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Research Article

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Traffic Signal Prediction Based on Anfis and Metaheuristic Algorithms Applied to a Vissim-Based Simulated Intersection

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Abstract

Traffic signs are among the most important traffic equipment that are used in urban and non-urban areas and their purpose is to increase road volume and reduce delays while ensuring safe movement. Over the years, due to the growing trend of car production and car use, which has increased urban and road traffic, traffic signs have increased and become more diverse and efficient. One of these traffic control methods at intersections is the use of traffic signal scheduling techniques, which despite the advantages of this method has a major drawback, and that is that due to the dynamic behavior of traffic, this method has issues in predicting traffic signal timing especially in times of peak traffic. Designing appropriate green times for traffic signal lights with Adaptive Neuro-Fuzzy Inference System (ANFIS) technique in traffic signal controller is a feasible solution to tackle this issue in urban network congestion during peak hours. The capability to learn from experience is one of the specifications of ANFIS that makes these techniques appropriate to mention genuine universe challenges. ANFIS Traffic Signal Controller is used to control the traffic density of an intersection so that it can reduce the queue length and latency to the minimum optimal time expected. ANFIS Traffic Controller is an intelligent controller with automatic learning sets the appropriate green time for each phase of the traffic light at the beginning of the phase, and the system generally depends on traffic information. The controller uses metaheuristic algorithms to tune ANFIS parameters during learning time. The first part of this article concerns the simulation of an isolated intersection in a VISSIM simulator, for the generation of the new phase distribution of it (optimum cycle). In the second part, ANFIS with metaheuristic algorithms is modelized and applied to the VISSIM simulated intersection. In the modelized system, for training and testing phases, 90 samples of newly generated data sets from VISSIM, and 40 others were considered respectively. By tuning the parameters using metaheuristic algorithms, we tried to increase the accuracy of the ANFIS network prediction to demonstrate the high performance of the ANFIS network in predicting and controlling traffic in intersections. The predicting system uses real-time data to predict the signal time. Results of the analysis demonstrated that our predictor system with ANFIS-GA indicates better predicts in comparison to ANFIS-PSO and ANFIS-HS. The predictor system presented a total and Relative Mean Square Error of 2.9619 and 8.4215 in the train set and 4.2209 and 11.8501 in the test respectively. The designed prediction model in the field of complex data showed an acceptable level of reliability and flexibility.

Keywords: ANFIS, Genetic algorithm, Optimization, Traffic Modeling

1. Introduction

Urban traffic experiences significant congestion problems at times and becomes one of the most critical adversities in developing countries which needs to be promoted to provide timely and effective service. Generating large amounts of greenhouse gases (CHG), increasing the number of accidents, and wasting time and energy in traffic queues are among the effects of traffic congestion's disadvantages [1]. The key strategy is to speed up the traffic flow by controlling traffic lights at the same time through adjusting and optimizing traffic lights in urban transportation networks. Therefore, well-aimed programming for a traffic light plan is an essential solution if the network capacity is to be increased and its performance improved in unsaturated situations. A simple method of controlling intersections is to determine the time of each traffic phase by using traffic signals. There are three types of traffic signal control systems. The first is the simple type of control that utilizes preset signal sequences and is called fixed-time or predefined. The efficiency of this method in determining preset signals has been presented in Robertson's research [2]. Signal periods regulate based on faced traffic status in the second type of control systems [3]. The split-cycle and offset optimization techniques [4] are well-known samples for the second type. The third type of control is fully compatible with sudden and unexpected changes, and all decisions are made dynamically [5]. RHODES is an example of this type [6]. As a result of growing demand, traditional methods of control will not be appropriate for controlling traffic congestion in newly developed and crowded urban networks [7].

Many impeccable pieces of research have been conducted in optimizing traffic light networks. According to Daganzo's theory the traffic situation and the outcome in network operating corruption can be significantly affected by the network when it is overloaded, even with a subtle expansion extra to the required amount of the input value. Network interference can be avoided by monitoring the flow entering amount in such changeable situations. A mathematical plan performed by Chiou, found the ideal charge specified for signal-controlled intersections in networks of city traffic where redirecting traffic is regarded [8,9]. Another research study to optimize traffic light was conducted by using "Ant Colony" method and the variables like delay time, stops and network capacity [10].

A microscopic analysis was used by Radhakrishnan and Mathew to enhance a congestion flow model which is related to dynamic passenger car units [11]. The study of Cantarella and his colleagues proves thet since the progress is not related to time therfore, the optimization signal timings under the equilibrium hypothesis may not assure an effective solution [12]. Varia and his group applied a genetic system for solving the optimization issue related to traffic light control together with the dynamic flow in congested networks [13].Gangi et al. proposed the maximization system method based on the optimization of single intersections (green timings) and network coordination [14]. Khodayari and his co-workers suggested a modified ANFIS model to resemble and predict the car-following behavior that establishes the feedback delay of the driver-vehicle systemThe outcome of the simulation indicates that the proposed model has high versatility with real-world data and returns the status of the traffic flow in a more adequate way [15]. The result of a study by Marciano et al. İndicates that signal setting optimization leads to significant decrease in general delays on the network and emptying times [16]. Chang and Lieberman worked on an optimized model and the results shosed that case it can be made for a possible use about a mixed-integer linear programming MILP algorithm. [17]. In another research which has been done by Leclercq et al. at 2014 the only method to have no bias in MFD is a wide knowledge regarding vehicle trajectories [18]. Afandizadeh Zargari et al. [19] proposed a metering-based way of solving signal control programs in city area networks. They recommended a model that was used to actual networks with a factual scenario in Tehran based on pure information. An improved method was shown by [20] based on the internal-external metering strategy (IETMS). Their outcome pointed out that by using the IETMS model, the average speed is 14 percent and the average delay is 19 percent of progress. The result of the simulation indicated that the best estimates were achieved with the use of multi-layer perceptron architecture which includes the best performance with a total Mean Square Error of 0.00927 in the training step and 0.01321 in the test step. By searching through these studies, the importance, superiority, and efficiency of artificial intelligence techniques (AI) in controlling traffic congestion, which is capable of thinking like humans, are more visible [21]. Many pieces of research have been conducted to use artificial intelligence techniques to enhance the efficiency of control and prediction [22,23]. Computationally intelligent methods are self-learning and react to dynamic shifts of pressure and situations. The combination of AI was proposed for implementing a cooperative multi-agent system for controlling a large-scale traffic control by Choy [24].

