ES-Band: A Novel Approach to Coordinate Green Wave System with Adaptation Evolutionary Strategies

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ABSTRACT

Urban arterial traffic coordination control catches great attention in the process of smart city construction. To achieve the optimum signal timing, many studies attempt to adjust green splits of a cycle time according to the distance between the road intersections. However, the existing green wave traffic control system usually has a sophisticated calculation, which depends upon the stability of vehicle speed and traffic flow, leading to weak robustness. Therefore, this short paper puts forward ES-Band, that is, a novel approach to control arterial traffic coordination with the help of artificial intelligence. ES-Band introduces the Covariance Matrix Adaptation Evolutionary Strategies (CMA-ES), a scalable alternative to reinforcement learning, into signal timing. Different traffic variables are adopted as parameters for searching the optimal value by CMA-ES. In order to evaluate the feasibility and effectiveness of ES-Band, we import the real traffic flow data of Zhongshan Road in Ningbo, Zhejiang Province, China, into traffic environment simulator for training and carry out a series of experiments. The results have shown that the ES-Band outperforms the traditional methods in terms of a better convergence, lower travel time, and fewer stops.

CCS CONCEPTS

• **Applied computing → Operations research**; *Transportation*

KEYWORDS

Intelligent Signal Control, CMA-ES, Green Wave Coordinate, Traffic Simulator

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1 INTRODUCTION

Nowadays, traffic congestion is one of the most challenging problems in urban management as the increasing number of car ownership in most cities in China. Urban arterial traffic coordination usually undertakes most of the traffic volume of a whole city and contributes significantly to alleviating traffic pressure. The green wave system, which becomes a trending topic in the process of smart city construction, plays an essential role in the intelligent transportation system. The green wave system maximizes the number of the green lights to be passed at the time when vehicles pass the first one. Therefore, the green wave system can reduce the average stops of vehicles and thereby improve the through efficiency of road network [1-3].

As shown in Fig.1, the traditional green wave method usually obtains the maximum bandwidth of the object function by mathematics or graphics according to the distance between signal lights and green wave velocity [4-10]. However, the existing approaches have their limitations in two-fold: 1. Similar velocities for all vehicles. Vehicles (even if only a minority) whose speeds are inconsistent with green wave velocity will break the order of the entire green wave queue; 2. Steady traffic flow. The randomness of traffic flow will change the split and the offset, which impairs the robustness of the green wave system.

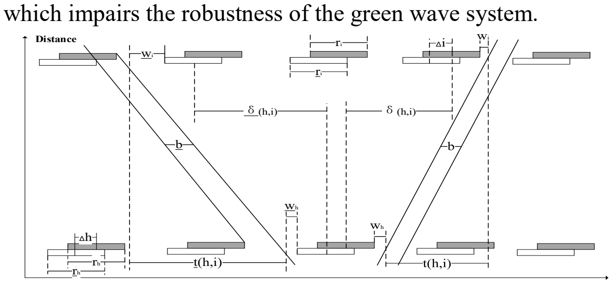

Figure 1: The illustration of computing process of MaxBand: a traditional way to coordinate the arterial traffic by formulating a mixed-integer linear program.

In recent years, the rapid development of state-of-the-art technologies in artificial intelligence, such as Fuzzy Logic [11], Genetic Algorithms [12, 13] and Expert System [14], brings new ideas into traffic signal control. One particular example is the application of deep reinforcement learning [15]. After defining step actions [16-19], reward function [20] and performance metrics, reinforcement learning algorithm can seek the optimal timing in corresponding traffic environment. Even though remarkable achievements have been made in the study of traffic trunk, these methods still have limitations. For example, they did not consider the variety of real-time speeds of different types of vehicles, such as large trucks, minicars and buses. Moreover, the sparse reward of traffic environment in reinforcement learning makes the training difficult to converge. In this short paper, we propose ES-Band, a novel approach to coordinate the traffic signal on the urban arterial. ES-Band introduce the Covariance Matrix Adaptation Evolutionary Strategies (CMA-ES), an alternative way to popular MDP-based RL techniques such as Q-learning and Policy Gradients [21]. ES-Band converts signal timing at each intersection into multiple search points and then find the optimal value under the objective function based on the evolutionary strategy. In addition, the proposed approach has been put practice with the help of Ningbo Traffic Bureau and proved that this solution is very useful.

The contributions of the ES-Band, comparing with its previous version, are summarized as follows:

1. An open-source simulator can construct the traffic scene [2], the vehicles can therefore have an arbitrary speed instead of a constant one.
2. The simulator can generate traffic flow under multiple random seeds according to the same departure probability. This way the robustness of algorithm is enhanced because various traffic environments are compatible with the optimization of timing schemes.
3. ES-Band use CMA-ES to find the optimal value that did not require a substantial effort to design reward function.

2 METHOD

This method is designed based on the following assumptions:

1. ES-Band changes the green light time in each phase (green split), cycle and offset for signal timing.
2. The phase sequence is not considered.
3. The non-green light is fixed in ES-Band.

Given the above assumptions, the specific process of ES-Band is described as the figure 2 shows.

