ANFIS Traffic Signal Controller for an Isolated Intersection

Sahar Araghi, Abbas Khosravi and Douglas Creighton
Center for Intelligent Systems Research (CISR), Deakin University, Victoria 3216, Australia

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Abstract: Traffic signal controlling is one of the solutions to reduce the traffic congestion in cities. To set appropriate green times for traffic signal lights, we have applied Adaptive Neuro-Fuzzy Inference System (ANFIS) method in traffic signal controllers. ANFIS traffic signal controller is used for controlling traffic congestion of a single intersection with the purpose of minimizing travel delay time. The ANFIS traffic controller is an intelligent controller that learns to set an appropriate green time for each phase of traffic signal lights at the start of the phase and based on the traffic information. The controller uses genetic algorithm to tune ANFIS parameters during learning time. The results of the experiments show higher performance of the ANFIS traffic signal controller compared to three other traffic controllers that are developed as benchmarks. One of the benchmarks is GA-FLC (Araghi et al., 2014), next one is a fixed-FLC, and a fixed-time controller with three different values for green phase. Results show the higher performance of ANFIS controller.

1 INTRODUCTION

Increasing traffic density is one of the unpleasant outcomes of the urbanization. Traffic congestion has many harmful side effects. Creating environmental and health hazards, generating a huge amount of green house gas, increasing the amount of fuel consumption, wasting time in traffic queues are some of these side effects (Iqbal et al., 2012a).

Through the studies, to control traffic signal timing, different categories have been defined for traffic control systems. One of these categories considers three generations; fixed-time or predefined method is the first generation that requires pre-set signal sequences. Traffic Network Study Tool (Robertson, 1969)(Vincent et al.,) is one of the methods for determining effective pre-set signals. In the second generation the signal timing adjusts based on the detected traffic situation. Split Cycle Offset Optimization Technique (Hunt et al., 1982), and Sydney Coordinated Adaptive Traffic System (Luk, 1984) are the popular samples of the second generation. Third generation is for distributed control and based on dynamic decision making. Control method in third generation is fully adaptive and optimization of signal timing is done progressively (Cai et al., 2009). OPAC (Gartner, 1982)(Gartner et al.,) and RHODES (Mirchandani and Head, 2001) are some examples of this generation.

Adaptive systems have both offline and online types. Offline type benefits a database of pre-stored signal control plans. The pre-stored plans are developed by historical traffic data. Plan selection is directly related to the date and time to have the best suitable plan for current traffic condition. For offline type there is always this issue that the registered traffic conditions considered for that time of the week may become out-dated or changed gradually then not be suitable anymore. Decision making in online type is based on real-time traffic situation detected and predicted values. progressive optimization is possible every five to fifteen minutes in online mode.

The conventional traffic controlling methods are not suitable solution for fluctuating and increasing traffic condition. Traffic flows in urban area are vague, complex, random and fuzzy that make it difficult to propose a pre-defined formula for traffic controlling (Wannige and Sonnadara, 2009). In this situation Artificial Intelligence (AI) techniques that are able to think like human are useful for controlling traffic congestion at an intersection (Udofia and Emagbetere, 2013).

Many attempts have been done to apply AI techniques to improve the performance of the controlling (Spall and Chin, 1997)(Chin et al., 2011)(Schouten, 2007)(Cai et al., 2009). For example, Choy(Chee,

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2005) proposed a hybrid approach in which they applied computational intelligence concepts to implement a cooperative, multiagent system for a large-scale traffic network. The problem of controlling the network was divided between various agents who made decision by fuzzy neural control systems. Applying the proposed system for controlling traffic signal timing in a part of the Central Business District of Singapore showed reducing total vehicle stoppage time by 50% and the total mean delay by 40% compared to real-time adaptive traffic control system.

Fuzzy logic system (FLS) is a powerful tool for situations where implementation of the exact mathematical model is difficult or impossible (Niittymki, 2001). Pappis and Mamdani are pioneers of implementation a fuzzy logic controller for an isolated intersection with two one-way streets (Pappis and Mamdani, 1977). Researchers (Favilla et al., 1993) have also applied FLS to control a single intersection with two-way streets. In this work the number of vehicles that had already passed the intersection and the length of the queue of the red approach formed the Fuzzy Logic controller (FLC) inputs and the amount of extension of green time was the output of the FLS.

