International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18 (2026) pp. 1-13

https://doi.org/10.70917/ijcisim-2026-0027
Article

Research on Adaptive Traffic Signal Control Algorithm for Intelligent Transportation

Chunhong He [1] and Bin Ren [2,*]

[1] School of Urban Construction and Intelligent Manufacturing, Dongguan City University, Dongguan 523000, Guangdong, China
[2] International School of Microelectronics, Dongguan University of Technology, Dongguan 523000, Guangdong, China
* Correspondence author: reb618757@163.com

Abstract: Multi-intersection traffic signal control is the key to improve the overall traffic efficiency. In order to more realistically reflect the real-time traffic conditions at intersections, this paper first establishes a multi-phase real-time control model using the average delay time as the objective function, so as to obtain the cycle of each intersection with the green light time of each phase. Then the communication capability between multiple intelligences is utilized to coordinate the execution of their own timing schemes. Simulation experiments are run in Vissim platform to verify the effectiveness of the adaptive traffic signal control algorithm proposed in this paper. The results show that the adaptive traffic signal control algorithm proposed in this paper is significantly better than the fixed timing and traffic weight timing algorithms in three aspects, namely, queue length, vehicle waiting time and average vehicle speed. The average queue length, the average waiting time of vehicles on each road and the average speed of vehicles on each road are 4.12m, 4.67s and 29.17 km/h, respectively.

Keywords: multi-intelligence; multi-phase real-time control model; adaptive traffic signal control algorithm; traffic conditions; simulation experiments

1. Introduction

With the increase in global population and economic development, the number of automobile ownership is increasing. According to the data released by the Ministry of Public Security, as of 2023, the number of motor vehicles in China has reached 435 million, of which 336 million are automobiles. The number of newly registered automobiles is 24.56 million, an increase of 1.33 million or 5.73% from 2022 [1]. However, according to the Gaode Maps 2023 Annual Traffic Analysis Report for China's Major Cities, congestion has increased in 85% of China's 50 major cities in 2023 compared to 2022 [2]. Traffic congestion has many negative impacts on residents and society, mainly including time waste, energy waste, and environmental pollution [3]. Long periods of slow travel increase commuting time, intensify fuel consumption and emissions, and lead to wasted energy and reduced air quality [4-6]. In addition, traffic congestion leads to an increase in traffic accidents [7]. Therefore, effective measures need to be taken to improve the traffic situation and enhance the quality of life of residents and urban development.

Among the many types of factors contributing to traffic congestion (e.g., inadequate transportation infrastructure, and irrational road planning), signal-controlled intersections are one of the most prevalent types of traffic congestion bottlenecks in the urban transportation environment [8-9]. Therefore, it is a promising approach to achieve effective organization and management of traffic flow at intersections based on the improvement of the existing traffic infrastructure, i.e., better use of limited road facilities [10]. In contrast to highway traffic scenarios, which are easier to model the formation and evolution of traffic congestion, urban traffic has more mixed autonomous stochastic and more complex scenarios [11-12]. It also features recurring similar traffic scenarios (e.g., high demand during peak traffic hours) and non-recurring disruptions with various uncontrollable risks (e.g., traffic accidents and road expansions) [13]. Among them, intersections are one of the most prevalent bottlenecks of traffic congestion in urban traffic scenarios [14]. Therefore, traffic signal control for managing intersections is one of the keys to urban traffic control, and its main task is to assign the right to use the road for different time periods to vehicles, pedestrians, cyclists, and other road users from different directions of movement [15-17]. Usually, well-designed traffic signals are expected to be effective in maximizing intersection capacity, i.e., increasing traffic throughput [18]. It also reduces the frequency and severity of certain types of collisions, i.e., improves safety, and provides opportunities for certain disadvantaged road users to use the road safely, i.e., ensures fairness [19].

Therefore, effective traffic signal control algorithms play a crucial role in urban traffic management, not only for the moving systems in the transportation network (e.g., alleviating traffic congestion, reducing vehicle travel time, etc.), but also for the other dynamic systems coupled with them (e.g., improving the efficiency of the output of socio-economic units, etc.) [20-22]. Currently, traffic signal control algorithms have been widely used in urban traffic management and play a great role in alleviating traffic congestion [23]. For example, the intelligent traffic signal control algorithms (ITLC and ATL) proposed in literature [24], which improve traffic flow and reduce queuing delays by coordinating traffic signals based on real-time traffic conditions, outperform other algorithms in terms of efficiency and delay reduction. Literature [25] proposed a two-phase algorithm for optimizing the phase order and duration of traffic signals, which significantly reduces travel time and is computationally efficient. Literature [26] proposed and constructed a traffic signal control system based on intelligent transportation system architecture and reinforcement learning, and the test results showed that the system can reduce vehicle queuing by 29%, waiting time by 50%, and delay time by 50%. Literature [27] proposed a novel traffic signal control algorithm based on proximal policy optimization (PPO) in its study, and demonstrated its superiority over existing methods in improving traffic efficiency through simulation experiments. The traffic control system proposed in the literature [28] incorporates the dynamic clustering function of V2X networks and aims to improve traffic flow, reduce waiting time and prevent congestion, while providing accurate real-time traffic information and balancing the traffic flow. In the above practical applications in the field of traffic engineering, the methods used are based on traditional mathematical modeling and optimization calculations, which can effectively facilitate traffic signal operation in relatively simple traffic environments [29-30]. In addition, traffic signal control algorithms usually involve pre-programmed cycles that are often obtained by offline optimization based on historical traffic flow observation data to implement traffic control [31].

In this paper, the multi-phase real-time timing model is combined with the green wave coordination algorithm of multi-intelligence to design the adaptive traffic signal control algorithm. According to the acquired real-time traffic flow, the multi-phase real-time timing algorithm is utilized to calculate the green light time of each intersection cycle and each phase. Then, using the excellent characteristics of multi-intelligent body system, such as autonomy, distribution, coordination, active learning, etc., each intersection of the ring road is regarded as an intelligent body, and the neighboring intelligences can communicate with each other, and use the memory storage and reasoning and learning ability of the intelligent body system to optimize the green wave coordination of multiple intersections on the ring road. A 2 × 2 grid-shaped urban road network is used as the simulation task scenario, and simulation experiments are run on the Vissim platform, so as to verify the effectiveness of the adaptive traffic signal control algorithm proposed in this paper.

