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Optimal Design of Traffic Signal Controller Using Neural Networks and Fuzzy Logic Systems

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***Abstract*—This paper aims at optimally adjusting a set of green times for traffic lights in a single intersection with the purpose of minimizing travel delay time and traffic congestion. Neural network (NN) and fuzzy logic system (FLS) are two methods applied to develop intelligent traffic timing controller. For this purpose, an intersection is considered and simulated as an intelligent agent that learns how to set green times in each cycle based on the traffic information. The training approach and data for both these learning methods are similar. Both methods use genetic algorithm to tune their parameters during learning. Finally, The performance of the two intelligent learning methods is compared with the performance of simple fixed-time method. Simulation results indicate that both intelligent methods significantly reduce the total delay in the network compared to the fixed-time method.**

I. Introduction

The increasing amount of traffic in cities has a significant effect on the road traffic congestion and therefore the time it takes to reach a certain destination, the amount of air pollution and related disease. Extending roads and increasing their capacity is not a sufficient solution, as there will be always an end point, like bottlenecks or intersections. Although bottlenecks cannot be prevented, there is a lot of room for the way intersections are controlled. A common way to control the intersections is using traffic signal light and adjusting the time of each traffic phase.

Many studies have been done to control traffic signal lights' timing. Three generations are considered for proposed solutions. The first generation, usually named the fixed-time method, requires pre-set signal sequences and manual maintenance. The Traffic Network Study Tool [1] [2] is an example of tools for calculating fixed-time plans. The second generation focuses on adjusting the signal timing based on traffic detection. Two successful products of second generation which has been used in many cities are: Split Cycle Offset Optimization Technique [3], and Sydney Coordinated Adaptive Traffic System [4]. The third-generation is characterized by dynamic decision making and distributed control systems. Third generation is fully adaptive and optimization of signal timing is done progressively [5]. Considering the current information gathered from detectors located in certain places of roads, associated signal time and their sequences are calculated. The estimation of the incoming and outgoing traffic in the next few seconds are important factors for these decision making. OPAC [6] [7] and RHODES [8] are some examples of this generation.

The obvious matter in this regard is that manually handling of the huge and increasing amount of traffic is not possible in modern cities. Various use of computational intelligent methods in research and industry provide evidence of their efficiency and importance in this area. Computational intelligent methods are self-organizing and respond to dynamic changes of constraints and conditions. These methods have the potential to address real world problems due to their ability to learn from experience. Many attempts have been done to apply these methods to improve the performance of the controlling [9]–[12]. Neural network and fuzzy logic system are two of these methods that widely have been used in this regards, by itself or in combination with other methods.

In this paper neural network and fuzzy logic system are applied to control traffic congestion by allocating appropriate time to traffic signal phases. Similar processes are considered for both methods to have a reliable comparison between their performances. Genetic algorithm is used to find the best weights for neural network and appropriate sigma and mean for membership functions of fuzzy logic controller system. By calculating the average delay of the intersection after each simulation, genetic algorithm recognizes the best parameters for related neural network or fuzzy controller. The proposed controllers make it possible to have different ranges of green times with flexible cycle time. Before start of each cycle the appropriate green times for all phases are estimated and sent to the controllers. In some studies fixed predefined green times are used based on traffic congestion [13] [14] which reduces the flexibility of cycle times. In some other works just extension or termination of the green phase are computable which cause not having any estimation of the end of the cycle [15]–[18].

The rest of this paper is organized as follows: The related work about using neural network and fuzzy logic system are discussed in section II. In section III, Our proposed neural network and fuzzy controllers are introduced. Section IV. represents Experimental results and discussion and finally conclusion is in section V.

II. Neural Network and Fuzzy Logic System for Traffic Signal Timing

A neural network is a universal approximator with the ability to approximate any nonlinear mapping with various degree of accuracy [19]. By this feature neural networks can recognize hidden patterns among imprecise and complicated data. In fact, neural network is a suitable option for a problem that is too complicated to be considered by either traditional data mining methods or humans.

Neural networks are usually trained by minimizing an error-based cost function in supervised learning. When the expected values are not clear, an appropriate cost function is defined and minimized that is the solution to obtain the optimal parameters. In this regard, simulated annealing (SA) [20] or genetic algorithm (GA) [21] are suitable methods.