Nair and Cai (Nair and Cai, 2007), proposed a FLC aimed to ensure smooth flow of traffic and reducing the delay time. It is usually attempted to optimize the performance of the network by maximizing traffic flows or minimizing traffic delays under typical traffic conditions, consequently, these controllers are not the optimal for exceptional traffic cases such as road accidents. This research proposes an FLC able to control traffic flows under both normal and exceptional traffic conditions by different traffic detector sensors placed at incoming and outgoing links. Many other studies also used FLC for a single intersection (Wei et al., 2001)(Wei et al., 2001)(Hu et al., 2007)(Zeng et al., 2007).

Different studies are done in controlling traffic signal lights at intersections, in some studies fixed predefined green times are used based on traffic congestion (Abdoos et al., 2011)(Abdoos et al., 2013) which reduces the flexibility of cycle times. In some other works just extension or termination of the green phase are computable (Pappis and Mamdani, 1977)(Favilla et al., 1993)(Bazzan, 2009)(El-Tantawy et al., 2013). The number of extensions can be continued up to reaching the maximum number. In this case there is no estimation of the end of the phase. Researchers who used FLS for designing traffic controller usually apply manually tunning process in generating fuzzy rules based on expert knowledge. Since there is no organized approach used by human to create these rules, the tunning process can be error-prone and time consuming.

In this paper, Adaptive Neuro-fuzzy Inference System (ANFIS) is applied to control traffic congestion by allocating appropriate time to traffic signal phases. ANFIS method utilized both neural network (NN) which is very fast process and FLS with the capability of human reasoning (Iqbal et al., 2012b). In this situation it is not necessary to predefine the rule base and ANFIS finds its optimal parameters through training. The proposed controllers make it possible to have different ranges of green times with flexible cycle time. Before start of each phase the appropriate green times for that phase is estimated and sent to the controller. We evaluate the performance of the ANFIS controller with one of our previous studies GA-FLC (Araghi et al., 2014) and a FLC uses predefined parameters in its fuzzy sets named fixed-FLC. In addition, a fixed-time controller with three different values for its green phase time is included in performance evaluation tests.

The rest of this paper is organized as follows. In section 2, the designed ANFIS controller is introduced. Section 3, represents experimental results and discussion and finally conclusion is in section 4.

2 PROPOSED ANFIS TRAFFIC SIGNAL TIMING CONTROLLER

ANFIS model has a combination of both NN and Fuzzy Systems (FS). One of the difficulty in applying FLC for a system is how to define the approporiate rule base to obtain the best efficiency of the FLC. In ANFIS system first order Sugeno model fuzzy system modifies the rules and adaptively learns to reach the optimal parameters for the rule base.

Here, an ANFIS controller is designed for a four-way intersection. This controller has four inputs and one output. The queue length of vehicles at each approaching link of the four-way intersection make the inputs of the controller and the output of the system is the proposed green time for the current phase of the cycle. At the end of each phase the detected length of queues of all the approaching links are sent to the ANFIS controller and the controller sends the green time for the next phase. During the training Genetic Algorithm (GA) evaluates the performance of the controller with different parameters until reach the optimal parameters for the ANFIS controller. Average delay time of a complete run of a simulation is considered as the cost function for the GA. It means GA aimed to reduce average delay time of the whole net-

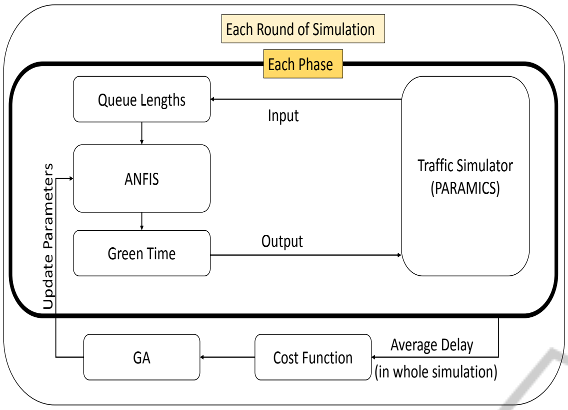

Figure 1: The figure shows the process of ANFIS training. ANFIS parameters are updated after each round of simulation through genetic algorithm optimization method.

work in finding optimal parameters Eq. 1.

$$cost\,function = \frac{\sum_{i=1}^{n} d_i}{k} \quad (1)$$

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

The implemented ANFIS controller is for intersection with four approaching links. This means the ANFIS controller has four inputs. ANFIS use Sugeno type fuzzy systems. Three membership functions are considered for inputs named small, medium, and large. The design and training process of ANFIC controller are presented in Fig. 1.