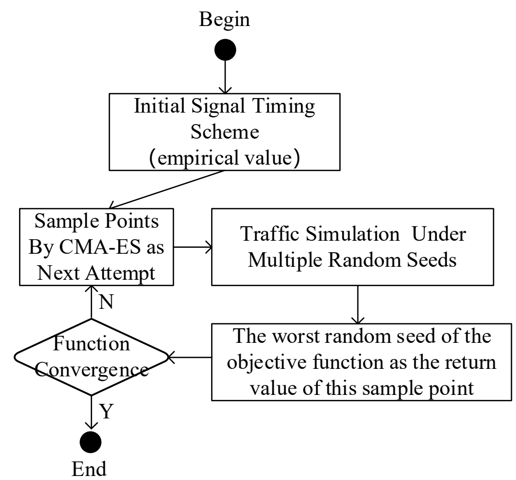

Figure 2: The flow chart of ES-Band algorithm. Note: In the sampling process, different random seeds are considered which improve the robustness for dealing with various traffic environment.

2.1 Definition of Search Points

CMA-ES samples the independent points from a specific distribution (e.g. normal distribution) and then iteratively choose the best points as the next generation. Consequently, the first step of ES-Band is defining the search points. Studies have shown an identical cycle (name it as the public cycle below) of lights at each intersection is required to maintain the green wave effect. For each intersection, we can obtain the green time in the last phase by subtracting the sum of other phase time from the public cycle. Suppose the intersection C_k have P_k phases, we have $P_k - 1$ dimensions for the green time needed to set at each intersection. In addition, each intersection, except for the first one, has an offset time plus the public cycle, so the total number of dimensions of search points as below:

$$\sum_{1}^{k=n} (C_k - 1) \times P_k + (n - 1) + 1$$

Simplified as:

$$\sum_{1}^{n} k\, C_k \times P_k$$

2.2 Traffic Simulation

The sampling from a normal distribution can generate a set of sample points, which are taken as traffic variables for the simulation. Ultimately, a set of traffic evaluation values will be obtained as return values. During the simulation, it is possible to generate traffic congestion in the traffic environment. For example, the simulator will fail to start normally when one of the lanes at a crossroad is full, in this case we will give the worst return value. Note that this step can be done in a multi-threaded or distributed manner to reduce the training time.

2.3 Offspring

A set of function values obtained through simulation are used as the next generation of CMA-ES. The generated offspring sample points are processed in the following steps:

1. The offset of the next generation can increase or decrease the integer multiple of the cycle to keep the value between zero and the public cycle.
2. Recalling the last green light time is calculated by subtracting the sum of other phase timing from the public cycle. Consequently, if the last green light time is less than minimum green light time, it is necessary to adjust the public cycle, which means the last green time at all sections will increase accordingly.

2.4 Over-Fitting

The corresponding timing scheme can be obtained after the convergence. However, this timing scheme has a great correlation with depart rules and it is hard to guarantee that our simulator's departure rule is same as that in the reality. Therefore, we need to find a timing scheme that can adapt to various environments and has better generalization ability to solve the over-fitting problem.

To do so, we rely on random factors that commonly appear in most simulators. Under the same departure probability, different random seeds of the simulator will produce different departure rules. Therefore, multiple groups of random seeds are used in the simulator and the worst result is taken as the return value. The above process can also be executed in parallel.

2.5 Definition of Objective Value

The definition of objective value of this paper consists of the following two parts:

1. Blocking Coefficient: No lanes should be blocked in the training process. Assume the blocking coefficient is α, we compute the occupancy ratios for all lanes at each step. If the occupancy ratios exceed threshold δ, then $\alpha = \alpha+1$.
2. Traffic Evaluation Indicator: the training should focus on minimizing a specific traffic evaluation indicator, such as the travel time, the number of stops, and the traffic throughput

Note that the priority of the blocking coefficient is higher than the traffic evaluation indicator. Besides, the calculation of blocking coefficient takes all lanes into account, while the traffic evaluation indicator only considers lanes in the direction of the main road.

3 EXPERIMENTAL DESIGN

As for case studies, the green wave traffic control system is tested at four consecutive intersections along Zhongshan Road in Ningbo, China. The feasibility of the ES-Band algorithm can also be verified using the above cases. This paper uses sumo [22] as the traffic simulator.

3.1 Road Selection

Zhongshan Road is a main urban arterial in Ningbo City, Zhejiang Province, China, which stretches to 20.2 km east-west throughout the whole city. The busiest section of Zhongshan Road is selected for this study, whose range is from Xiaowen Road in the east to Kaiming Road in the west. The total length of the selected road is more than 1 km. The road network are shown in Figure 3.