2. Adaptive Traffic Signal Control Algorithm Design

2.1. Description of the Problem

Under the premise of determining the road conditions, the longer the cycle time, the greater the capacity, but the vehicle stopping rate also grows: at the same time, in the case of low traffic flow saturation, when the extended cycle time to improve the capacity is greater than the traffic demand, but increase the delay time. In order to more realistically reflect the intersection traffic condition and establish an effective real-time intersection signal control model, the average delay time of vehicles in a cycle is chosen as the optimization objective function as the main performance index. A typical intersection traffic flow distribution is shown in Figure 1.

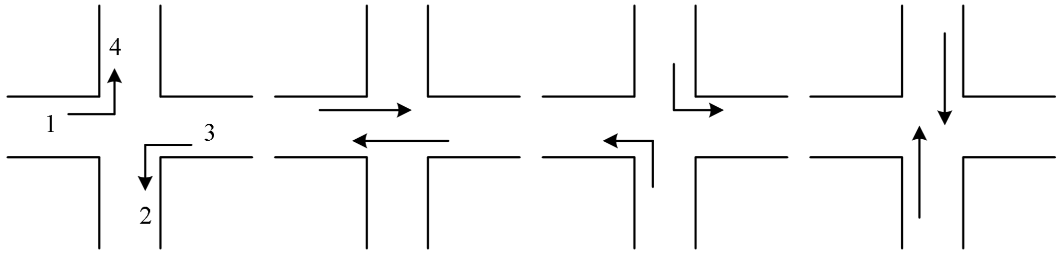


Figure 1. Schematic diagram of the four-phase and four-direction intersection.

Examining the k th phase in the j th direction of an intersection in a certain operating cycle, let q_s be the number of vehicles that can pass in that direction per unit time, r be the time of the red light, and n_g be the number of vehicles waiting at the moment of the arrival of the green light (which includes a -vehicles that are already waiting at the 0-start moment) [32].

Let t_n be the moment of arrival of the n th vehicle. Since the waiting time of any vehicle is equal to the difference between its departure and arrival moments, the waiting time d_n in different cases is considered as follows.

When $n \le a$, for the vehicles that have been waiting at the beginning of the cycle, it is considered that all of them have arrived at the stop line at the moment 0, then they only need to wait for the end of the time of the red light to pass in order, i.e., in sequence:

$$d_n = r + (n-1)\frac{1}{q_s}, \quad n \le a \tag{1}$$

When $a < n \le n_g$, for vehicles arriving during the red light time, similar to the previous case, i.e.,:

$$d_n = r + (n-1)\frac{1}{q_s} - t_n, \quad a \le n \le n_g \tag{2}$$

When $n > n_g$, vehicles arriving during the green time are divided into two cases:

If all vehicles have left before the arrival of the n th vehicle, it passes directly without waiting; if there are still vehicles waiting when the vehicle arrives, it waits for all current vehicles to leave before passing through the traffic light. i.e.,:

$$d_n = \begin{cases} 0 & t_n > r + \dfrac{(n-1)}{q_s} \\ r + (n-1)\dfrac{1}{q_s} - t_n & t_n \le r + \dfrac{(n-1)}{q_s} \end{cases} \tag{3}$$

Considering the limited number of vehicles that can be passed during the green time, the maximum number of vehicles that can be passed $b = q_s g$ and g is the green time of the intersection. Depending on the number of vehicles that can pass, the total waiting time D_{jk} for the k th phase in the j direction is calculated as follows.

When $b < a$, the number of vehicles that can pass is very small, and some cars still need to wait for two and more signal cycles, i.e.,:

$$D_{jk} = \sum_{n=1}^{b}(r + (n-1)\frac{1}{q_s}) + (a-b)r + \sum_{n=a}^{n_g+a} r - t_n \tag{4}$$

When $a \le b < n_g$, the vehicles that have arrived during the red light time have not passed through the intersection for part of the cycle, i.e.,:

$$D_{0jk}=\sum_{n=1}^{a}(r+(n-1)\frac{1}{q_s})+\sum_{n=a+1}^{b}(r-t_{n-a}+(n-1)\frac{1}{q_s})+\sum_{n=b+1}^{n_g}r-t_n \tag{5}$$

When $n_g \le b < n+a$, all vehicles pass through the intersection during the red light time, but some of the vehicles arriving during the green light moment are stranded due to the long queue, i.e.,:

$$D_{jk}=\sum_{n=1}^{a}(r+(n-1)\frac{1}{q_s})+\sum_{n=a+1}^{b}(r-t_n+(n-1)\frac{1}{q_s}) \tag{6}$$

When $b > n+a$, i.e., when all vehicles pass in a cycle.

i.e.,:

$$D_{jk}=\sum_{n=1}^{a}(r+(n-1)\frac{1}{q_s})+\sum_{n=a+1}^{n_g}(r-t_n+(n-1)\frac{1}{q_s})+\sum_{n=n_g+1}^{n_c}(r+\frac{n}{q_s}-t_n) \tag{7}$$

2.2. Multi-Phase Real-Time Timing Modeling

Urban road traffic signal timing optimization is based on the traffic flow of the key lanes in each phase, with the effective green time of the phase as the independent variable, so that the objective function is minimum [33]. According to the actual demand of the traffic situation, the average delay time $F(g_i,r_i)$ minimum as the objective function, the establishment of traffic signal timing nonlinear optimization model is as follows:

$$Min\ \ F(g_i,r_i)=\sum_{j=1}^{4}\sum_{k=1}^{4}D_{jk}\,/\sum_{j=1}^{4}(a_i+n_{ri}+n_{gi}) \tag{8}$$

