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Intelligent cuckoo search optimized traffic signal controllers for multi-intersection network

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ABSTRACT

Traffic congestion in urban roads is one of the biggest challenges of 21 century. Despite a myriad of research work in the last two decades, optimization of traffic signals in network level is still an open research problem. This paper for the first time employs advanced cuckoo search optimization algorithm for optimally tuning parameters of intelligent controllers. Neural Network (NN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) are two intelligent controllers implemented in this study. For the sake of comparison, we also implement *Q*-learning and fixed-time controllers as benchmarks. Comprehensive simulation scenarios are designed and executed for a traffic network composed of nine four-way intersections. Obtained results for a few scenarios demonstrate the optimality of trained intelligent controllers using the cuckoo search method. The average performance of NN, ANFIS, and *Q*-learning controllers against the fixed-time controller are 44%, 39%, and 35%, respectively.

1. Introduction

Managing road traffic congestion is one of the biggest challenges in densely populated cities. Traffic congestion besides its explicit effects such as wasting time and delay in daily activities has more side effects on humans lives. Creating environmental and health hazards, generating a huge amount of green house gas, and increasing the amount of fuel consumption are samples of the unpleasant side effects of traffic congestion. One of the solution is to widen roads and increase their capacity. However, it is not sufficient by itself as there is always a bottleneck. Controlling traffic congestion movement at intersections is another solution that still has room for improvement.

Traffic signal lights are common devices for controlling traffic at intersection. The main objective of traffic signals is to increase roads capacities and decrease delays while safe travel is guaranteed. Since the 1960s different methods have been presented to manage intersections and for controlling traffic signals' timing. Fixed-time or pre-timed controllers as one of the first controlling methods applied historical data to determine appropriate time for traffic signals (Cai, 2010). This method is not based on current traffic demands and therefore handling unexpected conditions in traffic is not feasible.

Considering unpredictable nature of urban traffic, it is not possible to have a pre-defined traffic control system with high efficiency. Traffic-adaptive control systems were created to take unpredictable elements in account in order to predict appropriate green times. In adaptive traffic control systems, the traffic condition is monitored continuously to set traffic signals timing accordingly. Adaptive systems adjust their parameters and internal logic in response to the significant change of the environment (Abdulhai, Pringle, & Karakoulas, 2003). SCATS (Sims & Dobinson, 1980), SCOOTS (Hunt, Robertson, & Bretherton, 1982), OPAC (Gartner, Tarnoff, & Andrews, 1991) and RHODES (Mirchandani & Head, 2001) are samples of famous adaptive systems currently in use in a number of modern cities around the world.

In 1990s artificial intelligence methods were considered as effective solutions for controlling traffic signal timing (Malej & Brodnik, 2007). The first research used fuzzy logic systems (FLS) for isolated traffic signal control was published in 1977 (Pappis & Mamdani, 1977). After the first applications that used FLS for traffic signal controlling, NN and genetic algorithm (GA) also were used in design of the intelligence traffic signal controllers. Next step in design of the intelligence traffic signal controllers were hybrid systems. These controllers use the combination of the aforementioned methods and enable the controllers to adapt to the traffic patterns (Malej & Brodnik, 2007).

Traffic signal timing controllers who apply artificial intelligence techniques have high performance. Their performance will be increased more if they obtain their parameters through training instead of using manual parameters. Appropriate selection of

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parameters is possible by optimization methods. Many studies have been done to compare the performance of different optimization methods and review their weak and strength points eg. Yang (2014) and Civicioglu and Besdok (2013). Among different optimization methods cuckoo search (CS) (Yang & Deb, 2009) shows high performance in finding optimal parameters and not being trapped in local optima. This optimization method is also more suitable for problems with huge number of parameters. In this regard, we use this method to optimize the parameters of the proposed NN and ANFIS controllers designed for a multi-intersection network.

In this paper, two main goals are considered: Firstly, we implement couple of intelligent controllers including Neural Network (NN), Adaptive Neuro-Fuzzy Inference System (ANFIS), and *Q*-learning techniques. Performance of these controllers are examined in a network of nine intersections. Secondly, CS is used for optimizing parameters of NN and ANFIS controllers. Based on the publications, this is the first time that CS is used for optimizing the parameters of traffic signal controllers. A fixed-time method with three different values is also used as a benchmark for measuring the performance of the proposed intelligent controllers.

The remainder of this paper is organized as follows. Section 2 is a review of intelligence traffic signal controllers. Section 3 introduces a background of artificial intelligent techniques. The detail of design for controllers are presented in Section 4. Simulation results are presented and discussed in Section 5. Finally, Section 6 concludes the paper and presents guidelines for the future works.