In some research works, neural network is applied to control traffic signal timing. Spall and Chin [9], employed simultaneous perturbation stochastic approximation (SPSA) based gradient estimates with a neural network feedback controller. SPSA method first proposed in 1992 by Spall [29], used for modeling the weight update process of a neural network. In [9], a function takes the current traffic information and generates the appropriate signal timings. In their work, the presented system is called S-TRAC with the following advantages: Do not need any system traffic flow model; automatically adapted to long-term changes in the system while providing real-time responsive signal commands; and work with existed hardware and sensor configurations at that time. For S-TRAC they used a feed-forward NN with 42 inputs and two hidden layers. The queue at each cycle termination for 21 traffic queues of the simulation, 11 nodes for per-cycle vehicle arrivals in the system, simulation start time, and nine outputs from the previous control solution are considered as inputs of the neural network. The output layer of the neural network contained nine nodes for each signal split. There were 12 and 10 nodes in hidden layers respectively. To evaluate the performance of S-TRAC, a simulation of a nine-intersection network of the central business district of Manhattan, New York was used. They have 10% and 11% improvement for both case of constant arrival rates and increase in mean arrival respectively against fixed-time method during 90 days.

Choy [22], proposed a new hybrid, synergistic approach in which they applied computational intelligence concepts to implement a cooperative, hierarchical, multiagent system for real-time traffic signal control of a large-scale traffic network. The problem of controlling the network was divided to various subproblems and each handled with an agent by fuzzy neural decision making capability. They applied their method for controlling traffic signal timing in a section of the Central Business District of Singapore. The experiments results showed reducing total vehicle stoppage time by 50% and the total mean delay by 40% compared to real-time adaptive traffic control system of the moment.

Srinivasan et al. in [30] presented an enhanced version of the SPSA-NN system for a multi-agent system. They measured the performance of the proposed method in a more complicated scenario. In that work authors claimed that besides the benefits of the SPSA algorithms for online updating of weights, the model proposed in [9] has some limitations influencing its performance. Spall and his team used a three-layer neural network and relevant traffic variables as inputs. In [30], two limitations were presented for that system; First, the system used heuristic method to identify the general traffic patterns (morning and evening peaks) and assignment of time periods for patterns. This has negative influence on the robustness of the system for the case of not periodic traffic patterns. Second, a neural network was considered for each time period, and weights updated only for the situation that similar traffic pattern and time period occurs. It may not be possible to respond appropriately to changes of the traffic inside the same time period. Srinivasan and her team improved that method and compared it with the hybrid multiagent architecture presented by Choy et al. [31]. Two multiagent model were developed in [30]. The first one employed hybrid computational intelligent techniques in which each agent used a multi-stage online learning process to update its knowledge base and mechanism of decision making. The second system integrate the SPSA in fuzzy neural network. To evaluate the performance they considered a model of large traffic network with 25 intersections based on Singapore Central Business District.

Sometimes, neural network is used in combination with other computational intelligence methods such as fuzzy logic system to control traffic signal timing. Fuzzy logic system or fuzzy set theory [23]–[25], is a suitable method to represent the vagueness and uncertainties of the linguistic phrases. Using fuzzy theory instead of crisp set theory provides the ability to implement the real-world scenarios in more details, and fuzzy logic systems make it possible to include an expert's knowledge during the design. Fuzzy logic system maps the inputs to the output of the system. The definition of a cluster or class of objects is just a simple two-valued characteristic function, zero and one in the case of no fuzziness, but by fuzzy set this domain is extended to the range of whole numbers between zero and one. In fuzzy sets, membership functions are used to show the degree of dependency to each fuzzy set. Input values may belong to more than one fuzzy set. Same conditions exist for the output space.