Fuzzy logic systems play an important role in transportation and traffic control (FLS). The concept of fuzzy logic was first introduced by Zadeh who suggested the possibility of forming logical theories for calculating ambiguity in mental judgments [25]. The utilization of a fuzzy logic controller (FLC) for an isolated intersection with two one-way links was performed by Pappis and Mamdani [26] Also, FLS has been used by many scholars to control a single intersection with two-way streets [27]. Jarkko [28] introduced a regular method for fuzzy traffic signal control based on expert knowledge. The results of his tests indicated that this system has better efficiency rather than the traditional vehicle-actuated control [29]. designed a neural network plan to predict daily traffic flow, after which the predicted traffic flow was compared with the real information collected by the traffic control body of Morocco. Many studies have been done in the traffic controlling field at isolated intersections using fuzzy logic controllers, and the ability and capability of these controllers have clearly been illustrated in normal and unpredictable situations to overcome traffic congestion at intersections [30] In recent years, many researchers have used the adaptive neuro-fuzzy network ANFIS presented by Jang to approximate problems and solve nonlinear functions in modeling their complex systems [31,32].

Right after the volume count is finalized, the peak hour standard is obtained. The high volume of vehicles in certain hours in the morning and around noon and the afternoon (the oversaturated situations) determines how the peak hour is going to be. The traffic lights' timetable program will be maximized in entering connections. This simulation in VISSIM is done based on maximizing the arterials' traffic flow which goes to the sub-network. It keeps queue length close to its optimal value and obtains optimal green time with minimum oscillations through cycles. The rate of congestion in the protected area stays below the critical value in such a situation. The ANFIS structure tries to be close to reality and therefore uses three observed peak times and VISSIM'S output (the data set of queue length and delay from VISSIM simulator) as inputs, and green signal time as an output for its structure.

There are three algorithms proposed in this research, that are compared to each other firstly the genetic algorithm (GA), secondly harmony search (Hs) and thirdly swarm optimization (PSO).The performance of the proposed algorithm with the genetic algorithm (GA), harmony search (Hs) and particle swarm optimization (PSO) has been compared. The appealing features of ANFIS are its quick and accurate learning, simplicity in being applied, perfect clarification through fuzzy rules, and its easy association with both numeric and linguistic values for increasing problem-solving abilities. There is no need to redefine the rule base because ANFIS finds its optimal parameters through training. Research carried out in the literature review related to the proposed area of this paper shows that despite the comprehensive studies on monitoring traffic lights in networks, there is no proposed model of a VISSIM simulator with ANFIS and metaheuristic algorithms in terms of predicting green signal time with real data in our study area. The general schematic of this study is indicated in Fig 1.

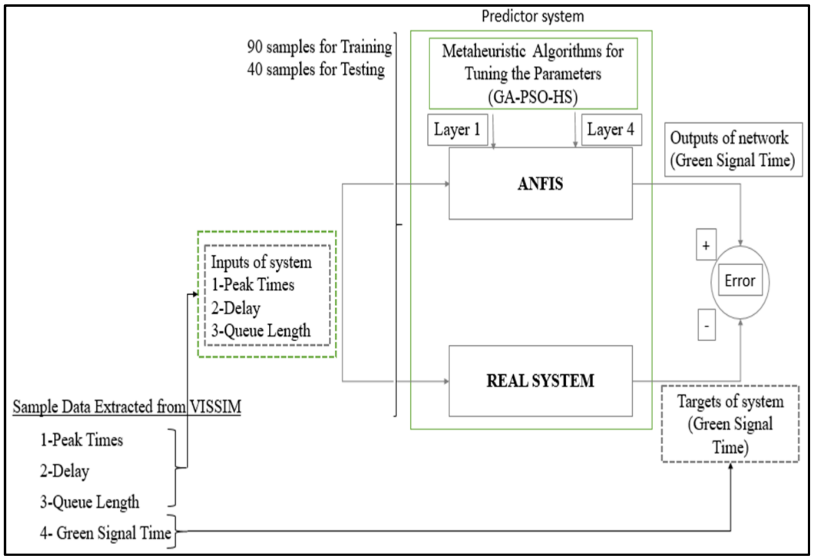


Figure 1: The General Schematic of Study

1.2. Study Area

By using datasets from our study area, (Figure 2) the queue length, the total number of vehicles passing through intersection arms during peak hours (by using the length of the vehicles), the maximum number of the cars can pass on each cycle (by using lines) delay and green signal time for the intersection was counted and calculated then the current status of the intersection was observed. Since the queue length on the intersection arms remains in each phase, there is a necessity for designing a new phase distribution. To improve the current state of the intersection and achieve the optimum amount of queue length, delay, and green time, we will model the intersection in the VISSIM space.

Figure 2: Signalized Intersection in İstanbul (study area)

2. Methodology

2.1. Simulation and Evaluation on VISSIM

In different countries, vehicle- or traffic-operated signal control policies are well documented in design manuals. However, the effectiveness of different strategies cannot be assessed in actual testing sites. Strategies have a wide variety, and setting standards of every single strategy cannot be tested in field trials due to the big number of possibilities, limitations of the present controllers, legal limitations, and consumer approvals. Simulation has proven to be a worthy tool in case of such limitations. For economic as well as environmental reasons, the signal control should be in optimal condition within a presented political framework. Tools are applied to assess the quality of vehicle-operated signal control. There is no explanatory formula to be used for this detailed assessment due to the stochastic features of traffic. Single vehicles are organized by sophisticated traffic control strategies. Examples of such programs are bus/tram priority programs. These variations in entry times cannot be modeled correctly enough by entirely analytical techniques. VISSIM is an innovative simulation tool for traffic-operated control system plans and is regarded as a total-goal, computer-based traffic simulation system. VISSIM models have great features and a high level of indicating details of links, junctions, and "small" networks. [33-35].

In this study, Figure (3-4) shows the optimum phase distribution, optimum green time, and movements designed in VISSIM for an intersection. The simulation was modeled in VISSIM, and the optimum cycle time for the Morning was 75 S, for Noon 60 S, and for Afternoon 75 S which have been calculated and presented in Fig 5. In our work, to assess the model and provide that more desirable results which are obtained in the model (after simulation), it was compared with the network's current status (before simulation). Table.1 shows better performance of the simulated model in 3 peak time hours during 1 hour of simulation (08:00-09:00, 12:00-13:00, and 16:00-17:00). Performance of the intersection before and after stimulation were compared. The results of the simulation show improvement in terms of queue length and delay by using optimal green signal time in the simulation.

