J. COMBIN. MATH. COMBIN. COMPUT. 127b (2025) 5333--5351

Journal of Combinatorial Mathematics
and Combinatorial Computing
www.combinatorialpress.com/jcmcc

Combinatorial Press

Optimization Research on Traffic Flow Scheduling of Intelligent Transportation Information Management System Based on MPSO Algorithm

Daofei Li[1], Hua Wang[2,✉]

[1] *Department of Transportation of Guangxi Zhuang Autonomous Region, Nanning, Guangxi, 530012, China*
[2] *Guangxi Transportation Science and Technology Group Co., Ltd., Nanning, Guangxi, 530007, China*

ABSTRACT

This study takes the intelligent transportation information management system as the basic framework and focuses on the technical scheme of the traffic flow regulation module in the system. Taking the intersection in urban traffic as the research scenario, we extract the characteristics of urban traffic time and regulation objective function to construct the traffic flow scheduling model. The particle swarm algorithm (PSO) is used to optimize the traffic flow control model, and the inertia weights and the four degree and position update mechanism are improved for the problems of PSO algorithm, such as easy to fall into local optimization. The improved particle swarm algorithm (MPSO) in this paper is utilized to solve the traffic flow scheduling problem, and compared with the PSO algorithm to highlight the effectiveness of the improved operation in this paper. The results show that the optimized traffic flow regulation model based on MPSO algorithm has significant performance advantages in indicators such as average parking delay. Compared with the PSO algorithm, the MPSO algorithm in this paper obviously has higher convergence accuracy and can achieve more excellent regulation solution set in the intersection traffic scheduling scenario. The application of the method in this paper can effectively solve the problems of vehicle congestion and frequent traffic accidents in urban intersections.

Keywords: traffic flow regulation, PSO algorithm, MPSO algorithm, intelligent transportation informatization

1. Introduction

With the rapid development of urbanization, the problem of traffic congestion is becoming more and more prominent, resulting in a series of problems such as longer travel time, wear and tear of vehicle

✉ Corresponding author.
E-mail address: wanghua15@mails.jlu.edu.cn (H. Wang).
Received 05 March 2024; Revised 10 May 2024; Accepted 05 December 2024; Published Online 16 April 2025.
DOI: 10.61091/jcmcc127b-295

components, energy waste, environmental pollution, increased risk of traffic accidents, and increased transportation costs [1-4]. The introduction of intelligent transportation information management system provides new ideas and solutions to solve these problems. It is based on information technology traffic management system, through the use of modern communications, computers, sensors and other technical means, to achieve intelligent management and optimization of traffic flow, road facilities, vehicles and travelers and other subjects [5]. The use of intelligent transportation information management system can alleviate traffic congestion from multiple perspectives. By means of optimizing signal light control, providing real-time traffic information, intelligent traffic management, intelligent parking management, traffic data analysis, traffic simulation, public traffic optimization, early warning and alert functions, intelligent navigation systems, and shared traffic optimization, the efficiency of road traffic can be improved and the occurrence of traffic congestion can be reduced [6-9]. The realization of these means are inseparable from the scheduling of traffic flow, traffic flow scheduling as the core block of the intelligent transportation information management system, for the realization of smooth traffic, reduce energy consumption, improve traffic efficiency is of great significance [10-11]. Intelligent scheduling refers to the dynamic scheduling and management of traffic flow through the information and technical means provided by the intelligent transportation system, so as to realize the rational use of traffic resources and optimization of traffic flow. However, urban traffic routes are complex and diverse, taking into account road capacity, traffic flow, traffic conditions, public transportation, emergencies, travel demand, environmental protection and energy saving and many other factors, the traffic flow scheduling process requires the interaction between these factors, making scheduling decisions difficult [12-15]. Therefore, optimization of traffic flow scheduling is needed.