Nair and Cai [26], proposed a fuzzy logic controller for an isolated signalized intersection aimed to ensure smooth flow of traffic by reducing the delay time. Most of the fuzzy traffic controllers attempt to optimize the performance of the network by maximizing traffic flows or minimizing traffic delays under typical traffic conditions. As a result of that, these controllers are not the optimal traffic controllers for exceptional traffic cases such as roadblocks and road accidents. In this research the authors proposed a fuzzy controller able to control traffic flows under both normal and exceptional traffic conditions. In their system, traffic detector sensors were placed at incoming and outgoing links (lanes) and the controller utilized the information received from them to make optimal decisions. They also developed a simulator to evaluate the performance of traffic controllers under different conditions. Results showed that the performance of their proposed traffic controller was similar to that of conventional fuzzy traffic controllers under normal traffic conditions and was better that of others under abnormal traffic conditions.

Researchers in [27] and [28] used fuzzy type-2 for controlling traffic signal lights. Non-stationary sensor noise, use of rules to control vehicles flow and signals, stochastic nature of drivers behavior, and use of expert knowledge for mining fuzzy rules from opinions are factors worth to be mentioned to make fuzzy type-2 more appropriate to be employed in designing such controllers. In [28], it was mentioned that although computational intelligence based method such as neural network had been used for designing signal controller, a large training data set with all uncertainties they may contain make it difficult to obtain a proper controller. They developed a distributed architecture signal timing control system based on type-2 fuzzy sets. In their multiagent structure all agents were homogeneous and had equal decision making capabilities. An agent calculated the appropriate green time based on averaged flow rate, queue length, and communicated data from the immediate neighbors, gathered by detectors attached to the intersection. Experiments results showed around 40% improvement against fixed-time method.

III. Proposed Neural Network and Fuzzy Logic Controller

The neural network controller for a 4-way intersection, is designed with a feed-forward network. It consists of four input neurons, a hidden layer with ten neurons, and four neurons for the output layer. During each cycle the detected length of queues are fed to neural network and the appropriate green times for each phase are estimated. Genetic algorithm method is used to find the best parameters for neural network during training. For this purpose, the cost function is defined as the average delay time of a complete run of a simulation. The new parameters for the neural network are generated considering reducing the average delay time:

$$costfunction = \frac{\sum_{i=1}^{n} d_i}{k} \tag{1}$$

where $i = 1, \ldots, n$ is the number of cycles, d is calculated delay time for each cycle, and k is the number of cars released in each simulation scenario.

Similar approach is considered for designing the fuzzy logic controller. Fuzzy controller has four inputs and one output. Length of queue at each approaching link is made one of the inputs and because of the modeling for an intersection with four approaching links the fuzzy logic controller has four inputs. The output of the controller is the related green time for each approaching link.

For an intersection with four approaching links, we need four fuzzy logic controllers each for estimating the appropriate green time for related link. The fuzzy set for all inputs and the output are considered similar for four fuzzy logic controllers. The fuzzy logic controller has four inputs (the length of queue for each approaching link) and one output (the green time). Each input and the output has three membership functions named small, medium, large. These are Gaussian functions whose sigma and mean are optimized during training. Here, genetic algorithm is applied for optimizing the parameters of fuzzy controller. In this case, we have a similar definition of cost function presented in equation 1.

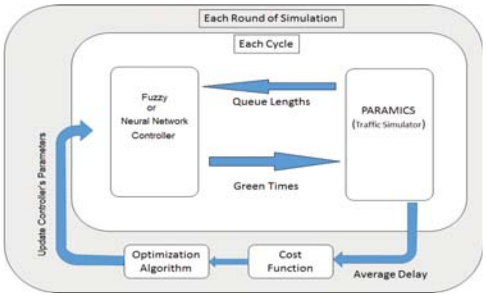

Fig. 1. The process of NN/FLS training. NN/FLS parameters are updated after each round of simulation through genetic algorithm optimization method.

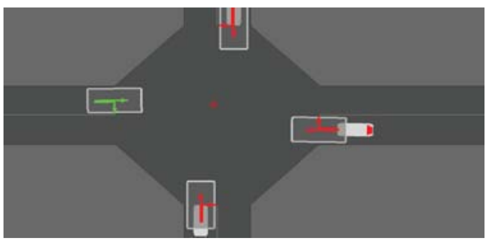

Fig. 2. Snapshot of four defined phases at an isolated intersection in Paramics.

Design of the fuzzy logic controller is very similar to the neural network controller. The design and training process is presented in Fig. 1. For both neural and fuzzy logic controllers it is aimed that controllers reduce the amount of delay time at the intersection during simulation period.