3 EXPERIMENTS ENVIRONMENT AND RESULTS DISCUSSION

An intersection with four approaching links and four phases is designed in Paramics V6.8.0. Fig. 2 shows the designed platform. The total time divided between defined four phases is the cycle time. This time is divided between these four traffic phases. Vehicles in each lane get permission to cross the intersection based on the related green time and direction of the phase. The cycle time is assumed to be unfixed to have more flexibility in controlling system according to traffic demand. Zones are the areas that vehicles are released from them to the intersection and we consider four zones in our simulation. Matlab R2011b is used to implement the controller.

As it is mentioned in previous section we have considered three membership functions for each in-

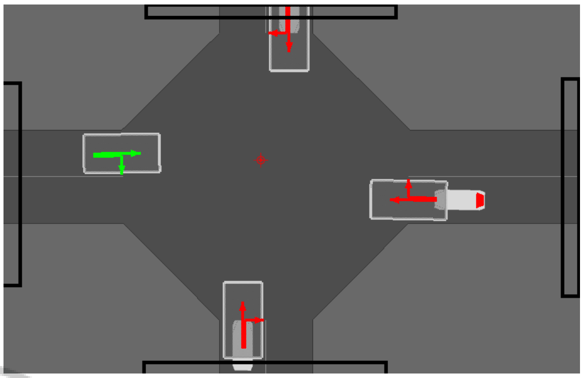

Figure 2: Snapshot of four defined phases at an isolated intersection in Paramics.

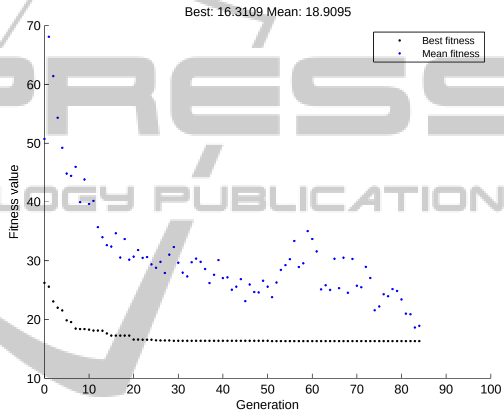

Figure 3: Convergence of genetic algorithm during optimizing ANFIS parameters.

put of the ANFIS controller. The range of the each membership function presented in Fig. 4, as the figure shows small is a trapezoidal function with the ranges: $[-1,-1,10,20]$, medium is triangular one with the range: $[10,20,30]$, and large is also trapezoidal function with the range: $[20,30,500,500]$.

We consider a scenario with 1,200 cars in one hour simulation time. Fig. 3 shows the convergence trend of genetic algorithm to find the optimal parameters for ANFIS controller. It shows that the optimization algorithm finds the optimal membership parameters in about 20 generations.

An GA-FLC (Araghi et al., 2014) is also implemented as a benchmark. Similar membership functions are designed for GA-FLC Fig. 4. GA-FLC has fixed parameters for its four inputs but parameters of the output membership functions are adjusted using the training method. In the case of fixed-FLC parameters of all inputs and output are fixed and pre-defined. The parameters of inputs membership functions are similar to ANFIS and GA-FLC Fig.4, and the parameters of the output for fixed-FLC after training pre-

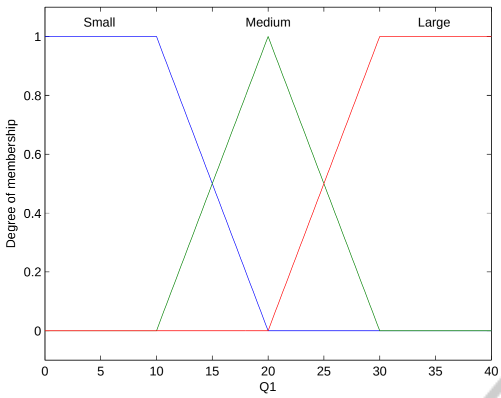

Figure 4: Membership functions of inputs for ANFIS, GA-FLC, and fixed-FLC .