Kumar et al [16] considered real-time traffic conditions and designed a traffic signal scheduling framework using a deep reinforcement learning model.Xu [17] proposed a cloud-edge collaborative computing architecture for deep reinforcement learning control, which is based on the collaborative task placement of deep reinforcement learning policies, driven by the policy and the computing architecture, the computational and communication resources are allocated and optimized, so as to complete the intelligent transportation vehicle road collaboration and task scheduling. Peng et al [18] used lion swarm optimization algorithm to prioritize time-triggered stream scheduling tasks, combined with dynamic queuing to continually update the scheduling order, as well as an imperialistic competition algorithm to evaluate the online scheduling tasks for audio-video bridging streams, to improve the real-time scheduling efficiency of traffic big data streams. Younes et al [19] proposed an efficient , low-energy and low-pollution intersection traffic signal scheduling algorithm SmartLight, which focuses on the intersection topology, competing traffic streams and their dynamic characteristics as traffic scheduling considerations, sets the signal cycle period in response to the emergency vehicles can pass through the intersection in a timely manner, and sets the waiting thresholds so that the average waiting time of each traffic stream is within the thresholds. Liu et al [20] proposed a novel three-tier service framework for group intelligence to transmit traffic information data and signal commands, and introduces an improved local model and an aggregation method for prediction, and then carries out traffic light control by dynamic traffic control algorithms for an ITS under dynamic changes. Wang et al [21] schedules the traffic flow on the road by focusing on the resources and traffic conditions of different roads with an adaptive scheduling model, and optimize the scheduling by combining collaborative decision making and path planning algorithms based on resource matching. The above scheduling means consider a single factor, in the actual traffic conditions there are a variety of complex factors, in order to achieve multi-intersection cooperative scheduling, intelligent transportation system also needs to be optimized design. Particle swarm optimization algorithm is a swarm intelligence-based algorithm that can solve complex optimization problems, and has been used in traffic scheduling [22]. It provides a reference for the traffic scheduling optimization of intelligent transportation. However, the basic particle swarm optimization algorithm has poor performance for dynamic regulation of traffic flow. And MPSO (Multiparticle Particle Swarm Optimization) algorithm is an optimization algorithm, which is based on the idea of particle swarm optimization and increases the search space and search ability of the algorithm. Different particles can share information to accelerate the convergence speed and improve the quality of the optimal solution, through iterative updating of the position and speed, the algorithm is gradually close to the optimal solution, and ultimately find the global optimal solution [23-24]. The MPSO algorithm is a kind of classical group intelligence algorithm, which has been widely used in the optimization problem solving.

This paper realizes the design of intelligent transportation information management system through the construction of four layers: perception layer, transmission layer, processing layer and application layer, and focuses on the key methods of the traffic flow control module in the processing layer. Aiming at the problems of serious vehicle congestion and frequent traffic accidents at intersections in urban transportation, this paper takes intersections as the research scenario to build a traffic flow control model. The perceptual layer of the intelligent transportation information management system is used to collect traffic big data information and introduce it into the constructed model to extract the vehicle frequency and time period characteristics of urban traffic. Construct the intersection traffic flow scheduling multi-objective function to realize multiple control objectives. The corresponding traffic scheduling scheme is constructed according to the set objective function, and the particle swarm algorithm is used to optimize the traffic scheduling model, and at the same time, the particle swarm algorithm is improved by optimizing the inertia weights of the standard particle swarm algorithm, so as to improve the convergence accuracy and solving accuracy of the algorithm. Compare and analyze this paper's algorithm with Dijstra and other algorithms to examine the average parking delay, conflict rate and other indicators under the optimization of traffic flow regulation model based on different algorithms. The performance superiority of this paper's MPSO algorithm in the traffic flow scheduling optimization problem is highlighted. In addition, the improved MPSO algorithm is compared with the PSO algorithm to illustrate the effectiveness of the improved operation in this paper.