2.3. Algorithm Model and Parameters

The model that defines the multi-intelligence of a roundabout intersection is shown in the following equation:

$$\begin{gathered}\langle Agent,S_t(i,j),C_k,T_k(i,j),P^i_{next}\rangle,i=1,2,\cdots,n;j=1,2,\cdots,m;\\ \text{Both } t \text{ and } k \text{ are positive integers}\end{gathered} \tag{9}$$

where: agent is the set of intersection multi-intelligence; $S_t(i,j)$ is the state of intersection multi-intelligence i; C_k is the cycle length of intersection multi-intelligence; $T_k(i,j)$ is the maximal phase time of each phase of intersection multi-intelligence i; and P^i_{next} is the next phase of the intersection multi-intelligence i:

$$Agent=[agent_1,agent_2,\cdots,agent_n] \tag{10}$$

$$S_t(i,j)=[s_t(i,1),s_t(i,2),\cdots s_t(i,m)] \tag{11}$$

$$C_{k-}[C_k(1),C_k(2),\cdots,C_k(m)] \tag{12}$$

$$T_i(i,i)=[t_i(i,1),t_i(i,2),\cdots,t_i(i,m)] \tag{13}$$

where: $s_t(i,j)$ refers to the state value of the j th phase of the i th intersection smart at moment t; $C_k(i)$ is the period value of the i th smart at the k th cycle; and $t_k(i,j)$ is the j th phase of the i th smart at the k th cycle at the Maximum phase time.

After defining the model of ring road intersection intelligences, solving the traffic parameters of each intersection intelligence is a very core part, and there are 3 main traffic parameters: cycle, green time of each phase, and phase selection strategy. The following is an elaboration of the solution of these 3 parameters cycle: the solution of cycle is as follows:

$$C_k(i)=\begin{cases}\dfrac{1-5L_i+5}{1-Y_i} & Y<0.9\\ \text{Contingency plan} & Y\geq 0.9\end{cases} \tag{14}$$

When the optimal cycle condition is satisfied, the optimal cycle is found according to Webster's algorithm, if not, the cycle duration in the preplan is enabled.

Phase green time: based on driving safety considerations, each phase should have a minimum passing time $t_{\min}$, which is usually taken as 10 s. Here, the flow rate of the j th phase of the i th intersection smart body is defined as $q_{(i,j)}$, and at the moment of t, the total passing traffic flow of the i th intersection is $Q_i(t)$, and $t_{(i,j)}$ is the green light duration that the i th phase of the i th intersection intelligence should acquire. Then, according to the traffic allocation principle:

$$t_{(i,j)}=\frac{q_{(i,j)}}{Q_i(t)}C_k(i) \tag{15}$$

Phase selection strategy: at this point, the design utilizes the characteristics of communication and information sharing of multi-intelligent body systems. Design Ideas: suppose the intersection intelligent body $agent_i$. At this time, it is releasing the traffic flow Tf, at this time, the intersection intelligent body $agent_i$; sends a notification Notification to the neighboring intersection intelligent body $agent_{i+1}$, where $agent_{i+1}$ denotes the downstream intersection intelligent body. Based on the sent notification, the intelligent body $agent_{i+1}$ gets the moment of release and calculates the moment of arrival of the green wave traffic, so as to adaptively adjust itself to optimize the capacity of the road [34].

To further illustrate the selection strategy of coordinated phases, here, the time-distance diagrams of adjacent intersections are analyzed to explain some parameters of the elevation, and the time-distance of 2 intersection intelligences is shown in Fig. 2.

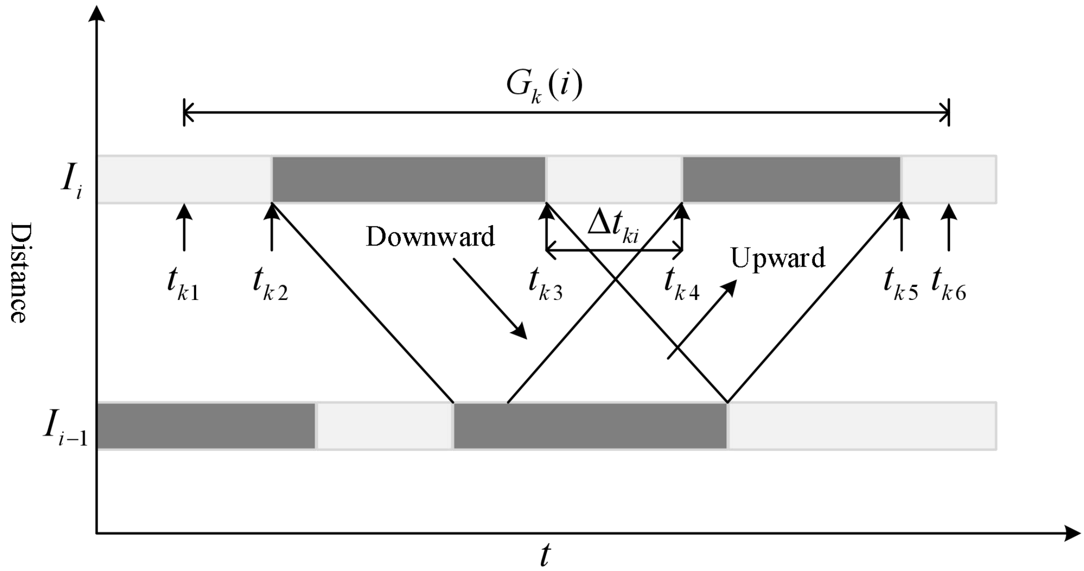


Figure 2. Phase time interval diagram of the intersection.

In the figure, I_i, I_i-1 are the adjacent intersections, $C_k(i)$ is the k th signal cycle duration of the intersection I_i, t_{k1} is the beginning moment of the signal cycle, t_{k6} is the ending moment, t_{k2} is the start moment of downstream green time, t_{k3} is the end moment of downstream green time, downstream green time is the green time of traffic flow from intersection I_i to I_{i-1}, and similarly, t_{k4}, t_{k5} is the start and end moment of upstream green time. The Δt_{ki} is the time interval between the 2 green wave bands, that is, the difference between t_{k4} and t_{k3}. Here the set of time intervals $\Delta t_k = \left[t_{k2} - t_{k1}, \Delta t_{ki}, t_{k6} - t_{k5}\right]$ The choice of time interval Δt_k directly affects the coordinated green wave control effect at the intersection of neighboring intelligences.