2. Intelligent traffic signal controllers

Artificial intelligence techniques and especially methods such as *Q*-learning, NN, FLS have emerged as an effective tools to improve the performance of the traffic signal control (Balaji & Srinivasan, 2011; Choy, Srinivasan, & Cheu, 2003; El-Tantawy, Abdulhai, & Abdelgawad, 2013; Spall & Chin, 1997). This high performance comes from the ability of these methods to learn from experience. In this section a review of some of the previous related work in applying *Q*-learning, NN, and FLS are presented, but before them a few terminologies in traffic controlling are introduced.

- Green time: Period of time in which vehicles in a lane are allowed to cross an intersection.
- Link: A group of adjacent lanes on which traffic forms a single queue.
- Phase: A set of unique traffic signal movements, where a movement is controlled by a number of traffic signal lights that change colour at one time. Phase is the part of the cycle assigned to a fixed set of traffic movements, when any of these movements change, the phase changes.
- Cycle: The time required for one full cycle of signal indications.
- Offset: Time lag between the start of green time for two adjacent intersections to allow free flow of vehicles without facing any red signals.
- Delay: The total stopped time per vehicle for each lane in the road traffic network.

Pappis and Mamdani (1977) for the first time applied FLS for traffic signal timing. Their proposed fuzzy logic controller (FLC) had three inputs, one output and it was designed for a two-phase intersection with random vehicle arrivals. The developed fuzzy rules made decision about the suitable extension of current green phase. The designed system was compared with the efficient vehicle-actuated method. The result of simulation showed the better performance of FLC. In the beginning of 90s, the first application of FLS in a multi-intersection network was published (Chiu et al., 1993).

Spall and Chin (1997) proposed their adaptive traffic controller by applying simultaneous perturbation stochastic approximation (SPSA) (Spall, 1992) based gradient estimates with a Neural Network Controller (NNC). In this paper SPSA was used for modeling the weight update process of a NN. They used a feed-forward NN with 42 inputs and two hidden layers for their model (S-TRAC). The performance of S-TRAC is evaluated in a network of nine intersections of the central business district of Manhattan, New York. For both case of constant arrival rates and increase in mean arrival their proposed model had 10% and 11% improvement respectively against fixed-time method.

First time Thorpe (Thorpe & Anderson, 1996) studied using reinforcement learning for traffic signal control (Wiering, Vreeken, van Veenen, & Koopman, 2004). Thorpe applied State-Action-Reward-State-Action (SARSA) (Sutton, 1996) to a traffic control problem. In his study, states were defined by the number and position of vehicles in all directions ending to an intersection and changing the traffic signal color from red to green and vice versa made his actions.

There are some other studies that applied similar techniques for controlling traffic signal timing. As some of the recent works, Prashanth and Bhatnagar (2011) proposed the feature based reinforcement learning for controlling traffic signals. It is claimed that using feature based state-action algorithms made their proposed model to an appropriate one for high-dimensional setting of a multi-intersection network. However, the prior work like Abdulhai et al. (2003), required full state representation and it was not practically possible to implement them. To perform the model the queue length is divided in three sets: low, medium, high. The performance of the proposed method is compared against fixed-time, longest queue and also the algorithms proposed in Abdulhai et al. (2003) and Cools, Gershenson, and DHooghe (2008), the paper indicates that the proposed feature based algorithms outperformed all the others.

Abdoos, Mozayani, and Bazzan (2011) presented a similar approach for state definition and applied it for a network of 50 intersections. In their research, the average length of queue in all approaching links and different forms of their permutations were considered as the states of *Q*-learning. However, considering just the different permutation causes neglecting the number of cars already make the queue (more definition presented in Araghi, Khosravi, Johnstone, & Creighton (2013)). The other problem about this work is considering some special values as the green time and applying different ranges of green time is not possible. Furthermore, the proposed amount of green time for all phases in a cycle produce at the start of that cycle, while, there should be different arrangement of traffic after finishing each phase. In this regard, it seems better that the controller produce the appropriate value of green time for each phase at the start of that phase instead of the start of the cycle. Their next work (Abdoos, Mozayani, & Bazzan, 2013), presents a holonic multi-agent. The structure of each controller is similar to Abdoos et al. (2011). The result of their research revealed that the performance of the individual *Q*-learning and holonic *Q*-learning is almost the same. The average standard deviation of delay time for holonic *Q*-learning was less than the individual *Q*-learning, which shows that they are clustered more closely in holonic *Q*-learning and are more reliable.

El-Tantawy et al. (2013) also proposed an adaptive QLC. They proposed two possible modes: independent mode and integrated mode. They tested the model on a network of 59 intersections. Their results showed reduction in the average intersection delay ranging from 27% in mode 1 to 39% in mode 2.

NN is usually applied as a traffic controller in combination with the other methods such as *Q*-learning or FLS. For example, Choy et al. (2003) used a hybrid approach that applied computational intelligence concepts to implement a cooperative, hierarchical, multiagent system. The problem of controlling the network was divided