2.0 cars. Bus (more than 25 seats) and truck are taken equivalent as the 2.5 cars. Bicycle is taken equivalent as the 0.20 cars, but a motorcycle is taken equivalent as the 0.15 cars [43].
- Finally, simulation and evaluation the performance of the proposed method for different scenarios using the VISSIM-MATLAB simulator are sequently provided.

III. SIMULATION EXPERIMENTS AND RESULTS DISCUSSION

A. INTERSECTION STATEMENT

In this section, we use the traffic flow data from Hanoi City, Vietnam, to evaluate our proposed model and compare the performance of our model with other models. Like other cities in Vietnam, Hanoi City is dealing with traffic problems characterized by mixed traffic flow including different categories of vehicles such as motorized and non-motorized vehicles with a wide variation in sizes. All the vehicles, including cars, buses, trucks, motorbikes, and bicycles, are grouped into different categories. For measuring the traffic volume, cars are selected as the reference vehicle. Area ratio is a criterion for finding the equivalent factor of the reference vehicle and the other vehicles.

A typically isolated intersection of four approaches, namely Ham Nghi - Nguyen Dong Chi (Coordinates: longitude = 21.035194, latitude = 105.763771) in Hanoi City has been selected as the research object to test the efficiency of the proposed method using ANFIS through series of computational experiments using VISSIM-MATLAB simulator. Ham Nghi (main road) axis running east-west direction is a six-lane road with a raised median of 3m. Nguyen Dong Chi (minor road) axis running north-south is a two-lane road without a raised median (see Figure 12).

Traffic volume is 8,559 vehicle movements during a peak hour in a working day (20th October 2020), including 2,006 cars, 6,318 motorcycles, 178 bicycles, 12 mini-buses, 19 buses, and 26 trucks. The proportion of motorcycles, cars, and other vehicles are 73.8%, 23.4%, and 2.8%, respectively. The number of PCUs converted is 3,126 units.

The 3-phase fixed-time signal control system with cycle time of 115s without all-red time. The first phase corresponds

FIGURE 12. The structure of isolated intersection understudy.

to a green duration of 60s for the straight direction of the east and west approaches. The second phase corresponds to a green duration of 19s for the north and south approaches. The third phase corresponds to a green duration of 24s for the left-turn movements of the east and west approaches. This signal timing is installed based on the personal experience of traffic engineers.

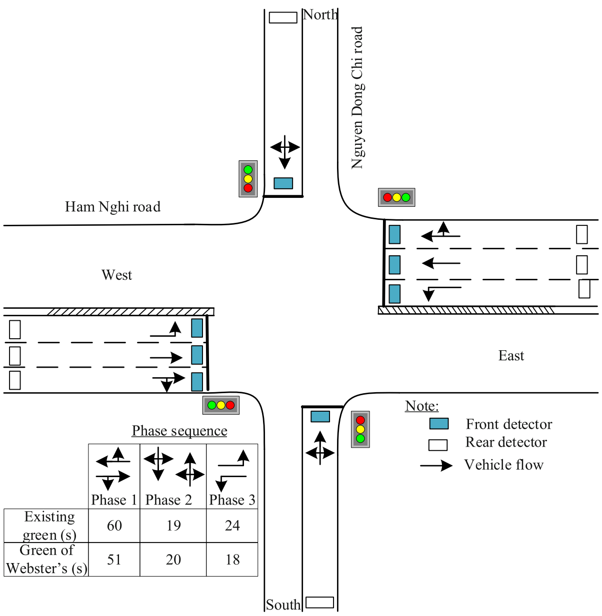

FIGURE 13. The geometry model and existing signal timing of the intersection.

After optimizing by the Webster model [37] (i.e., Equation 11 and Equation 12) with the yellow interval of 3 seconds and all-red interval of 2 seconds for each phase, the green time of phase 1, phase 2, and phase 3 are 51s, 20s, and 18s with a cycle time of 104s, respectively (see Figure 13).

