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IMPROVING ADAPTIVE TRAFFIC SIGNAL CONTROL AT URBAN INTERSECTIONS BASED ON ARTIFICIAL INTELLIGENCE

Boltaboyev Javohir Yusufjon ugli
KIUT student

Abstract:

This article addresses the problem of improving an adaptive traffic signal control algorithm at urban intersections by taking into account the dynamic characteristics of traffic flow. Fixed-time control under conditions of rapidly changing traffic demand may lead to excessive waiting times and increased queue lengths. To address this problem, an adaptive control approach based on reinforcement learning principles is proposed. The approach considers the current state of traffic flow, queue lengths, waiting times, and service balance among different traffic directions. The article describes the algorithm's state vector, control actions, reward function, and safety constraints. To evaluate the proposed approach, an experimental methodology is developed using the SUMO microscopic traffic simulator and the TraCI interface.

Keywords: drone, cybersecurity, cyberattack, information security, DoS attack, Man-In-The-Middle, GPS spoofing, jamming, wormhole, drone communication, data protection, innovative security solutions.

INTRODUCTION

The rapid development of cities, the growing number of vehicles, and the increasing demand of the population for transport services make the effective organization of traffic flow in street and road networks a pressing issue. In particular, at signalized intersections in large cities, the uneven distribution of vehicles, the variation of traffic intensity over time, and the accumulation of queues in certain directions negatively affect the overall efficiency of the transport system. In traditional traffic signal control methods, the durations of signal phases are often organized on the basis of a predetermined schedule [1]. Such an approach may be useful under conditions where traffic flow is relatively stable. However, a sharp change in traffic demand, road traffic incidents, an increase in pedestrian flow, or the occurrence of congestion in certain directions causes the fixed control regime to become inconsistent with the real situation.

Adaptive traffic signal control aims to change signal timings on the basis of real-time traffic data. In this case, the outcome depends on the quality of the existing control system, the reliability of detector data, and the characteristics of the control algorithm [2], [3]. In recent years, the use of artificial intelligence, in particular reinforcement learning methods, has made it possible to develop decisions suited to the

complex and variable states of traffic flow [4], [5]. At the same time, taking into account only the number of vehicles does not fully describe the situation at an intersection [6]. Queue length, waiting time, imbalance among directions, and pedestrian safety should also influence the control decision. Giving constant priority to a high-intensity direction may cause excessive waiting in secondary directions. Therefore, there is a need for an algorithm that jointly takes into account control efficiency and safety requirements.

The aim of the research is to develop a conceptual and mathematical model of an adaptive traffic signal control algorithm based on reinforcement learning principles, which takes into account the current state of traffic flow, queue length, and waiting time at urban intersections, and to propose a methodology for its evaluation.

Research objectives: (1) to analyze traffic signal control methods; (2) to identify the main indicators describing traffic flow; (3) to formulate the state, action, and reward function of the algorithm; (4) to define safety constraints; (5) to develop a methodology for conducting comparative experiments in the SUMO environment.

METHODOLOGY

The research envisages the use of systems analysis, mathematical modeling, optimization, and microscopic computer simulation methods. The SUMO (Simulation of Urban MObility) simulator may be chosen for testing the algorithm [7]. SUMO models the individual movement of vehicles, queues at intersections, and traffic signal phases [8]. The TraCI interface, in turn, makes it possible to obtain the traffic state during the simulation and to influence traffic signal control through an external program [9], [10]. The experiment will consist of the following stages: creating the intersection geometry; defining inflows and turning proportions; configuring baseline control regimes; implementing the artificial intelligence agent in software; conducting repeated simulations under different traffic loads; and comparing the results under identical conditions. If real observation data are available, the simulation parameters are calibrated on the basis of these data.

The effectiveness of traffic signal control depends on the correct assessment of the traffic state in each approach direction of the intersection. The following indicators are proposed for forming the state vector:

- $q_i(t)$ — traffic flow intensity in direction i;
- $n_i(t)$ — number of vehicles in the queue;
- $w_i(t)$ — waiting time in the direction;
- $o_i(t)$ — occupancy level of the road section;
- $p_i(t)$ — pedestrian demand in the corresponding direction;
- s(t) — current traffic signal phase and the time elapsed since the phase change.

The state vector can be expressed as follows:

$$x_t = [q_1,\ldots,q_m, n_1,\ldots,n_m, w_1,\ldots,w_m, o_1,\ldots,o_m, s_t, p_t]$$

Here, m is the number of directions entering the intersection, and t is the time step. It is recommended to normalize the variables in the state vector before training. For indicators that cannot be measured, a reliable proxy or a suitable value obtained from the simulation should be chosen. The proposed model is based on a reinforcement learning agent [11]. The agent observes the traffic state, selects one of the permitted control actions, and receives a reward depending on the next state. DQN (Deep Q-Network) [12] may be used as an initial option for the discrete phase selection task; PPO [13] may be considered as an alternative algorithm. In the article, a single algorithm should be chosen as the main method, and its parameters should be described precisely.