The phase selection of the intersection intelligent body is based on 2 considerations: 1) one is the current state of the intelligent body itself, a single intersection is an adaptive control strategy, a single intersection is considered as an intelligent body, and if you do the selection of the current phase, it will inevitably affect the control effect of the adaptive control. 2) It is necessary to consider the time interval between the moment of the coordinated traffic (that is, the green-wave traffic) arriving at this intersection and the current moment. On the basis of 2 neighboring intersections intelligent body to meet the green wave conditions, to be coordinated traffic arrival time and the intersection of the intelligent body of the remaining optional phase time duration of the size of the difference, that is, the degree of matching between the two will affect the control effect of the intelligent body: if the two are equal, then the coordinated traffic can be without stopping continuously through the 2 neighboring intersections, if not equal, certainly have an impact on the effect of the green wave.

After the above analysis, it can be obtained that the current phase selection strategy of the intelligent body is mainly determined by 2 factors, i.e.: the current state of the intelligent body and the time matching degree. The current state parameter of the intelligent body is denoted by $s_i(i, j)$, and the Time Match is denoted by Time Match, respectively. Where Time Match is defined as follows:

$$TimeMatch = \begin{cases} 1 & \Delta t = t_{(i,j)}, \Delta t \in \Delta t_k \\ \dfrac{\Delta t - t_{\min}}{\Delta t - t_{(i,j)}} & \Delta t \neq t_{(i,j)}, \Delta t \in \Delta t_k \end{cases} \tag{16}$$

where $t_{\min}$ is the minimum phase time mentioned and Δt is the value taken in the set of time intervals Δt_k.

Since the phase selection strategy is mainly determined by the above 2 parameters, the coordinated adaptation variable of the current intelligence is defined:

$$Adapt = s_t(i, j) \times TimeMatch \tag{17}$$

2.4. Algorithmic Flow

After analysis, the green wave coordination algorithm based on multiple intelligences utilizes the communication ability between intelligences to transmit the useful information needed to be transmitted to the neighboring intelligences, and after the reasoning and calculation of the intelligences, the coordinated control parameters as well as the next execution strategy of the intelligences are obtained.

Here the expression of sending information communication between neighboring intelligences is defined as:

$$Send\_Info = \{t_s^u(i), t_e^u(i), t_s^d(i), t_e^d(i)\} \tag{18}$$

where: $t^u(i)$ is the starting moment of the coordinated green light in the upward direction; $t_e^u(i)$ is the ending moment of the coordinated green light in the upward direction. Similarly $t_s^d(i), t_e^d(i)$ are the start as well as the end moments of the coordinated green light in the downstream direction.

In addition, define the accepted information exchange expression between neighboring intelligences as:

$$Receive\_Info = \{t_s^u(i-1), t_e^u(i-1), t_s^d(i+1), t_e^d(i+1)\} \tag{19}$$

Combining the multi-phase real-time timing algorithm and the multi-intelligent body based filtering coordination algorithm, the total flow of the algorithm is shown in Fig. 3, and the proposed algorithm is described as follows:

1) Obtain the real-time traffic flow in different directions at each intersection.

2) Get the cycle of each intersection and the green light time of each phase according to the multi-phase real-time timing algorithm.

3) Based on the idea of multi-intelligent body information interoperability, different intersections send their own cycle and green light time of each phase to neighboring intersections.

4) Judge whether the period between each intersection is the same or an integer multiple, if yes, then the filter coordination control can be carried out, each intersection intelligent body according to the neighboring intersection's period and the coordinated phase green light time, adjust their own coordinated phase green light time; if not, it does not satisfy the conditions of the green wave coordination, each intersection intelligent body to implement their own time allocation scheme can be [35].

5) The update frequency of real-time traffic flow data is 5min, so the number of times each intersection signal timing program is executed: $n = \lfloor 5/T \rfloor$, that is, the time of n cycles is the closest to 5min, n that is, the number of times the cycle is executed during this time period. After executing n cycles, continue to obtain the real-time traffic flow and continue step 1.

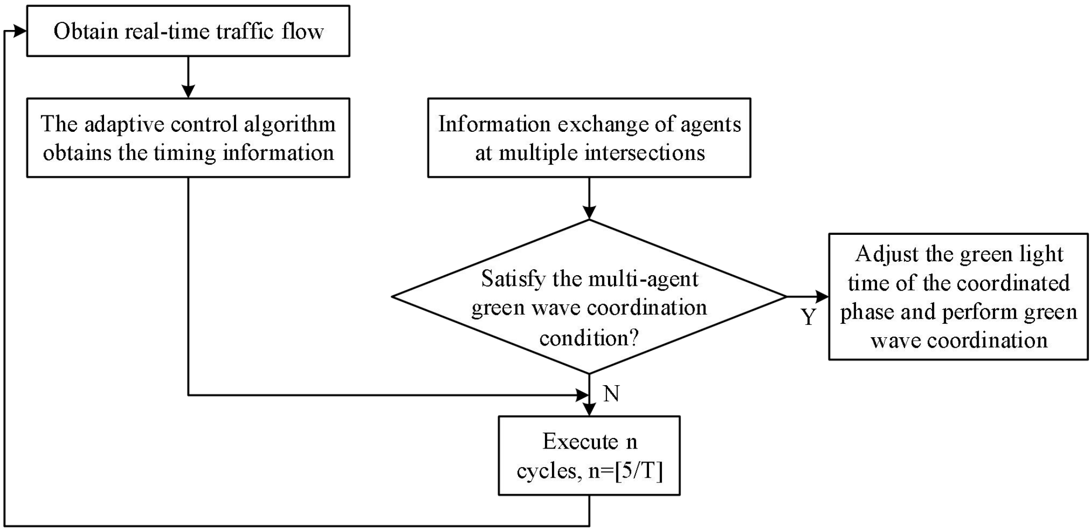


Figure 3. General flowchart of the algorithm.

3. Experimental Simulation

In order to verify the effectiveness of the adaptive traffic signal control algorithm proposed in this paper, the control algorithm is simulated on the Vissim platform, which is a microscopic, discrete-time based driving behavior simulation modeling tool that can accurately simulate urban traffic scenarios and be used to model and analyze urban traffic.