2. Overview of intelligent transportation information management system

2.1. System architecture

The intelligent transportation information management system in this paper adopts a layered architecture design, which is divided into four layers: perception layer, transmission layer, processing layer and application layer [25]. The perception layer is responsible for collecting various data and information, the transmission layer transmits these data reliably, the processing layer analyzes and processes the data, and finally the application layer provides the processing results to the users. This design makes the system have a clear hierarchical structure, which is easy to expand and maintain, and improves the reliability and flexibility of the system. The overall architecture design of the system is shown in Figure 1. The perception layer is located at the bottom of the system and is responsible for collecting traffic-related data and information through sensors, RFID tags, cameras, GPS and other devices, and the collected data include vehicle position, speed, traffic flow, road conditions, and environmental parameters (temperature, humidity, etc.). The transport layer is responsible for safely and reliably transmitting the data collected in the sensing layer to the processing layer. This layer utilizes the low-power, long-range LoRa (Long Range) wireless communication technology to achieve remote transmission of data. The processing layer stores, manages and analyzes the received data to extract useful information and support decision making. This layer is realized using data processing techniques. The application layer is the level of direct user interaction, where the results of the processed and analyzed data are presented to the user in the form of visualization, and a variety of traffic management application services are provided to the user.

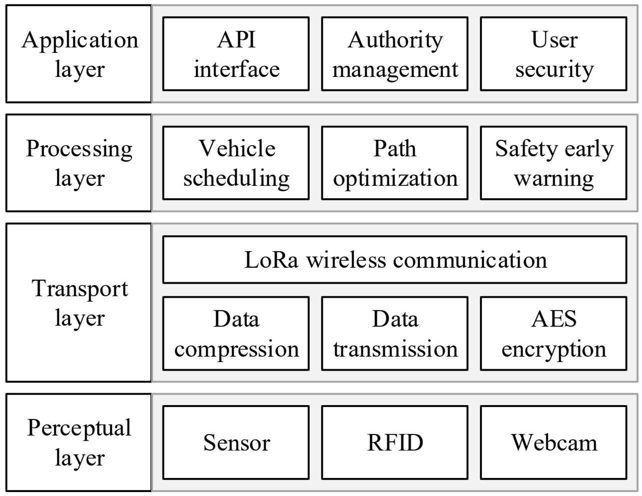


Fig. 1. Overall architecture design of the system

2.2. The Role of Traffic Scheduling in Intelligent Transportation Systems

In this paper's intelligent traffic information management system, traffic flow scheduling [26] is an extremely critical function, and its role is mainly manifested in the following aspects: First, optimize the traffic flow distribution, avoid excessive traffic flow several kinds of traffic flow in certain road sections by reasonably planning the vehicle travel paths, and improve the capacity of the road network. The second is to reduce vehicle delays, according to real-time traffic conditions, dynamically adjust the departure time and speed of vehicles to reduce the waiting time of vehicles at intersections. Thirdly, it improves traffic safety and reduces traffic accidents by coordinating the driving behavior between vehicles. After comprehensively considering the real-time location of vehicles, routes, traffic conditions and other factors, this paper adopts the improved particle swarm algorithm (MPSO) for traffic flow scheduling optimization, which will be focused on the detailed analysis of the problem later.

3. Traffic flow scheduling optimization study

With the proliferation of vehicles on urban roads, the traditional traffic command has been unable to meet the current development of urban traffic, traffic flow optimization and scheduling has become the main solution to urban traffic problems, and has also become an urgent need for the development of urban roads. Intersection is more likely to become a traffic congestion and traffic accidents because of the type and number of vehicles converging into it, and the control of vehicles at intersections can significantly reduce the probability of traffic congestion and traffic accidents, and improve the efficiency and safety of urban traffic operation and management. Therefore, the research in this paper mainly focuses on the optimization problem of traffic flow scheduling in urban intersections.

3.1. Traffic flow scheduling model

In this model, the traffic big data is used as the main basis of the traffic flow scheduling model. Traffic big data information is collected using the perception layer in the intelligent transportation information management system, and after transmission through the transmission layer, it reaches the traffic flow scheduling module in the processing layer and is introduced into the traffic flow scheduling model in this section.