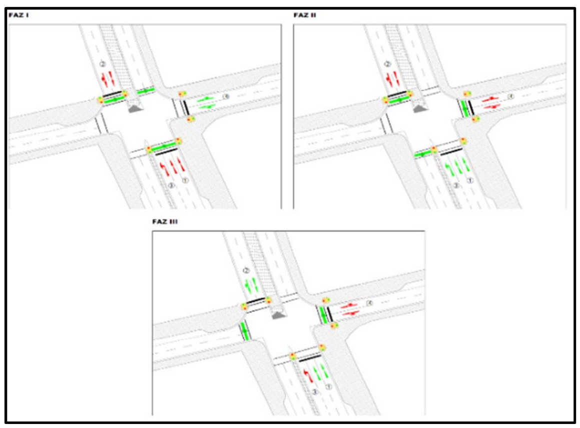


Figure 3: Phase Distribution Designed in VISSIM

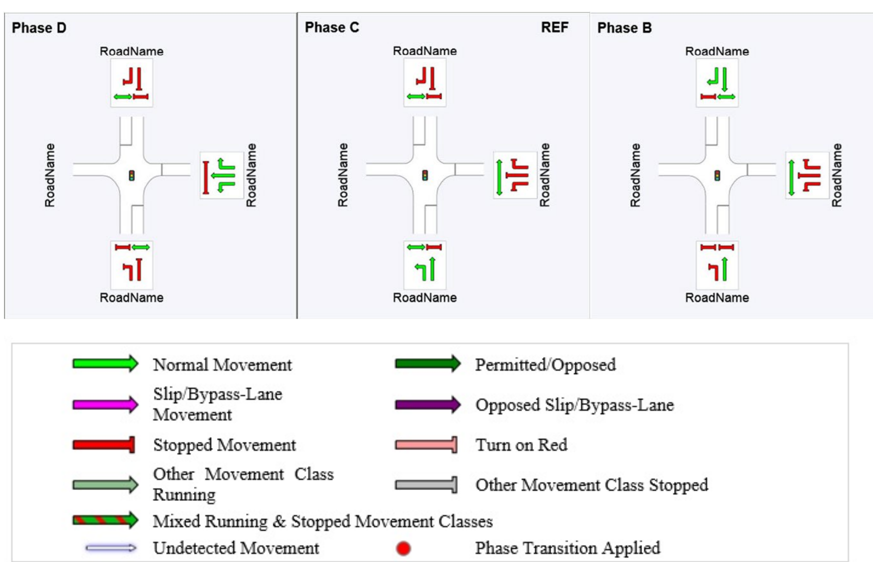
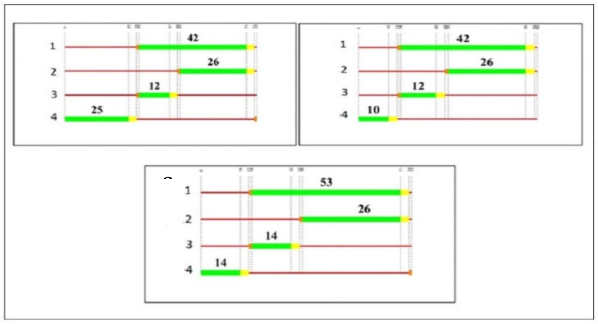


Figure 4: Phase Distribution and Movements



1.

Figure 5: New Phase Distribution Simulated by VISSIM for the a) Morning, b) Noon, and c) Afternoon

The Total Comparison	***Morning (8:00-9:00)***		***Noon (12:00-13:00)***		***Afternoon (16:00-17:00)***	
	Before	*After*	*Before*	*After*	*Before*	*After*
Delay	*18.09*	*10.61*	*18.09*	*9.74*	*20.21*	*9.42*
Queue length	*47.84*	*36.30*	*58*	*39.20*	*59.36*	*41.97*

Table 1: Comparison of Total Delay and Queue Length Before and After Simulation in VISSIM

2.2. Designed ANFIS Structure

Both Neural Networks (NN) and Fuzzy Logic (FL) are utilized in ANFIS architecture [36]. The network structure of ANFIS includes two sections, namely the premise and consequence parts. Layer one is the premise, and layer four is the consequence; they are considered as decision parameters for metaheuristic algorithms (GA, PSO, and HS). There are two steps in ANFIS. The first step is training %80 of the data set and includes input and target values. The decision-making parameters of this network are tuned with metaheuristic algorithms. The optimum amount of (peak time, queue length, delay) and green signal time amounts extracted from the simulated intersection in the VISSIM environment are considered as input and output of ANFIS respectively. The second step is testing %20 of the data set. It is initialized with input values (peak time, queue length, delay), and the green signal time, or output, is predicted based on the input [30]. The ANFIS system is included in five layers, as seen in Figure 6. In this figure, the ANFIS structure has 3 inputs. For the first input (peak time), we considered three membership functions, namely Morning, Noon, and Afternoon. For the second input (queue length), we considered five membership functions: VS (very small), S (small), M (medium), L (large), and VL (very large); and finally, for the last input (delay), we considered the three membership functions S (small), M (medium) and L (large). There are two ranges of membership functions, namely lower bound and upper bound. By considering 11 membership functions with two ranges, we have a total of 22 decision variables of individuals (called chromosome vectors) in the first layer. The range of each membership function is illustrated in Figure 9. Through multiplying membership functions by each other (3×5×3) we have a total of 45 rules symbolizing 45 linear equations. Each linear equation consists of 4 parameters. Thus, we have a total of 180 decision variables of an individual (4×45) in the fourth layer. In this structure, we have a total of 202 decision variable parameters tuned by metaheuristic algorithms.

The layer structure of ANFIS, according to the ANFIS structure given in Figure 6, is described as follows. As is mentioned, the ANFIS structure presented in the figure has five layers. The first and fourth layers comprise an adaptive node, while the other layers comprise a fixed node. The ANFIS first order SUGENO-Type FIS has a total of five layers:

First rule: If (x is A_1) and (y is B_1), then ($f_1(x)=P_1 x+q_1 y+r_1$).
Second rule: If (x is A_2) and (y is B_2), then ($f_2(x)=P_2 x+q_2 y+r_2$).

Where A_1, A_2, and B_1, B_2 are the membership function of each x and y input (part of the functions), and p_1, q_1, r_1 and p_2, q_2, r_2, are the part of the linear parameters of the Takagi – SUGENO fuzzy inference model (last part).