3.1. Experimental Setup

The simulation task scenario is a 2 × 2 grid-shaped urban road network. All intersections have the same structure and are separated from each other by 400 m. Each intersection has the same entering traffic volume, and the initial traffic volume is set to 650 vehicles per hour (veh/h). It is assumed that the signal controller does not have a buffer time for an all-red light, i.e., it enters the next phase immediately after the end of one phase. In the Agent training phase, each scenario contains 150 time steps, which is equivalent to 30 min of simulation time. In the next experiments, the stability of Agent performance will be improved by optimizing the hyperparameters, and methods that can effectively improve the performance and stability of the intelligences will be proposed.

3.2. Hyperparameter Optimization

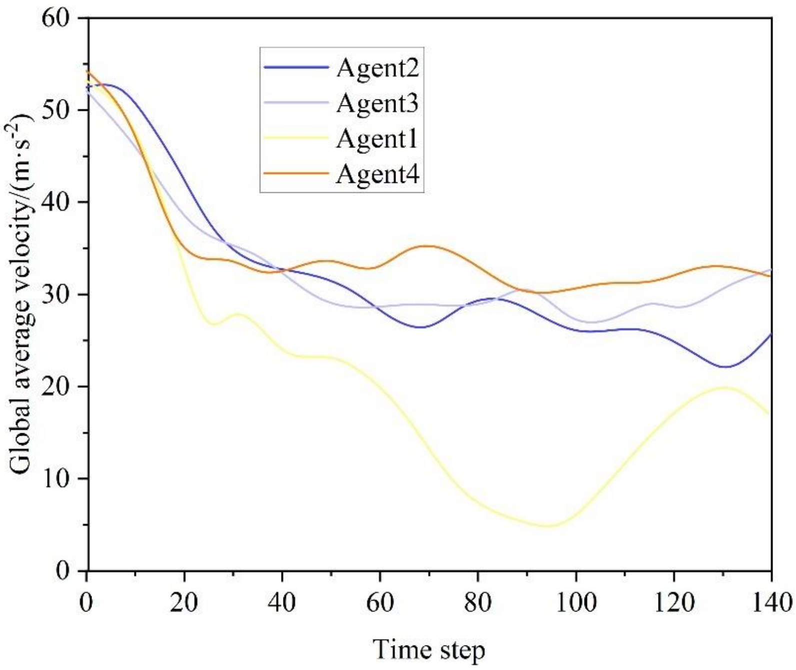
In the initial stage of training, the hyperparameters of the Agent are set as usual: the learning rate is 10-4, the size of the cache pool is 3200, the discount factor is 0.9, the initial epsilon is 0.6, the decay rate is 0.99, and the minimum epsilon is 0.02. In the testing stage after the training, the Agent is tested for 30 min in the reset Vissim environment. In this paper, the global average speed is used as the evaluation metric, because this metric not only describes the state of the traffic network, but also correlates with the objective function of the Agent, i.e., the cumulative reward value.

The four Agents with different hyperparameters are shown in Table 1, in which the traffic flow in the training phase of Agent1~Agent3 is fixed at 650 veh/h, while the traffic flow in the training phase of Agent4 fluctuates between 450~550 veh/h. The reason is that the changing traffic volume can increase the diversity of the training scenarios, which in turn prompts the Agent to learn more strategies. In addition, in order to better evaluate the method in this paper, the baseline method is introduced for comparison. The control algorithm represented by the baseline uses the DQN algorithm to implement traffic signal control at a single intersection, in which the Agent structure is a small deep-stack self-coding neural network. The state of the network is represented by the length of the waiting queue entering the intersection; the reward value function is defined as the absolute value of the difference between the waiting queue lengths in the north-south and east-west directions. In this paper, this method is extended to road network control, where each intersection is controlled by one Agent, and the average performance index of this method is used as a baseline.

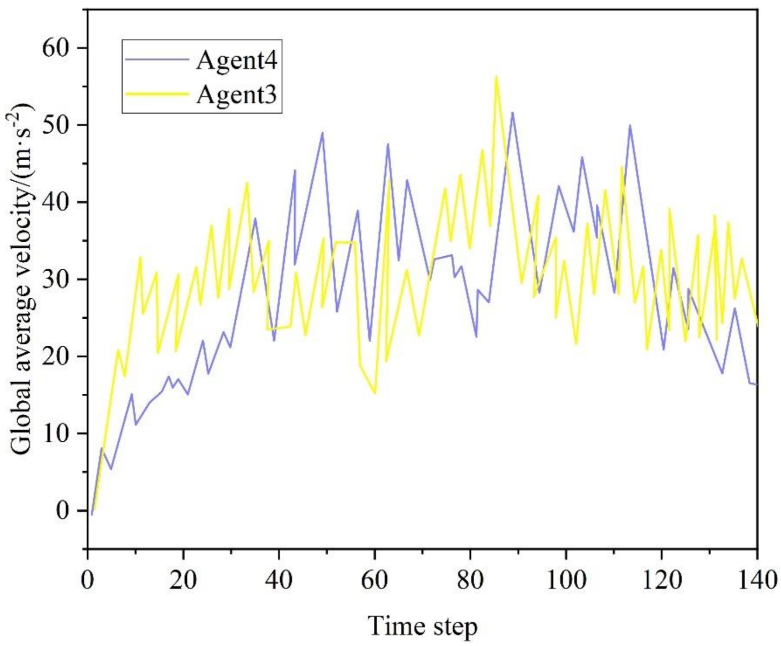
Table 1. Hyperparameter settings of DQN Agents.

Agent		Replay size	Epsilon	Train steps	Flow rate
Agent 1		3200	0.73	3200	650
Agent 2		1200	0.73	3200	650
Agent 3		1200	0.94	3200	650
Agent 4		1200	0.94	4800	mix

In addition, the average waiting queue length was introduced as a supplementary evaluation index. The experimental results are shown in Fig. 4: After the 50th time step, Agent1 makes wrong decisions continuously, which will lead to the deterioration of the traffic condition of the road network. Next, the performance of Agent will be improved by optimizing the hyperparameters. The Xavier method is used to initialize the neural network weights of Agent in the training phase. From the figure, it can be seen that Agent3 and Agent4 can effectively control traffic signals and have stable performance, i.e., reducing the size of the experience playback cache and eliminating the old experience in time are beneficial to the learning of the Agents.