The speed of vehicles entering the intersection is determined through speed guns for motorcycles (200 samples) and cars (200 samples). The average speed of motorcycles is 28.34 km/h (standard deviation of 5.89, maximum speed of 43 km/h). The average speed of cars is around 28.38 km/h (standard deviation of 6.41, maximum speed of 49 km/h). The maximum queue length of 90m is determined by observing 60 cycles. The mean travel time of 82.4s is determined by a total of 80 samples through two testing motorcycles.

B. SIMULATION RESULTS AND DISCUSSION

The simulation time used in the simulation is 900 seconds. Real traffic data which is formerly collected is used in the simulation to represent real traffic signal conditions. The traffic signal control interfaces with both traffic light system and traffic data through VISSIM micro-simulation is implemented on MATLAB, as shown in Figure 14.

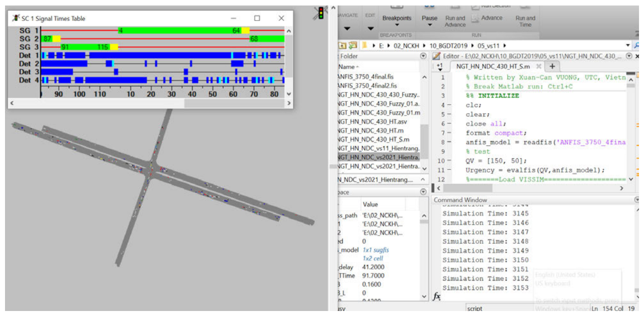

FIGURE 14. Snapshot of intersection simulation using VISSIM-MATLAB.

Simulation results with the existing signal scheme are shown in Table 2. From the results in Table 2, it is shown that the error between simulation and reality is less than 10%, which proves the appropriateness of the simulation models built on VISSIM-MATLAB, so we can use this model to perform the following analysis.

TABLE 2. Simulation results with the actual survey in existing signal scheme.

Parameter	Throughput (vehicles /15min)	Maximum queue length (m)	Mean travel time(s)
Actual survey	2140	90	82.4
Simulation	2090	96.6	88.5
Error (%)	2.3	7.3	7.4

A comprehensive test in the form of simulation is conducted to evaluate the ANFIS proposed model compared to other models, including fixed-time signal system (i.e., Webster model [37]), FLS of our previous study [12]. The comparison of simulation results in different models in peak hour are shown in Table 3, Table 4, Table 5, and Table 6.

Based on these results, the proposed method using ANFIS algorithm outperforms the other methods in terms of the average delay time, and average travel time as indicated in Tables 3, and 4. From the results in Table 5, maximum queue length of the proposed method is shorter than that of other methods. Similarly, the throughput of the proposed method also has a slight increase compared to other method as in Tables 6. Therefore, from the results in Table 3 to Table 6,

TABLE 3. The comparison of adaptive and other methods in terms of average delay.

Model	Average delay (s)	Improvement (%)
Existing scheme	40.6	-
Webster's	39.8	1.97
FLS	35.0	13.79
Our model (ANFIS)	30.4	25.12

TABLE 4. The comparison of adaptive and other methods in terms of average travel time.

Model	Average travel time (s)	Improvement (%)
Existing scheme	88.5	-
Webster's	86.4	2.37
FLS	82	7.34
Our model (ANFIS)	76.6	13.45

TABLE 5. The comparison of adaptive and other methods in terms of maximum queue length.

Model	Maximum queue length (m)	Improvement (%)
Existing scheme	96.6	-
Webster's	78.3	18.95
FLS [12]	76.4	20.87
Our model (ANFIS)	68.4	29.16

TABLE 6. The comparison of adaptive and other methods in terms of throughput.