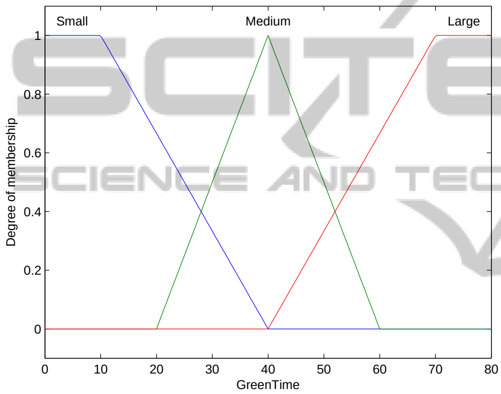

Figure 5: Membership functions of output for fixed-FLC.

sented in Fig. 5.

In all controllers, the appropriate green time for each phase is generated based on the queue length in four links. ANFIS controller uses the rule base obtained during training and GA-FLC and fixed-FLC apply the same rule base that presented in our previous work (Araghi et al., 2014). Rule base is presented in table 1. It is defined in a way to consider neighbors situations in green time proposing. Queue length of vehicles at current link (CL), next link (NL), second next link (2NL), and third next link (3NL) are the factors considered in the rule base definition. For example, the first rule is defined as this:

*If CL is **small**, NL is **small or medium or large**, 2NL is **small or medium or large**, and 3NL is **small or medium or large**, then Green Time is **small**.*

Based on the research is done in (Araghi et al., 2014), parameters of GA-FLC are optimally tunned using genetic algorithm with the purpose of minimizing delay times. The genetic algorithm used has 30 populations for optimizing seven parameters of eleven output membership functions. Fig. 6 shows the parameters of output membership functions after training with GA.

Table 1: FLC Rule Base. In this table S stands for small, M for medium, L for large, and ∼ is for negation (eg., ∼S means not-small, which could be either medium or large) (Araghi et al., 2014).

	CL	NL	2NL	3NL	Green Time
(1)	S	S/M/L	S/M/L	S/M/L	S
(2)	M	S	∼M	∼M	S
(3)	M	M	M	M	M
(4)	M	L	S/M/L	S/M/L	M
(5)	L	∼L	∼L	∼L	M
(6)	L	L	∼L	∼L	L
(7)	L	∼L	L	∼L	M
(8)	L	∼L	∼L	L	M
(9)	L	∼L	L	L	M
(10)	L	L	∼L	L	L
(11)	L	L	L	∼L	L
(12)	L	L	L	L	L

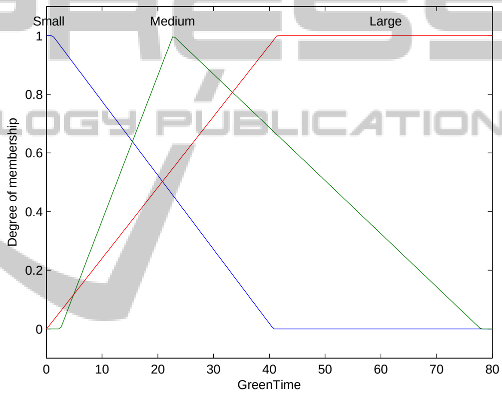

Figure 6: Membership functions of the GA-FLC output after optimizing the parameters (Araghi et al., 2014).

Fixed-time or pre-timed controller is usually used as a benchmark for evaluating the performance of designed controllers. In the fixed-time controller, a constant amount of time is set for each phase. Considering constant time for each phase reduce the flexibility of the fixed-time controller to adapt traffic demands. The deigned fixed-time controllers use equal time for all green phases. We have designed a fixed-time controller with three different values as green phase time: 20, 40, and 60 seconds values. This is done to have a more comprehensive comparison by considering three different values fixed-time controller.