(a) Global average velocit



(b) Total length of the queue

Figure 4. Performance evaluation of Agent1~Agent4.

Comparison of Agent3~Agent5 performance metrics is shown in Table 2.In addition,it is noted that Agent4 slightly outperforms Agent3.Compared to the baseline method its global average speed is improved by about 1.17(km·h^{-1}) and the average waiting time captain is reduced by about 4.73/veh.The difference between Agent3 and Agent4 is that In the training phase, Agent4 is trained in an environment where the traffic flow fluctuates over a wider range. It can be seen that the traffic flow has an important influence on the final performance and stability of the Agent.

Table 2. Performance index comparison of Agent3~Agent5.

Agent	Global average velocity/(km·h^{-1})	Total length of the queue/veh
Agent3	31.89	28.89
Agent4	33.46	29.04
Agent5	34.85	21.57
Base line	30.72	33.62

3.3. Comparison Algorithm Analysis

3.3.1. Fixed Timing

According to the overall law of traffic flow design to determine the fixed timing for each intersection, the four phases of north-south straight, north-south left turn, east-west straight, east-west left turn timing for 23s, 14s, 38s, 15s, respectively. The rest of the parameter settings are shown in Table 3.

Table 3. Remaining parameter Settings.

Parameter name	Numerical value
Actor network learning rate	0.0006
The learning rate of the student network	0.0006
Discount factor gamma γ	0.98
Soft exchange coefficient τ	0.99
Memory size	12200
Batch size	33
Bonus coefficient $w_1, w_2,, w_3, w_4$	-1,-1,-0.03,0.03
Periodic coefficient $c_{\min}, c_{\max}$	0.7,3

Fixed period T	82

3.3.2. Flow Weight Timing

The traffic weight timing algorithm observes the traffic flow data of each phase in the previous cycle, and then traverses the weights of each phase in the scheme library, and compares the two to find the scheme with the smallest Euclidean distance as the optimal timing strategy for the next cycle, which is adaptive to a certain extent, but due to the limitation of the number of square sets in the scheme library, it is not possible to find the optimal strategy every time. Given the number of phases, cycle length and number of schemes, the K-Means clustering method is used to realize the uniform distribution of time, generate a list of schemes, and based on this, the fixed time allocation scheme data are added to form the final flow weight time allocation scheme library as shown in Table 4.

Table 4. Flow weight matching program library.

Scheme number	Phase 1	Phase 2	Phase 3	Phase 4
0	25	15	40	20
1	15	15	55	15
2	15	55	15	15
3	15	15	15	55
4	15	30	40	15
5	15	15	35	35
6	15	40	15	30
7	35	35	15	15
8	35	15	30	20
9	35	20	15	30
10	55	15	15	15

3.4. Experimental Evaluation and Analysis of Results

Queue length, waiting time, average speed of vehicles and other indicators can well reflect the capacity of the intersection, in this subsection, three intersections are evaluated and analyzed in these aspects of performance. In this subsection, the performance of the three intersections in these aspects is evaluated and analyzed. 400 rounds of training are conducted for the three intersection scenarios, and the reward value changes in each round are shown in Fig. 5. At the beginning, when the intelligent body is in the exploratory stage, the reward value is in the range of -45,000~5,000, and the reward value starts to change obviously near 100 rounds, and gradually tends to stabilize after 300 rounds, and finally stabilizes at about -10,000. Next, the trained adaptive traffic signal control algorithm is compared and analyzed with the remaining two timing algorithms.

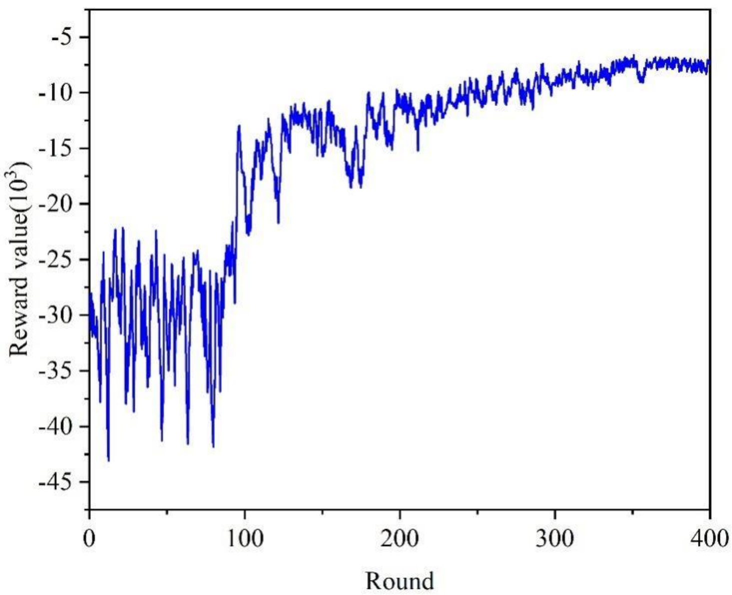
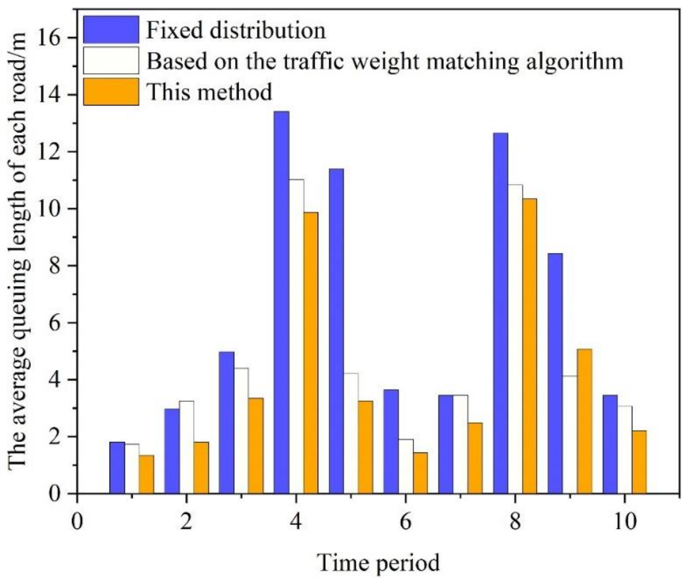
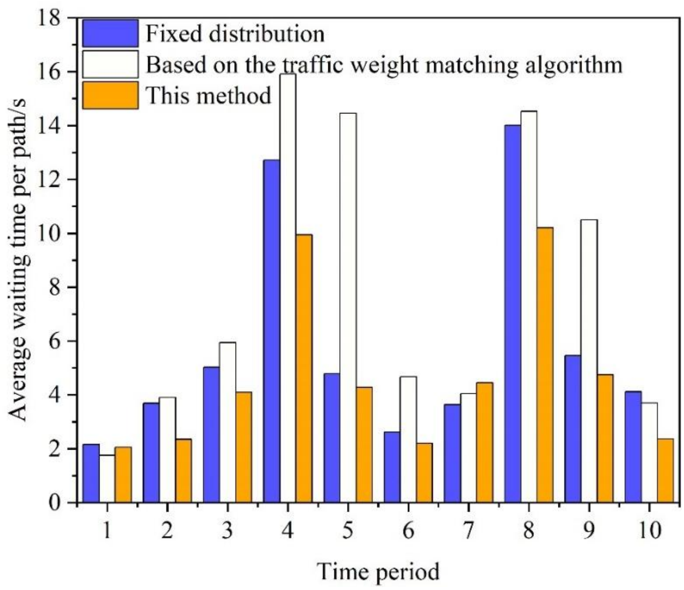