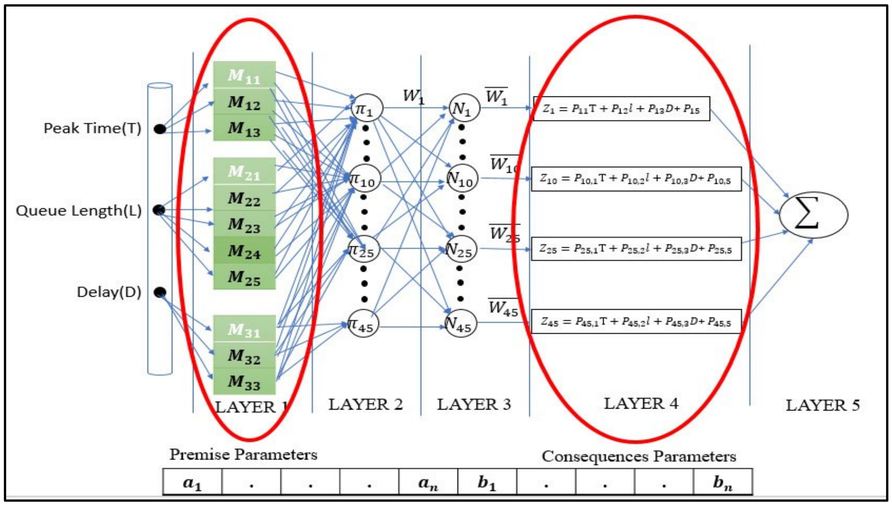


Figure 6: the ANFIS Structure that Has Three Inputs and One Output

There are some nodes in first layer in figure 6 and each node is related to a parameter in funcion. And the output from it is a degree of the membership value given by the entry of membership functions. An explanation of the first layer has been provided below.

$$O_{1,i} = \mu A_i (x), \quad i = 1,2 \tag{1}$$

$$O_{1,i} = \mu B_i (y), \quad i=3,4 \tag{2}$$

μAi and μBi are the degrees of membership functions for sets Ai and Bi, respectively, and {ai, ci} are parameters of the membership function that can change the shape of the membership function. The parameters in this layer are typically referred to as precursor parameters.

The second layer is called the rule layer. In this layer, the Gaussian function is the node function. μ Ai (x) and μ Bi (x) are usually selected as Gaussian functions and are given in the following equation. The firing power for each rule (wi) value is found by multiplying the membership values as follows.

$$\mu\, x_i (T)=\exp \left[-\left(\frac{x-ci}{2ai}\right)^2\right] \tag{3}$$

$$O_{2,i} = w_1 = \mu A_i (x) \times \mu B_i (x), \quad i=1,2 \tag{4}$$

Where ai and ci are the standard deviation and center parameters of the membership function, respectively. The output for per node in the layer is in the range [0-1] implying the degree of membership of the input by the membership. These parameters will be modified during backpropagation.

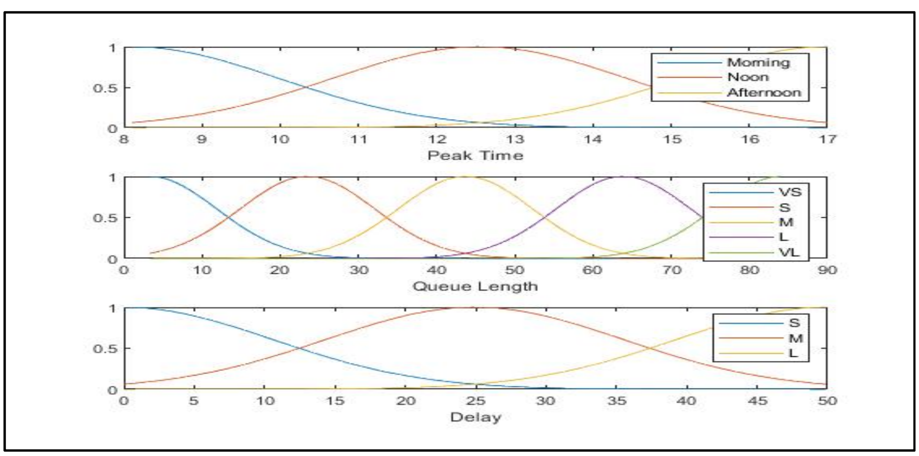


Figure 7: Membership Functions of Inputs

The third layer is called the normalization layer. Each node in this layer is either fixed or non-adaptive, and the circle node is labeled N. Each node is the ratio between the firing rules and the sum of the firing powers of all rules. This result is known as normalized firing power.

$$O_{3,i} = \bar{w}_1 = \frac{w1}{w1+w2}, \; i=1,2 \tag{4}$$

The output of the standardization layer is $\bar{wi}$, which is called the defuzzification layer. Weighted values of rules are calculated in each node of the fourth layer as given in (5). This value is determined by using first order polynomial.

$$O_{4,i} = \bar{w}_i f_i = \bar{w}_i(P_i x + q_i y + r_i), \; i=1,2 \tag{5}$$

Where $\bar{wi}$ is the normalized firing power from the previous layer (third layer) and a parameter in the node (P_i x+$q_i y$+r_i). The parameters in this layer are called the resulting parameters.

The fifth layer is called the output layer. In this layer, the output of the neurons of the previous stage are added together, and finally, through defuzzification, the fuzzy outputs are converted into numerical outputs. There is only one neuron in this layer.

$$O_{5,i} = \sum_{i=1}^{2} \bar{\omega}i\, fi = \frac{\sum_{i=1}^{2} wi\, fi}{w1+w2} \tag{6}$$

3. ANFIS Training

3.1. ANFIS Training Approaches

ANFIS training means establishing the related standards in a system while applying an optimization algorithm. Prosperous training plays a crucial role in gaining efficient outcomes with ANFIS, thus for the improvement of ANFIS, toachieve the best performance various methods is evaluated, which consists of three main part, firstly derivative-based, secondly heuristic-based, and a hybrid of the two as third part. When derivative-based optimization algorithms are applied in ANFIS training, the risk of local minimum may arise. Thus, metaheuristic algorithms are used extensively in ANFIS training. A survey in the literature reveals that all parts of ANFIS, or a related portion of it, are trained by metaheuristic algorithms. For ANFIS training, metaheuristic algorithms are applied. The amount of metaheuristic algorithms used in ANFIS training has increased rapidly in recent years. The metaheuristic algorithms are GA, PSO, HS, ABC, DE, CS, FA, SA, MBA, and HS. The parameters which are related to input membership functions are [ai, ci]. Which are known as premise parameters. [pi, qi, rí] are modifiable parameters and are related to the first-order multinomial. These parameters are called consequent parameters. There are two steps in ANFIS. The first step is training %80 of the data set, which includes input and target values, and tunes decision parameters with metaheuristic algorithms. The simulated (peak time, queue length, delay) and green signal time amounts extracted from isolated intersections in VISSIM environments are considered as inputs and output of ANFIS respectively. The second step is testing %20 of the data set which is initialized as input value (peak time, queue length, and delay) and green signal time is predicted. The parameters of the premise and consequence are tuned and analyzed by applying the Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Harmony Search (HS) optimization methods. The mentioned algorithms attempt to find the best parameters for the ANFIS. The Process of integrating metaheuristic algorithms to achieve the best parameters is shown in Figure 8 the iteration steps of each algorithm are shown separately in their respective sections