3.1.1. Feature Extraction of Urban Traffic Hours. Based on the collected traffic big data, the vehicle frequency and time period characteristics of urban traffic are extracted to provide a data basis for subsequent intersection traffic flow optimization. The proposed process of calculating the vehicle frequency of urban traffic is as follows:

$$A_j = \max\left(\frac{c_{mj}}{e_{oj}}, A_{mj}\right) \tag{1}$$

where, A_j denotes the intersection vehicle traffic interval during j the time period, c_{mj} denotes the maximum value of passable traffic flow on urban roads during j the time period, and e_{oj} denotes the degree of congestion on urban roads during j the time period. e_{oj} can be expressed as by Eq:

$$e_{oj} = g_i *_v \tag{2}$$

where, g_i denotes the adjustable factor for urban traffic vehicles. V denotes the maximum traffic flow that can be accommodated by a single road in the city. According to the above formula, obtain the characteristics of the traffic flow time period. Set the initial moment point of the increase in traffic flow is $t_{i,1}^c$, the vehicle growth to the peak of the time point is $t_{i,2}^c$ then there are:

$$t_{i,2}^z = t_{i,1}^c + D(1,2)/V(1,2) \tag{3}$$

where $D(1,2)$ represents the miles traveled during the $t_{i,1}^c$ to $t_{i,2}^c$ time periods. $V(1,2)$ denotes the average speed traveled by the vehicle. This leads to the $t_{i,2}^c$ integrated equation:

$$t_{i,1}^z = t_{i,2}^c + T_j(2) \tag{4}$$

In the above equation (4), $T_j(2)$ represents the dwell time for a vehicle to experience the next traffic light, and $T_j(2)$ the calculation formula can be expressed as follows:

$$T_j(2) = \max(T_j^{2a}, T_j^{2b}) \tag{5}$$

where, T_j^{2a} denotes the initial moment of the vehicle's stay at the traffic light. T_j^{2b} denotes the end moment of the vehicle's stay at the traffic light. From the above data, the final time for the vehicle to reach the destination can be obtained by the following formula:

$$t_{i,n}^z = t_{i,1}^c + \sum_{i=1}^{n=1} D(i+1,i)/V(i+1,i) + \sum_{i=2}^{n=1} T_j(i) \tag{6}$$

The point in time at which a vehicle leaves the intersection during time period j can be expressed as:

$$t_{i,n}^c = t_{i,1}^z + \sum_{i=1}^{n=1} D(i+1,i)/V(i+1,i) + \sum_{i=2}^{n=1} T_j(i) \tag{7}$$

According to the above calculation part, the time characteristics of the traffic flow and the traveling characteristics of the road can be effectively obtained. This part of the data is used as the basis of scheduling to complete the intersection traffic management.

3.1.2. Multi-objective scheduling function for intersection traffic flow. In past designs, optimization is mostly carried out for a single objective, and less attention is paid to other parts, which leads to the fact that the expected results are not achieved after using the scheduling model. Therefore, a multi-objective function for intersection traffic scheduling is constructed in this study in order to realize multiple control objectives. Firstly, the optimal change time h_0 setting of intersection traffic signals is calculated using Webster's timing formula:

$$h_0 = \frac{3/2G + 5}{1 - U} \tag{8}$$

$$G = \sum_{i=1}^{n} (w + Q - K) \tag{9}$$

$$U = \sum_{i=1}^{n} \max\{u_{i1}, u_{i2}, u_{i3}, \ldots\} \tag{10}$$

where, G represents the traffic light signal delay, U represents the sum of the highest traffic flow ratio in the traffic light change cycle, w represents the car start delay, Q represents the sum of the yellow light time and the red light time in the green light interval cycle, K represents the response time of the yellow light, and u_i represents the traffic flow ratio in the cycle. According to this formula, the traffic light change time objective function h_z can be obtained:

$$h_z = \frac{G}{1 - \sum_{i=1}^{n} \max\{u_{i1}, u_{i2}, u_{i3}, \ldots\}} \tag{11}$$

According to the principle of multi-objective optimization can be obtained green light time period h_v, the specific formula is shown below:

$$h_v = \sum_{i=1}^{n} s_{\min} + G \tag{12}$$

In the above equation, $S_{\min}$ represents the shortest green light period. Similarly, the longest period of red light can be obtained h_d:

$$h_d = \frac{1}{n-1}\left(\sum_{i=1}^{n} s_{\max} - G\right) \tag{13}$$

where $S_{\max}$ denotes the longest period of the red light. From this, the objective function in traffic scheduling can be obtained as shown in the following equation:

$$\begin{gathered} \min X = \sum_{i=1}^{n} \frac{h_z}{h_v + h_d}(s_{\max} + s_{\min}) \\ s.t.\ s_{\min} \le s \le s_{\max} \end{gathered} \tag{14}$$

According to the above set objective function, the corresponding traffic flow scheduling scheme is constructed, and then it is solved according to the set constraints to obtain the optimal traffic flow scheduling scheme.