Figure 5. Changes in the reward value of the round in the course of the training.

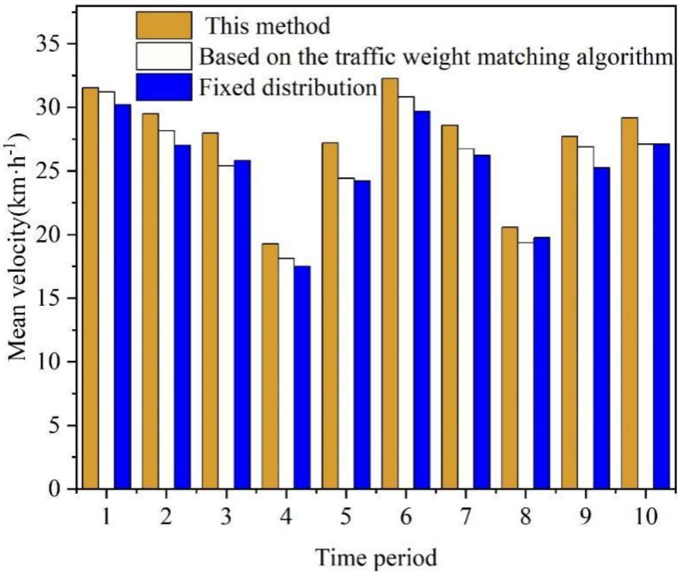
For the multi-intersection scenario in the simulation time period, the average queue length, vehicle waiting time and average vehicle speed of the three intersections are shown in Fig. 6, which divides 10800 s into 10 time periods according to the interval of 1080 s, and draws its average data for each time period. From the figure, we can visualize the changes of traffic flow in different time periods, and it can be seen from the figure that the proposed adaptive traffic signal control algorithm is significantly better than the other two timing algorithms in the three aspects of queue length, vehicle waiting time and average vehicle speed. In the case of using adaptive traffic signal control algorithm, the average queue length of each road is 4.12 m, the average waiting time of vehicles on each road is 4.67 s, and the average speed of vehicles is 29.17 km/h.



(a) Line length contrast



(b) Vehicle waiting time contrast



(c) Average velocity contrast of vehicle

Figure 6. Experimental evaluation and results analysis.

4. Conclusion

The adaptive traffic signal control algorithm proposed in this paper combines a multi-phase real-time timing model with a multi-intelligent green wave coordination algorithm to alleviate the surging traffic flow and improve the road capacity. The urban traffic scenario is simulated and validated in a 2 × 2 grid-shaped urban road network. The results show that compared with the fixed timing and traffic weight timing algorithms, this method improves the efficiency of multi-intersection traffic signal control and reduces the overall vehicle travel time in both simple and dynamic complex environments. It reduces the traffic delay than the traditional fixed traffic signal timing scheme, and at the same time, the method has good generalizability.

Acknowledgements

2022 National Natural Science Foundation of China “Research on Traffic Control Technology of Smart Cities Based on Cyber-Physical System" (Project No.: 62273096); 2023 SongSan Lake Sci-tech Commissioner Program “Research and industrial application of a new generation intelligent unmanned boat autonomous control system” (Project No.20234379-01KCJ-G); 2024 Guangdong Provincial University Key Area Special Project "Research on Interactive Online Self - learning Methods for Collaborative Robots" (Project No.: 2024ZDZX3063); 2023 Higher Education Teaching Reform Project of Guangdong Provincial Department of Education, "Innovation and Practice of Industry-Education Integration Education Mechanism for Science and Engineering Majors in Applied Undergraduate Universities" (Project No.: JY2023012402).

References

1. Wang, Z. (2024). Annual Report on the Big Data of New Energy Vehicle in China (2023) (p. 340). Springer Nature.
2. Xu, S., Sun, C., & Liu, N. (2024). Road congestion and air pollution-analysis of spatial and temporal congestion effects. Science of The Total Environment, 945, 173896.
3. Wang, P., Zhang, R., Sun, S., Gao, M., Zheng, B., Zhang, D., ... & Zhang, H. (2023). Aggravated air pollution and health burden due to traffic congestion in urban China. Atmospheric chemistry and physics, 23(5), 2983-2996.
4. Wang, Y., & Zhong, H. (2023). Mitigation strategies for controlling urban particulate pollution from traffic congestion: Road expansion and road public transport. Journal of Environmental Management, 345, 118795.
5. Dong, S., Zhang, H., Li, S., Jia, N., & He, N. (2024). A Study on Urban Traffic Congestion Pressure Based on CFD. Sustainability, 16(24), 10911.
6. Shang, W. L., Song, X., Chen, Y., Yang, X., Liang, L., Deveci, M., ... & Yu, Q. (2024). Congestion and pollutant emission analysis of urban road networks based on floating vehicle data. Urban Climate, 53, 101794.
7. Retallack, A. E., & Ostendorf, B. (2019). Current understanding of the effects of congestion on traffic accidents. International journal of environmental research and public health, 16(18), 3400.