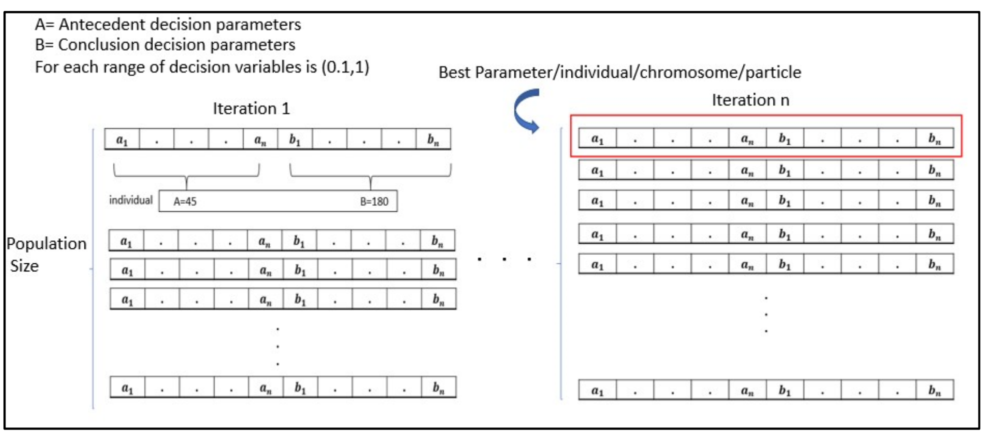


Figure 8: General Relationship between ANFIS and Metaheuristic Algorithm

The relative error is the difference between the estimation value (output from ANFIS) and its actual value (target value), normalized to the actual value. Absolute error is the difference between the output of ANFIS structure and a target value and is evaluated by calculating standard deviation Sd (σ), MSE, and RMSE error functions. Errors can be calculated as follows:

$$SD=\sqrt{\frac{\sum(x-\bar{x})^2}{n-1}} \quad (7)$$

$$MSE=\frac{1}{N}\sum_i^n(\mathrm{fi}-\mathrm{yi})^2 \quad (8)$$

$$RMSE=\sqrt{\frac{1}{N}\sum_i^n(\mathrm{fi}-\mathrm{yi})^2} \quad (9)$$

Where x is individual observation, $\bar{x}$ is an average amount, and n is the number of observations. In equations 8 & 9, N is the number of data points, f_i is the value returned by the ANFIS, and Y_i is the target value for data point I. These heuristic algorithms are used to minimize the mean square error MSE and relative mean square error RMSE.

3.2. ANFIS Training Based on GA

The search and optimization abilities of genetic algorithms (GA) are based on Darwin's natural selection and theory of evolution [36]. GAs are one of the most popular optimization algorithms which can be used to maximize or minimize a specific function to obtain the optimal responses of computational models. Genetic algorithms illustrate an evolutionary computation branch in which they mimic biological and natural selection to find suitable solutions. Evolutionary algorithms use natural evolutionary principles such as mutation, crossover, and selection to get better answers from the actual population of solutions. GA continues this process until it reaches the optimal parameters for the controller [37,50]. In this paper, GA tried to reduce the peak time, queue length, and delay parameters to obtain optimal green signal timing. The number of chromosomes will illustrate the signal timing corresponding to the peak time, queue length, and delays. The mentioned signal timings are obtained by using neural network capabilities. The set of chromosomes chosen at the beginning behave as parent chromosomes. The timetable, queue length, and delays are altered by a value of 0.1 randomly in child chromosomes. The minimum amount of signal timing is obtained from parent chromosomes. If the signal timing obtained from the set of parent chromosomes is less than the child chromosome set, the chromosome will be transmitted to the next generation; otherwise, the chromosome is retrained [39].

The process continues for 10 iterations with 1000 function evaluation numbers (error functions). So the minimum amount of green signal timing is obtained by the chromosome (decision variable) which is related to the parameters of layer 1 (premise) and layer 4 (consequence) of ANFIS.

3.3. ANFIS Training Based on PSO

Collective intelligence is a organized property in which the agents collaborate locally. The allocation of collective behavior of all agents leads to meeting at a point close to the optimal global solution. The advantage of this algorithm is its lack of need for global control. Two well-known algorithms of collective intelligence are the Ant's Nest and the PSO. Both of these algorithms can be used to train neural networks. The common behavior of PSO and evolutionary algorithms is the tendency of both algorithm types to use a population of solutions or agents to achieve the best solution (Guntsch & Middendorf 2015) In 1995, Kennedy and Eberhart first presented the PSO as an indeterminate search method for function optimization. This algorithm was inspired by the flock movements of birds seeking food [40]. A flock of birds randomly looks for food in the environment. There is only one piece of food in the search area. Each solution in the search space is called a particle. Also, each particle in the search area has an ideal value called the objective function. The distance of the particle from its target is the criterion of the particle merit in the search space. Assuming that a search space consists of d dimensions and n particles that i_{th} particle at a position X_i (X_i1, X_i2, …, X_id) with a velocity V_i (V_i1, V_i2, …, V_id), each particle includes own best particle, P_i (P_i1, P_i2, …, P_id) which indicates best performance in the swarm. A total best performance of a particle concerning the swarm outlined global best is g_{best}. Each particle attempts to amend its position using current positions, current velocities, and distances between the current position and g_{best}. Particle motion is controlled by updating its velocity and position characteristics [42]. In this paper, the PSO algorithm attempts to adjust swarm behavior by exploring the decision variable related to the parameters of layer 1 (premise) and layer 4 (consequence) of ANFIS. Specific parameters of PSO through training are mentioned in Table 2.

$$v_i^{t+1}=wv_i^t+c_1v_1(x_{best}-x_i^t)+c_2v_2(x_{gbest}-x_i^t) \quad (11)$$

$$x_i^{t+1}=x_i^t+v_i^{t+1} \quad (12)$$

In which the parameters are as below;

w; interior weight

c_1; cognitive acceleration coefficient

c_2; social acceleration coefficient

r_1 and r_2 ;random values between [0,1]

x_{best}; personal best of the particle

g_{best}; global best of the particle

X_i^t ; current position of the i^{th} particle at iteration t

V_i^t ; velocity of the i^{th} particle at iteration t.