Model	Throughput (vehicles/15min)	Improvement (%)
Existing scheme	2090	-
Webster's	2116	1.24
FLS	2119	1.39
Our model (ANFIS)	2121	1.48

it is shown that the performance indexes for our model are better than those of other models, i.e., our model has a better improvement.

In the proposed method, vehicle arrival is converted into the passenger car unit so that the research results from the homogeneous traffic flow can be consulted. However, the selection of conversion coefficients which is suitable for each vehicle type is still a big challenge, partly affecting the research models. The literature review shows that there are no uniform conversion coefficients between countries, even between cities in a country. Considering the change in the conversion coefficient of all vehicles affecting the

TABLE 7. The parameters of signal timing under different PCU coefficients.

Parameter	PCU coefficient of motorcycles			
	0.15 [43]	0.17 [44]	0.21 [44]	0.22 [45]
Optimal cycle time using Webster's (s)	104	117	161	179
Maximum green time of phase 1 (s)	51	58	83	92
Maximum green time of phase 2 (s)	20	23	33	38
Maximum green time of phase 3 (s)	18	21	30	34
Minimum green time (s)	15	15	15	15

TABLE 8. The performance of proposed method under different PCU coefficients.

Index	PCU coefficient of motorcycles			
	0.15 [43]	0.17 [44]	0.21 [44]	0.22 [45]
Average delay (s)	30.4	35.2	41.2	48.4
Average travel time (s)	76.6	81.0	87.9	94.6
Maximum queue length (m)	68.4	74.8	87.5	93.3
Throughput (vehicle/15 minutes)	2121	2121	2097	2067

research models will be very complicated and impractical for a mixed traffic flow depending on motorcycles mainly like in Hanoi. Here we instead attempt to investigate the influence of variation in PCU for motorcycles on the proposed method to find a more suitable coefficient of motorcycles while the coefficients of other vehicles remain the same as suggested in [43]. In the texture of Vietnam's transport, the PCU coefficient of motorcycles at intersections is in range of 0.15 to 0.22 [43]–[45]. Based on the PCU coefficients and Equation (11) and Equation (12), we can easily determine some signal timing parameters of proposed method, as shown in Table 7. The results in Table 7 show that when the PCU coefficient of the motorcycle increases, the cycle time as well as the green time of the phases also increase accordingly. According to the previous research results regarding the cycle time, it should not exceed 120s. Because if the cycle time is too high, the delay time will increase rapidly, meanwhile the throughput will increase very slowly, which adversely affect the efficiency of the traffic signal control system. Therefore, the PCU coefficients of the motorcycles of more than 0.17 are not appropriate in this study.

Besides, through running simulations in VISSIM-MATLAB environment with different PCU coefficients, we have achieved the performance indexes of proposed method, as shown in Table 8.

The results in Table 8 show that when the PCU coefficient of the motorcycle increased as well, the performance indexes increased. The average delay, average travel time, and maximum queue length of the traffic flow increased rapidly while the throughput increased very slowly, the efficiency of proposed method was reduced significantly.

At a PCU coefficient of less than 0.17, corresponding to cycle time of less than 120s, the performance indexes are relatively good and consistent with the actual operation of the intersection. A PCU coefficient of 0.15 gives the highest efficiency and this is also the value suggested in this study.

IV. CONCLUSION

In this paper, an adaptive method for implementation of the ANFIS model was suggested to make the traffic signal operations adaptive to mixed traffic conditions in Hanoi City, the capital of Vietnam. The ANFIS model was used to adjust the cycle time and signal timing at an intersection.

The ANFIS model regularly investigated the traffic condition to decide for a length of green time. Results obtained from the deployment of the ANFIS model in VISSIM-MATLAB simulator found that vehicle delays, average travel time and maximum queue length are reduced as compared to that of other models, such as Webster's and FLS.

The study is only at a stage of simulation for an isolated intersection and has not been tested in the field yet. Further studies can be conducted in this direction with real-time traffic data and multi-intersection to make better improvement.

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