IV. Experiments Environment and Results

For evaluating and comparing the performance of designed controller, an intersection with four approaching links and four phases is designed in Paramics V6.8.0. Figure 2 shows the designed intersection. The cycle time is the total time considered for all four phases. This time is divided between these four phases. The permission is given to vehicles in each lane to cross the intersection based on the related green time and direction of the phase. During our implementing the cycle time was not fixed to have more flexibility according to traffic demand. Four zones, the areas that vehicles are released from them to the intersection is considered in simulation. Matlab R2011b is used to implement the controller.

Three scenarios are considered for evaluation of controllers. In scenario one we have 5500 vehicles, 3000 vehicles in scenario two, and 1500 vehicles for scenario three. All scenarios are set to run in five hours. Table I shows the details of the number of cars released from each zone.

TABLE I
Number of vehicles are released from each zone to the intersection for three scenarios.

	Zone1	Zone2	Zone3	Zone4	Total
Scenario-1	2200	600	1500	1200	5500
Scenario-2	800	830	600	750	3000
Scenario-3	250	250	350	650	1500

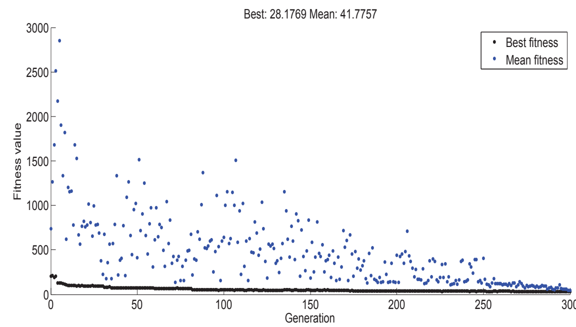

Fig. 3. The convergence profile of cost function iteration for neural network controller for scenario one.

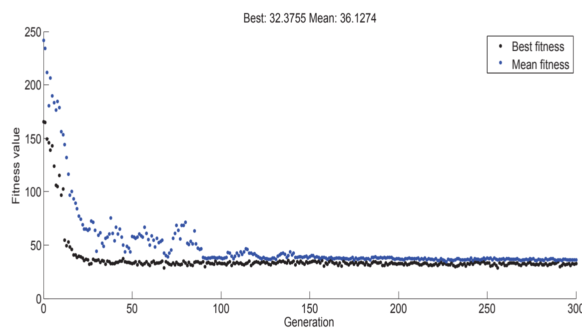

Fig. 4. The convergence profile of cost function iteration for fuzzy logic controller for scenario one.

Optimization process for both neural network and fuzzy logic controller is repeated until there is no further improvement in the result of the cost function for several iteration or after reaching to a maximum iteration number set in genetic algorithm options. During the implementation we have 300 iterations. Each iteration has 20 members in its population. This means each controller has 6,000 simulation runs during training time. Different seed numbers are set for each iteration during training. Fig. 3 and 4, show the neural network and fuzzy logic controller parameters optimization during training respectively.

The performance of each controller is evaluated with three different scenarios. Each scenario is repeated for 10 times with 10 different seed numbers during the test time. Beside neural network and fuzzy logic

TABLE II
AVERAGE TOTAL DELAY TIME FOR TEN FIVE-HOURS SIMULATIONS FOR THE MODELED INTERSECTION IN EACH SCENARIO PER VEHICLE

	FT10	FT30	FT50	FT70	NN	FLS
One	89.89	79.77	89.88	108.31	32.98	36.91
Two	17.33	40.30	64.17	87.70	25.81	10.88
Three	15.85	39.54	63.75	87.78	17.92	7.40

controller, we also implement a fixed-time controller. A fixed-time controller or pre-timed controller has a constant value for each phase. Therefore, based on different traffic demands the performance of the fixed-time controller is changing. Four fixed-time controllers with different constant times are developed to have better evaluation compared to two proposed intelligent method. The value of all phases in each of these four fixed-time controllers are set to 10, 30, 50, 70 respectively. Permissible green time for neural network (NN) and fuzzy logic system (FLS) controllers is set to be between zero and 100. Zero is allowed to jump a phase if there is no demand. The intelligent controllers during the training get fixed with the most appropriate parameters to produce green times in the range between 0 to 100. The fixed-time (FT) controllers use one of these four numbers for their green phase time: 10, 30, 50, 70. Table II presents the average total delay time from ten runs for an intersection per vehicle in five hours of the simulation for each controller in each scenario.