3.4. ANFIS Training Based on HS

One of the well-known metaheuristic algorithms is the Harmony

Search optimization algorithm. The recently-developed population-based HS optimization algorithm is expanded by a musical improvisation process that is based on a search for better harmony. HS algorithm emerged from Zong Woo Gem's Ph.D. thesis [43]. Furthermore, the HS was developed by [44]. Despite the algorithm that was newly presented, it was already known from the first publication [43]. The performance of the HS algorithm is largely affected by harmony memory size (HMS), harmony memory consideration rate (HMCR), and pitch adjusting rate (PAR). Other parameters such as a maximum number of improvisations and bandwidth vector (bw) have been used in pitch adjustment for implementing the algorithm [45].

By considering all these parameters, the convergence of the basic HS algorithm was argued by Geem and his colleagues as obtained from the results of the research of [43, 47 ,45 and 49]. In the other study, proposed a modified firefly algorithm that is suitable for a combination of ANFIS with GA, PSO, and HS [50].

4. Results and Discussion

In the beginning, an assessment of the prior studies in this area is reported as a literature review. Various techniques are offered in this field and in general, can be divided into 3 categories. The first category is fixed-time controllers, which are not dependent on traffic fluctuate and compute signal times via ancient data. The subsequent category is operated controllers, where signal controlling is executed with the assistance of sensors stationed in parts close to stopping lines and the running traffic request determinants transit times. Adaptive signal timing is the ultimate category with more workability to suit signal times depend on traffic changes. About utilizing intelligent techniques, previously almost all mentioned AI techniques have disclosed their advantages in various aspects and applications, especially in traffic signal timing against traditional controllers. A general evaluation of researches in traditional traffic signal timing and VISSIM-based is compared, also results of computational intelligence methods for predicting the optimum signal time for a single intersection are investigated. Giving consideration to prior studies and using a combination of encouraging AI methods and novel optimization techniques makes it possible to design efficient controller for traffic signal timing. This study contributes to expanding traffic signal timing controllers aiming to reduce expected and predicted error values at the intersection. Modeling an isolated intersection network with 3 phases in VISSIM. Moreover, considering various traffic scenarios for the network to test the accuracy and reliability of the designed controller before and after modeling is illustrated in Table.1. These results are following the findings of who have explained the significant negative effects of fix-time methods. The traffic volume will fluctuate over time, so, designing the green time at the beginning of a phase for the present phase can be more compatible with the present traffic situation [51-56]. During the test process, Our results also support that designing a phase-based controller can be more accurate as explained by [57,58]. The controller in this study used Optimum cycle time extracted from the VISSIM simulator. In prior studies, the controller could consider a fixed amount of time as a green time extension while the chance of having ongoing green time. The results concerning this method are in good agreement with those found by [59,60]. It is decided to performing the most powerful techniques for traffic signal timing with a unique ANFIS structure and VISSIM-designed unique testbed and compare their performance with metaheuristic algorithms for the first time. Detailed examination of computational intelligence techniques containing the combination of ANFIS with metaheuristic algorithms for traffic light timing is one of the novels in this field. ANFIS is an appropriate method due to its speed and accuracy in learning and approximating hidden samples in big data. The efficiency of this method depends on its initialization and training process. In addition, The findings of [61,62] which explained the superiority and accuracy of both ANFIS types in predicting are supporting our selection. In the ANFIS structure, the first-order SUGENO model fuzzy system tunes the rules and adaptively learns to attain the optimal parameters for the rule base, so there is no need for a pre-defined rule base. To bound the number of parameters in the ANFIS structure and enhance the rapidity of convergence tendency, we presume three, five, and three membership functions for three inputs. Membership functions are Gaussian with 2 ranges of membership functions, namely lower bound and upper bound. By considering 11 membership functions with 23 ranges, we have a total of 11*2=22 decision variables of individuals (called chromosome vectors) in the first layer. Also, in the ANFIS controller, the number of membership functions is fixed and set manually. Dedicating more membership functions will lead to a faster and more robust controller, however, using useless membership functions can force negative results. Hence, detecting fully the right numbers is helpful in the efficiency of the controller. Our membership function selection seems to be consistent with previous studies and the performance is following the findings of [63,64]. Following the results explained by metaheuristic algorithms used in training play a significant role in getting effective results with ANFIS [65-67]. There are two steps in ANFIS training. In this study, the first step is training %80 of the data set, which includes input and target values, and tunes decision parameters with metaheuristic algorithms. The simulated (peak time, queue length, delay) and green signal time amounts extracted from isolated intersections in VISSIM environments are considered as inputs and output of ANFIS respectively. The second step is testing %20 of the data set which is initialized as input value (peak time, queue length, and delay) and green signal time is predicted. The prediction efficiency of our designed ANFIS structure has also been compared with 3 metaheuristic algorithms, namely GA, PSO, and HS. ANFIS-GA runs 10 times with 1000 function evaluation numbers [68]. All the general and specific parameters of each algorithm used in this study have been listed separately in Table 2. Tables 3-5 illustrate the best cost, Root Mean Square Error (RMSE), Error of Standard Decision (ER.St.D) and Error Mean for Training (Tr) and Testing (Ts) samples for GA, PSO, and HS, respectively. The best cost results for each algorithm have been presented in Table 6. One of the best cost results of the ANFIS-GA with 40 samples (test data) was predicted and presented with the statistic evaluation as in Figure 9. 90 samples (train data from the output of VISSIM) were trained and analyzed with statistic evaluation as in Figure 10. Likewise, The GA algorithm has the best cost at 8.8828 in the same criteria compared to other algorithms. ANFIS-GA, with the best cost and properly lower variance, outperformed all others. The results concerning GA are in good agreement with those found by [19] who detected rapid convergence tendency of GA with metaheuristics. As Figure 11 shows, it can be concluded that in our VISSIM-modeled intersection, the prediction ability of ANFIS-GA has better performance than the others.