8. Qadri, S. S. S. M., Gökçe, M. A., & Öner, E. (2020). State-of-art review of traffic signal control methods: challenges and opportunities. European transport research review, 12, 1-23.
9. Varga, I. (2018). A congestion detection based traffic control for signalized intersection. Periodica Polytechnica Civil Engineering, 62(2), 398-403.
10. Postranskyy, T., Boikiv, M., Afonin, M., & Rogalskyi, R. (2020). Selection of a Traffic Management Scheme at an Intersection Taking Into Consideration the Traffic Flow Composition. Eastern-European Journal of Enterprise Technologies, 1(3), 103.
11. Hu, W., Wang, H., Qiu, Z., Yan, L., Nie, C., & Du, B. (2018). An urban traffic simulation model for traffic congestion predicting and avoiding. Neural Computing and Applications, 30, 1769-1781.
12. Billones, R. K. C., Bandala, A. A., Lim, L. A. G., Sybingco, E., Fillone, A. M., & Dadios, E. P. (2018). Microscopic road traffic scene analysis using computer vision and traffic flow modelling. Journal of Advanced Computational Intelligence and Intelligent Informatics, 22(5), 704-710.
13. Choudhary, A., & Gokhale, S. (2019). On-road measurements and modelling of vehicular emissions during traffic interruption and congestion events in an urban traffic corridor. Atmospheric Pollution Research, 10(2), 480-492.
14. Al-Dabbagh, M. S. M., Al-Sherbaz, A., & Turner, S. (2019). The impact of road intersection topology on traffic congestion in urban cities. In Intelligent Systems and Applications: Proceedings of the 2018 Intelligent Systems Conference (IntelliSys) Volume 1 (pp. 1196-1207). Springer International Publishing.
15. Eom, M., & Kim, B. I. (2020). The traffic signal control problem for intersections: a review. European transport research review, 12, 1-20.
16. Hu, W., Wang, H., Du, B., & Yan, L. (2017). A multi-intersection model and signal timing plan algorithm for urban traffic signal control. Transport, 32(4), 368-378.
17. Haddad, T. A., Hedjazi, D., & Aouag, S. (2022). A deep reinforcement learning-based cooperative approach for multi-intersection traffic signal control. Engineering Applications of Artificial Intelligence, 114, 105019.
18. Shaikh, P. W., El-Abd, M., Khanafer, M., & Gao, K. (2020). A review on swarm intelligence and evolutionary algorithms for solving the traffic signal control problem. IEEE transactions on intelligent transportation systems, 23(1), 48-63.
19. Mou, J. (2020). Intersection traffic control based on multi-objective optimization. IEEE Access, 8, 61615-61620.
20. Balaji, P. G., German, X., & Srinivasan, D. (2010). Urban traffic signal control using reinforcement learning agents. IET Intelligent Transport Systems, 4(3), 177-188.
21. Baldi, S., Michailidis, I., Ntampasi, V., Kosmatopoulos, E., Papamichail, I., & Papageorgiou, M. (2019). A simulation-based traffic signal control for congested urban traffic networks. Transportation Science, 53(1), 6-20.
22. Wang, Y., Yang, X., Liang, H., & Liu, Y. (2018). A review of the self-adaptive traffic signal control system based on future traffic environment. Journal of Advanced Transportation, 2018(1), 1096123.
23. Majstorović, Ž., Tišljarić, L., Ivanjko, E., & Carić, T. (2023). Urban traffic signal control under mixed traffic flows: Literature review. Applied Sciences, 13(7), 4484.
24. Younes, M. B., & Boukerche, A. (2015). Intelligent traffic light controlling algorithms using vehicular networks. IEEE transactions on vehicular technology, 65(8), 5887-5899.
25. Lee, S., Eom, M., & Kim, B. I. (2024). Two-stage algorithm for traffic signal optimization and web-service system development. IET Intelligent Transport Systems, 18(9), 1697-1715.
26. Hurtado-Gómez, J., Romo, J. D., Salazar-Cabrera, R., Pachon de la Cruz, A., & Madrid Molina, J. M. (2021). Traffic signal control system based on intelligent transportation system and reinforcement learning. Electronics, 10(19), 2363.
27. Huang, L., & Qu, X. (2023). Improving traffic signal control operations using proximal policy optimization. IET Intelligent Transport Systems, 17(3), 592-605.
28. Liu, W., Qin, G., He, Y., & Jiang, F. (2017). Distributed cooperative reinforcement learning-based traffic signal control that integrates V2X networks' dynamic clustering. IEEE transactions on vehicular technology, 66(10), 8667-8681.
29. Noaeen, M., Naik, A., Goodman, L., Crebo, J., Abrar, T., Abad, Z. S. H., ... & Far, B. (2022). Reinforcement learning in urban network traffic signal control: A systematic literature review. Expert Systems with Applications, 199, 116830.
30. Lee, W. H., & Chiu, C. Y. (2020). Design and implementation of a smart traffic signal control system for smart city applications. Sensors, 20(2), 508.
31. Joo, H., Ahmed, S. H., & Lim, Y. (2020). Traffic signal control for smart cities using reinforcement learning. Computer Communications, 154, 324-330.
32. Wei Jingya & Ju Yongfeng. (2024). RETRACTED: Data-driven traffic signal adaptive control algorithm integrating vehicle perception and traffic flow data. Journal of Intelligent & Fuzzy Systems,47(5-6, Supplement 1),1027-1039.
33. Ireneusz Celiński & Grzegorz Sierpiński. (2014). Real time model for public transportation management. LogForum,10(1).
34. Yang Shantian & Yang Bo. (2022). An inductive heterogeneous graph attention-based multi-agent deep graph infomax algorithm for adaptive traffic signal control. Information Fusion,88,249-262.
35. Yang Shantian & Yang Bo. (2021). A semi-decentralized feudal multi-agent learned-goal algorithm for multi-intersection traffic signal control. Knowledge-Based Systems,213.