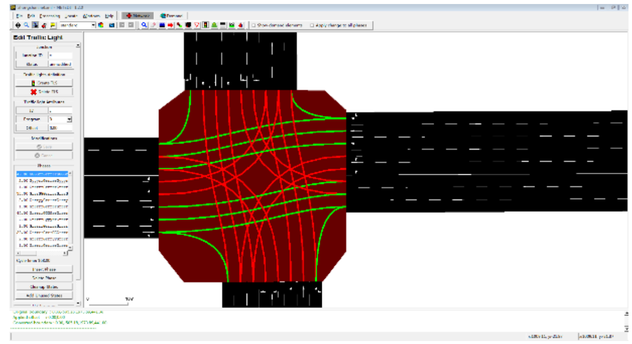

Figure 4: The road network illustration in Sumo. Note: Diagram of the all phases of the traffic signal in Beida Road. Sumo can define the trajectory for vehicles running on the intersections.

3.2 Traffic Data

We obtain the original traffic flow data from the camera at all intersections on Nov. 26, 2018. The traffic flow is categorized into big vehicles (cn_b) and small vehicles (cn_s). The big vehicles represent as transport whose length over 10 meters, such as large trucks, whereas buses and the small vehicles small and medium-sized cars. Since the traffic flow data is collected between 7:00 AM-11:30 AM every 5 minutes, some simple processing is needed to get the departure probability of each direction into the simulator.

3.3 Experimental Result

We firstly investigate the relationship between the blocking coefficient and the number of iterations of ES-Band (Figure 6). Then, we find the relationship between the number of iterations and the traffic evaluation (the travel time and the number of stops; Figure 7). Lastly, as shown in Figure 8, we compare the traffic evaluation result in ES-Band and that in the traditional maximum green wave band method (MaxBand).

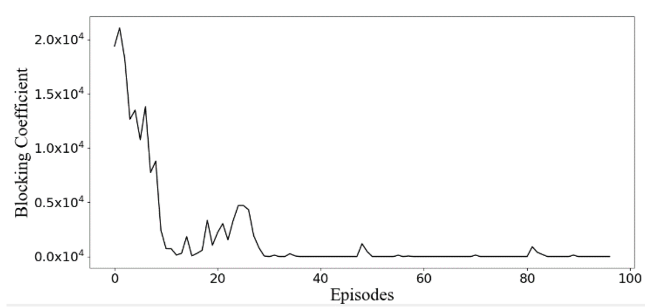

Figure 6: Calculation of the congestion degree in each episode. Note: We put detectors, which could monitor whether any vehicles running on it, at the end of each lane. If vehicles stay on the detectors for more than one minute, the value of blocking coefficient will plus one.

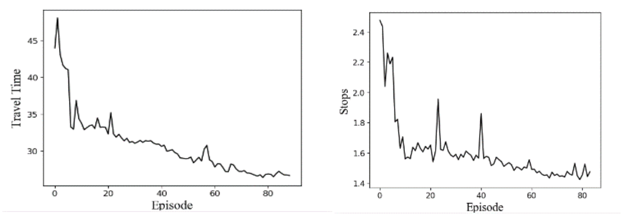

Figure 7: The relationship between the number of iterations and the traffic evaluation. Note: There is significant reduction on both travel time and the number of stops as the iterative process goes on. After a couple of iterations, the algorithm can be finally converged to an (almost) optimal solution.

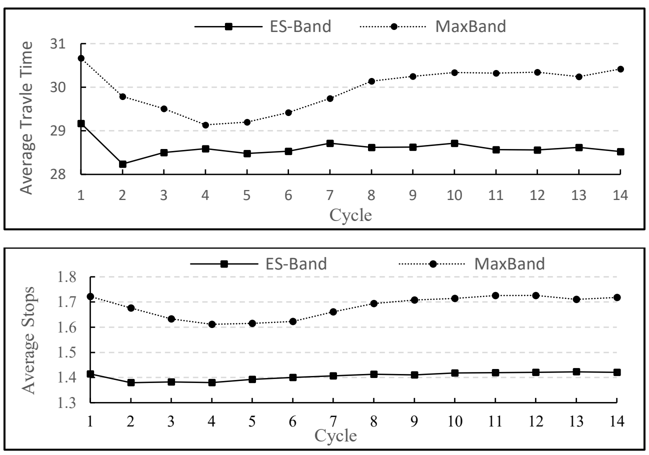

Figure 8: The comparison between the traffic evaluation result in ES-Band and that in the traditional maximum green wave band method (MaxBand). Note: We choose another group of random seeds that are different from the applied ones to compare the average travel time and stops between ES-Band and MaxBand.

From the experiments, we find that ES-Band can quickly figure out a plausible solution, which avoids the traffic jam in the simulator after about thirty iterations. As iteration goes, both the average travel time and the number of stops decrease significantly until they reach a stable value (convergence). Moreover, both average travel time and the number of stops using ES-Band are less than those using MaxBand. As a result ES-band enables vehicles to move faster through a series of traffic lights, indicating better feasibility and effectiveness.

4 CONCLUSIONS

In this paper, we put forward ES-Band, which introduces the evolutionary strategy into the traffic signal control on urban arterial. We find that when the timing scheme is used as search points in ES-Band, the training can be well converged. Compared with the traditional way, ES-Band can deal with more complex traffic scenarios as well as improve the traffic efficiency. It is also an alternative attempt of the deep reinforcement learning that treats traffic simulator as the environment variable in the training of machine learning.

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