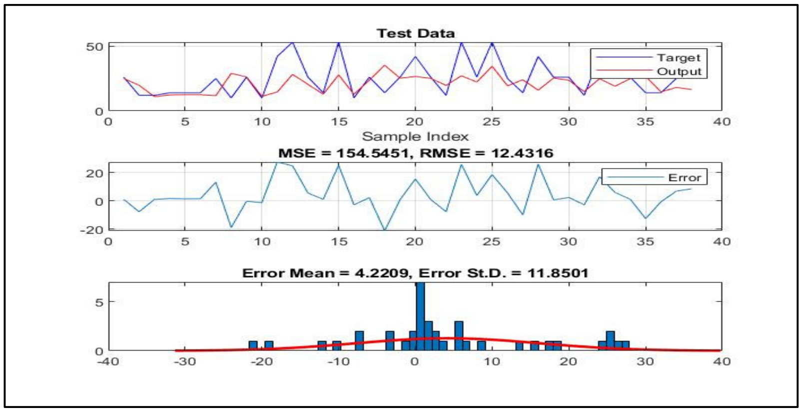


Figure 9: Best Cost Result of the GA Test

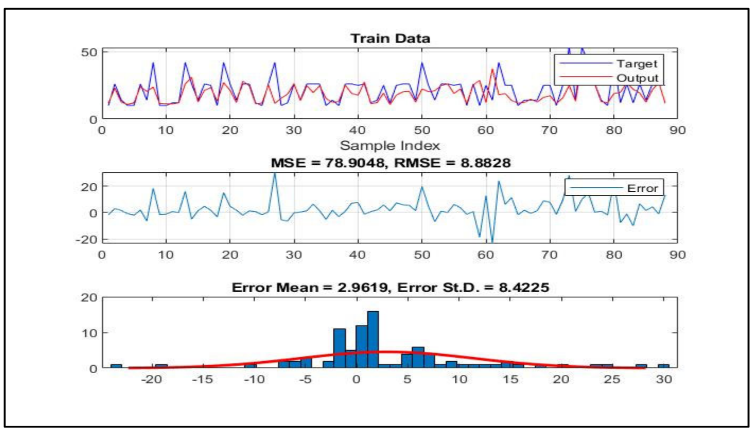


Figure 10: Best Cost Result of the GA Train

Parameters for Each Algorithm					
General Parameters for Each Algorithm					
Row	*Population Size*	*Cost Function Number*	*Number of Decision Variables*	*Upper Bound/Lower Bound*	
1	*25*	*1000*	*202*	*0.1/1*	
Specific Parameters for Each Algorithm					
Name		*Gama*	*Mutation Percentage*	*Mutation Rate*	*Selection Pressure*

GA	*pc=0.4*	*0.7*	*pm=0.7*	*mu=0.15*	*beta=5*
Name	*Inertia Weight*	*Inertia Weight Damping Ratio*	*Personal Learning Coefficient*	*Global Learning Coefficient*	
PSO	*w=1*	*W damp=0.99*	*c1=1*	*c2=2*	
Name	*Harmony Memory Consideration Rate*	*Pitch Adjustment Rate*	*Fret Width Damp Ratio*		
HS	*HMCR=0.9*	*PAR=0.1*	*FWdamp=0.995*		

Table 2: General and Specific Parameters of GA, PSO, and HS

Iteration	*Best Cost*	*RMSE(Tr)*	*ER.St.D(Tr)*	*ER.Mean(Tr)*	*ER.RMSE(Ts)*	*ER.St.D(Ts)*	*ER.Mean(Ts)*
1	*11.76049985*	*11.7605*	*11.7459*	*1.3828*	*16.8792*	*17.1005*	*0.41884*
2	*8.882838884*	*8.8828*	*8.4225*	*2.9619*	*12.4316*	*11.8501*	*44.2209*
3	*10.66358885*	*10.6636*	*10.0981*	*3.5914*	*10.0468*	*9.0969*	*4.5924*
4	*10.46555928*	*10.4656*	*10.1778*	*2.6678*	*12.9987*	*13.0968*	*1.3972*
5	*11.37986919*	*11.3799*	*10.8959*	*3.4852*	*12.175*	*12.0907*	*2.4277*
6	*10.09006546*	*10.0901*	*9.5103*	*3.5203*	*14.3815*	*14.0431*	*3.8483*
7	*9.568401517*	*9.5684*	*9.2578*	*2.6116*	*11.8227*	*10.8292*	*5.0587*
8	*10.54950012*	*10.5495*	*10.5855*	*0.71533*	*14.6317*	*14.8272*	*-0.16032*
9	*12.05980484*	*12.0598*	*11.7917*	*2.8239*	*9.8268*	*9.2893*	*3.5419*

10	*11.76049985*	*11.7605*	*11.7459*	*1.3826*	*16.8792*	*17.1005*	*0.41844*

Table 3: GA Experiments in 10 Iterations with 1000 Function Evaluation Numbers

Iteration	*Best Cost*	*RMSE(Tr)*	*ER.St.D(Tr)*	*ER.Mean(Tr)*	*ER.RMSE(Ts)*	*ER.St.D(Ts)*	*ER.Mean(Ts)*
1	*10.24274337*	*10.1327*	*9.9132*	*3.1016*	*14.9602*	*15.1424*	*0.74143*
2	*11.38296531*	*11.383*	*10.5295*	*4.4671*	*11.4969*	*11.3076*	*2.7716*
3	*10.14274137*	*10.1427*	*9.7122*	*3.1016*	*14.9602*	*15.1424*	*0.74143*
4	*10.89375463*	*10.8938*	*10.1777*	*4.0331*	*11.762*	*10.3535*	*4.2786*
5	*10.80272467*	*10.7422*	*10.0904*	*3.5440*	*11.2243*	*11.102*	*2.0272*
6	*10.73027223*	*10.7303*	*10.2134*	*3.4655*	*11.6683*	*11.7177*	*1.5673*
7	*10.75195862*	*10.752*	*10.1948*	*3.5851*	*11.3179*	*11.194*	*2.4672*
8	*10.96160988*	*10.9616*	*10.7472*	*2.4427*	*10.3179*	*10.2493*	*-2.0432*
9	*11.01776643*	*11.0178*	*10.4485*	*3.6688*	*11.2907*	*11.4217*	*0.6768*
10	*11.14744368*	*11.1474*	*10.455*	*4.0249*	*13.6499*	*13.3446*	*3.5954*