1. Collecting traffic flow data and forming the state vector.

2. Determining the permitted signal phases and actions.

3. Selecting the next phase or the green signal duration with the help of the agent.

4. Checking the decision through a safety filter [14].

5. Updating the traffic signal control and observing the new traffic state.

6. Calculating the reward and updating the agent parameters during the training process.

The goal of the control agent is to increase the overall efficiency of traffic flow. For this purpose, a reward function combining delay, queue, waiting time, and stops is proposed:

$$r_t = -(\alpha \cdot D_t/D_0 + \beta \cdot N_t/N_0 + \gamma \cdot W_t/W_0 + \delta \cdot S_t/S_0)$$

Here, D_t is the total delay of vehicles; N_t is the aggregate indicator of queue lengths; W_t is the aggregate indicator of waiting time across directions; S_t is the number of stops; D_0, N_0, W_0, and S_0 are reference values for normalization; α, β, γ, and δ are weights that determine the relative importance of the criteria. The weights should be calibrated experimentally, and their selection should be justified in the article.

To protect directions that have gone unserved for a long time, an additional constraint can be introduced: $w_i(t) \leq W\max$. This constraint helps to control the maximum waiting time; however, its value should be set in accordance with local norms and the experimental conditions.

The artificial intelligence agent must not be able to switch traffic signal phases arbitrarily. The minimum and maximum green times, the yellow signal interval, the required all-red interval, and the rules for separating conflicting traffic flows are protected through the safety filter. The time allocated for pedestrians is also maintained in accordance with demand and safety conditions. These requirements are implemented as strict constraints that take precedence over the efficiency objective of the algorithm.

The proposed algorithm is compared with at least two baseline control methods. All methods must be evaluated under the same traffic demand, intersection geometry, and simulation duration. The compared methods are summarized in Table 1.

Table 1. Baseline and proposed control methods compared in the study

Control method	Main feature	Role in the study
Fixed-time	Phases operate on a predetermined schedule	Baseline for comparison
Detector-based	The signal regime changes depending on traffic demand	Adaptive baseline method [15]
Proposed AI	Queue, waiting, flow, and safety are considered jointly	Main method under evaluation

Traffic demand is varied through scenarios with low, medium, and high levels, as well as unevenly distributed across directions. For each scenario, it is recommended to conduct repeated simulations with several random seeds. The training and final evaluation scenarios must be separated.

The main evaluation criteria are: average delay (seconds/vehicle), average and maximum queue length, the mean and upper percentile of waiting time, the number of vehicles passing through the intersection per unit of time, and the number of stops. The results are presented with the mean value, the dispersion, and, if necessary, a 95 percent confidence interval.

RESULTS

At this stage, the conceptual model of the algorithm and the methodology for its experimental evaluation have been developed. Since simulations in the SUMO environment have not been performed, numerical results for average delay, queue length, or other indicators are not presented. Table 2 is intended to be filled in after the experimental results are obtained.

Table 2. Evaluation results of the control methods (to be completed after the experiments)

Indicator	Fixed-time	Detector-based	AI algorithm
Average delay, s/vehicle	Experimental result to be entered	Experimental result to be entered	Experimental result to be entered
Average queue length	Experimental result to be entered	Experimental result to be entered	Experimental result to be entered
Maximum waiting time, s	Experimental result to be entered	Experimental result to be entered	Experimental result to be entered
Throughput, vehicles/hour	Experimental result to be entered	Experimental result to be entered	Experimental result to be entered
Number of stops	Experimental result to be entered	Experimental result to be entered	Experimental result to be entered

DISCUSSION

The main difference of the proposed approach is that it seeks to express the traffic state not by a single indicator but through several criteria. While the joint assessment of delay and queue is aimed at improving overall efficiency at the intersection, the waiting time criterion may serve to reduce the risk of certain directions being neglected for a long time. However, the use of artificial intelligence does not mean that it will give better results than fixed-time control under all conditions. In stable traffic flow, a well-tuned schedule may work effectively; the advantage of adaptive control should be examined in situations where demand changes rapidly or where there is an imbalance among directions. Therefore, it is necessary to compare the algorithm under several load scenarios and under identical conditions.

The limitations of the study include the correspondence of the simulation model to real traffic conditions, the completeness of detector data, the computational resources for training the algorithm, and the issue of fully representing the requirements of pedestrians and public transport. Before applying the results obtained in SUMO in practice, it is advisable to calibrate the model with real observation data and then to conduct limited pilot tests. At the next stage of the research, the components of the reward function may be examined separately, different algorithms may be compared, and robustness to unexpected changes in traffic demand may be assessed. In addition, coordination among several intersections may be considered as a separate research direction.

CONCLUSION

The article considered the problem of improving adaptive traffic signal control based on artificial intelligence at urban intersections. The variability of traffic flow, the accumulation of queues, and the increase in waiting time across directions create the need to adapt traffic signal control to the current situation. Within the research, a control architecture was proposed based on a reward function combining traffic flow, queue length, waiting time, and stops, as well as on safety constraints. This model is expected to allow the artificial intelligence agent to select the signal phase appropriate to the traffic state.

The practical effectiveness of the algorithm has not yet been confirmed quantitatively. To evaluate it, it is necessary to compare fixed-time, detector-based, and AI control under identical conditions in the SUMO and TraCI environment, to conduct repeated experiments, and to perform statistical analysis. Future experiments will serve to determine the effect of the proposed approach on delay, queue, waiting time, and safety indicators.

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