The performance of each controller is evaluated by considering the total delay time of the intersection. Fig. 7 shows the accumulative delay time of the intersection in a one-hour simulation after utilizing each controller.

The diagram illustrates that the ANFIS controller

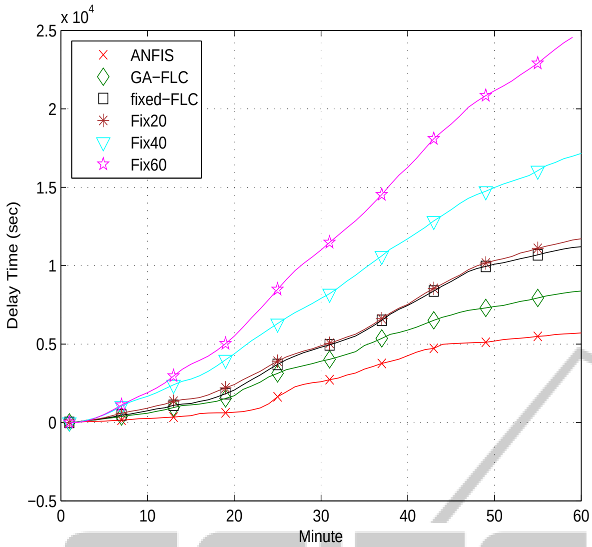

Figure 7: Accumulative total delay time of the intersection in one hour.

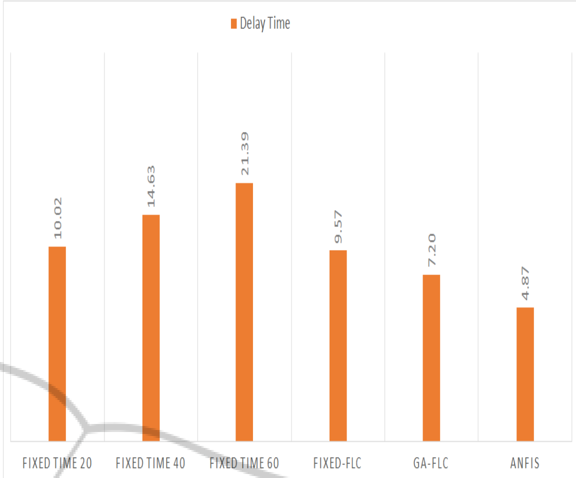

Figure 8: Total delay time per vehicle for the intersection.

has a better performance than GA-FLC, fixed-FLC, and fixed-time controller. Second best controller is GA-FLC and then we have the fixed-FLC controller. Fixed-time controller has a different result for each green phase value. These differences prove that the efficiency of the fixed-time controller is variable and highly depends on the traffic conditions.

Fig. 8 shows the total delay that impose to the intersection per vehicle in each hour. The bar chart also shows that the best performance is achieved by ANFIS controller. It shows the amount of delay per vehicle per hour for the intersection and these delay times are presented in seconds. Fuzzy logic controllers have totally better performance than fixed-time controller. GA-FLC which is a version of fuzzy controller with optimized output membership function parameters obtains better result that fixed-FLC, and ANFIS controller that has optimized rule base obtains the best results between other controllers.

4 CONCLUSIONS

In this paper, we implement and examine the performance of ANFIS for controlling traffic signals for an isolated intersection. ANFIS gives the opportunity of using fuzzy logic system in traffic signal controlling while there is no need to pre-defined rule base. Parameters of the ANFIS controller are optimally tuned using genetic algorithm and ANFIS controller obtains its optimal rule base. The purpose of tuning and optimization is to minimize the total delay in the network. GA-FLC (Araghi et al., 2014), a fuzzy controller with fixed and predefined parameters, and a fixed-time controller with three different values are also designed and implemented to evaluate the performance of the ANFIS controller. Trapezoidal and triangular membership functions are considered for queue lengths in fuzzy controllers. Results of the experiments for the simulation scenarios show the better performance of the ANFIS controller compared to two others fuzzy controllers and fixed-time method. For our future work designing and implementing fuzzy logic controllers for a multi-intersection network has been planned. Considering the situation of the neighbor intersections is a noticeable factor in designing controllers for a multi-intersection network.

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