Table 4: HS Experiments in 10 Iterations with 1000 Function Evaluation Numbers

Iteration	***Best Cost***	***RMSE(Tr)***	***ER.St.D(Tr)***	***ER.Mean(Tr)***	***ER.RMSE(Ts)***	***ER.St.D(Ts)***	***ER.Mean(Ts)***
1	*10.96031598*	*10.9603*	*10.5717*	*3.1046*	*7.3678*	*7.2607*	*1.7183*
2	*8.954222742*	*8.9542*	*8.726*	*2.2137*	*10.8775*	*10.8836*	*1.7275*
3	*9.788586236*	*9.78.86*	*9.3292*	*3.126*	*12.1447*	*12.082*	*2.3149*
4	*13.85598915*	*13.856*	*13.8428*	*1.5949*	*14.2084*	*14.3982*	*-0.1562*
5	*9.009749371*	*9.0097*	*8.7582*	*2.3111*	*12.6672*	*12.7944*	*1.0339*
6	*9.255105177*	*9.2551*	*9.028*	*2.2537*	*12.5431*	*12.6575*	*1.1546*
7	*10.10974672*	*10.97*	*9.8905*	*2.3445*	*10.0512*	*9.1912*	*4.3326*
8	*9.659392225*	*9.6594*	*9.4998*	*2.3223*	*10.1669*	*9.5308*	*3.8627*
9	*9.358697992*	*9.3587*	*9.2467*	*1.7481*	*17.9272*	*18.2386*	*-0.86387*
10	*10.43044628*	*10.944*	*9.1465*	*2.1027*	*10.9815*	*9.4526*	*4.7193*

Table 5: PSO Experiments in 10 Iterations with 1000 Function Evaluation Numbers

	Best Cost		
Row/Name	**PSO**	**HS**	**GA**
1	**10.96031598**	**10.14274137**	**11.76049985**
2	**8.954222742**	**11.38296531**	**8.882838884**

3	**9.788586236**	**10.14274137**	**10.66358885**
4	**13.85598915**	**10.89375463**	**10.46555928**
5	**9.009749371**	**10.80272467**	**11.37986919**
6	**9.255105177**	**10.73027223**	**10.09006546**
7	**10.10974672**	**10.75195862**	**9.568401517**
8	**9.659392225**	**10.96160988**	**10.54950012**
9	**9.358697992**	**11.01776643**	**12.05980484**
10	**10.43044628**	**11.14744368**	**11.76049985**
Mín	**8.954222742 (2)**	**10.14274137 (3)**	**8.882838884 (1)**
Max	**13.85598915 (3)**	**11.38296531 (1)**	**12.05980484 (2)**
Variance	**2.110913086 (3)**	**0.157109225 (1)**	**1.065655198 (2)**
Mean	**10.13822519 (1)**	**10.79739782 (3)**	**10.71806278 (2)**

Table 6: Best Cost Results in the Same Criterions with Ranking

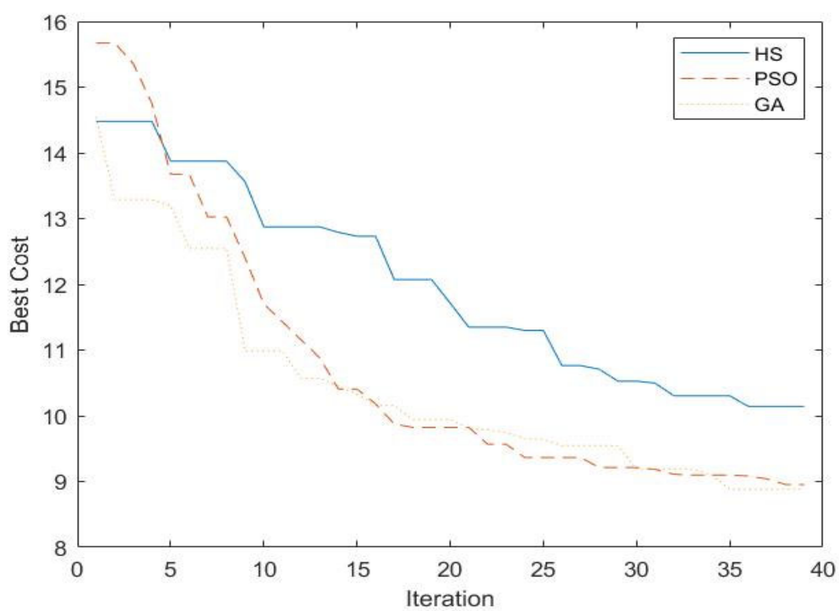


Figure 11: Comparing the Performance of the Metaheuristic Algorithms

Test Results for ANFIS -GA	
Signal Target Value	Signal Output Value
26	25.98392271
12	11.73902
12	11.9625162
14	13.34917415
14	13.5490892

14	13.48701588
25	24.73183246
10	9.91159936
26	25.22100347
10	9.27301582
42	41.51346323
53	52.18975964
26	25.4519122
14	13.90522145
53	52.75836313
10	9.82100825
26	25.68173131
14	13.23073958
26	25.21447959
42	43.50373076
26	25.0709079
12	11.68127238
53	27.08942356
26	25.23624833
53	52.42282128
25	24.334454
14	13.97929146
42	41.9702167
26	25.32984779
26	25.57916615
12	11.84281852
42	41.90447475
25	24.98475016
26	25.877241
14	13.58096021
14	13.69277419
25	24.07389602
25	16.47553846

Table 7: Comparing the Signal Target Value & Signal Output Value

5. Conclusion

This study contributes to expanding traffic signal timing controllers which is tried to reduce expected error values at the intersection and indicated best best prediction. We modeled an isolated intersection network with 3 phases in VISSIM. Moreover, considering various traffic scenarios for the network to test the accuracy and reliability of the VISSIM-designed controller before and after modeling is illustrated better performance after modeling. It was concluded that the documented information delivered accurate outcomes which can be stored as reference data for future studies. The recognition of a traffic-forecasting tool based on the ANFIS and metaheuristic algorithms is the contribution of the current article in this survey; ANFIS and metaheuristic algorithms were implemented in MATLAB. We tried to quantify the parameters of ANFIS by considering the ability of metaheuristic algorithms in the interaction between exploration and exploitation to find the best parameters. This prevented the algorithm from prematurely converging. By using the metaheuristic algorithm's ability in tuning the parameters, we observed better performance stability of ANFIS-GA in comparison with its rivals in terms of prediction. Our model predicts with a total Mean Square Error and Relative Mean Square Error of 2.9619 and 8.4215 in the train set and 4.2209 and 11.8501 in the test set respectively. Considerable studies are done in the field of traffic signal timing, but still, there is remarkable time need to be spent on this issue over the world. One of the reasons should be the gap between the methodical works and what is done in the industry. The further cause could be related to the laxity of techniques that these days are used. However, the effect of enhancing the number of vehicles and travel in urban areas is undeniable. Also, in the ANFIS controller, the number of membership functions is fixed and set manually. Dedicating more membership functions will lead to a faster and more robust controller, however, using useless membership functions can force negative results. hence, detecting fully the right numbers is helpful in the efficiency of the controller. Providing intelligent techniques for this purpose is useful.

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