The results in table II illustrate, FLS controller has a much better performance in all cases compared to FT method. NN also has a better performance in comparison to FT one in most cases. About NN and FLS controllers, in scenario one better result belongs to NN, but for scenario two and three less delay times are obtained using FLS controller. It can be concluded that sometimes there can be good results by using FT controller, however it is not always guaranteed and depends on traffic demand. As traffic demand does not have a constant behavior and usually is unpredictable, then FT method is not a good solution. Accordingly, intelligent methods are more appropriate in this regard.

Fig. 5–7 show accumulative delay for an intersection in five hours simulation for scenario one to three respectively. Fig. 5 belongs to scenario one with 5,500 vehicles. Both NN and FLS controllers have less amount of delay compared to all FT controllers and NN has the higher performance among all controllers in first scenario. For the second scenario with 3,000 vehicles, FLS controller has the best performance. However, FT controller with 10 second predefined time shows the better performance compared to NN controller. 1,500 vehicles are considered for scenario three. In this case we still have best performance for FLS controller and 10 seconds FT controller has better performance than NN. The performance of 10 seconds FT and NN controllers are very close to each others in scenario three.

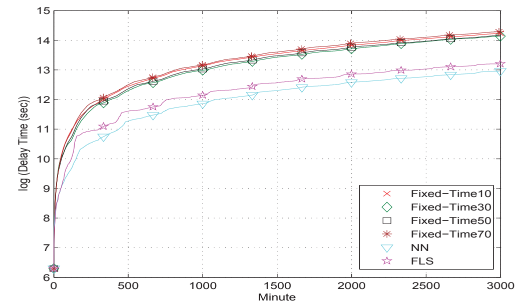

Fig. 5. Accumulative delay for ten runs of scenario one. Scenario one releases 5,500 vehicles in a five hours simulation.

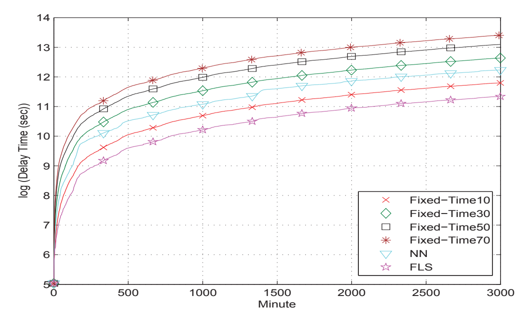

Fig. 6. Accumulative delay for ten runs of scenario two. Scenario two releases 3,000 vehicles in a five hours simulation.

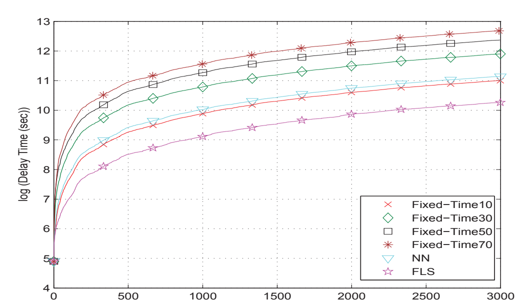

Fig. 7. Accumulative delay for ten runs of scenario three. Scenario three releases 1,500 vehicles in a five hours simulation.

V. Conclusions

Two intelligent controllers are designed for controlling traffic signal timing. Unpredictable nature of traffic demand causes fixed time controllers to not have a good performance. The neural network and fuzzy logic controllers designed in this study learn to adapt to traffic demand and generate the most appropriate green time for each phase based on traffic demand. In this study, three different scenarios are considered to compare the performance of the intelligent controllers. Most of the time the performance of the neural network and fuzzy logic controller are close to each other, but much better than the fixed-time controller. Designing and implementing neural network and fuzzy logic controllers for a multi-intersection network is planed for our future work. Adjacent intersections status is an important factor essential to be considered in designing controllers for a multi-intersection network.

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