3.2. Optimization of Traffic Flow Scheduling Model

There are many optimization algorithms in the existing vehicle scheduling optimization problem, and the particle swarm optimization algorithm (PSO) is a very representative algorithm, which has the advantages of fast convergence speed, easy to modify the parameters, and has a lot in common with the principles of other optimization algorithms. Therefore, this paper chooses particle swarm optimization algorithm to optimize the constructed traffic flow scheduling model, and improves the standard particle swarm algorithm to improve the optimization performance of the algorithm for the problems existing in the standard particle swarm algorithm.

3.2.1. Particle Swarm Algorithm. Particle swarm algorithm is a process that simulates a large number of particles in a certain space by simulating the behavior of birds foraging in flocks, simulating a large number of particles in a certain space to constantly change the position of the particles themselves ultimately in order to find the optimal solution [27]. It is an intelligent algorithm that can optimize multi-peak functions and can solve many problems including nonlinear problems. Compared with other algorithms, this algorithm retains the concepts of evolutionary process and population, and the fitness value obtained from the computational process is screened and judged, and the goodness of the fitness value is used as the basis for the optimization process. It has excellent parallelism in the process of optimization, not only learning the experience of other particles in the process of optimization, but also retaining its own learning experience. The particle swarm algorithm, with its high robustness, low requirement of initial values of parameters, and fast convergence, has received attention in many disciplines and many improved algorithms have been derived from this algorithm. The following is the basic principle of particle swarm algorithm.

The iterative formula of the particles is as follows:

$$V_i^{k+1} = \omega V_i^k + c_1 r_1 (P_{best} - X_i^k) + c_2 r_2 (G_{best} - X_i^k) \tag{15}$$

where V represents the initial velocity of the particle. X denotes the initial position of the particle. ω denotes the inertia weight. c_1, c_2 represents the acceleration factor. k denotes the number of iterations of the particle. r_1 and r_2 represent random numbers in the range of (0, 1). x_i denotes as the position of the ith particle, and the formula is as follows:

$$X_i^{k+1} = X_i^k + V_i^{k+1} \tag{16}$$

P_{best} denotes the individual optimal particle position with the following equation:

$$P_{best}^{k+1} = \begin{cases} P_{best}^k, f(X_i^{k+1}) \leq f(P_{best}^k) \\ X_i^{k+i}, f(X_i^{k+1}) > f(P_{best}^k) \end{cases} \tag{17}$$

G_{best} denotes the global optimal particle position with the following equation:

$$G_{\mathrm{best}}^{k+1} = \begin{cases} G_{\mathrm{best}}^k, f(X_i^{k+1}) < f(G_{\mathrm{best}}^k) \\ X_i^{k+i}, f(X_i^{k+1}) \geq f(G_{\mathrm{best}}^k) \end{cases} \tag{18}$$

where f is the particle adaptivity function.

The particle swarm algorithm does not have mass and direction when it is initialized, and each independent particle in the optimal solution space moves according to its own speed, and the mass of each particle is determined by the adaptivity function, and the direction and displacement of the particle is determined by its speed variable. In the process of moving, the particle continuously adjusts its own moving path and direction through its own moving experience and with the help of other particles' moving experience, and usually the particle can find its optimal position in the space and get the optimal solution.

3.2.2. Improvements to the Particle Swarm Algorithm. The PSO algorithm disperses all particles into the search space through initialization at the beginning of the particle iteration, and then moves individual particles toward the location of the true solution. As the particles approach the local optimum of the fitness function, they will lose the original population diversity advantage, and then the iteration speed of the particles plummets, and it is easy to converge to the suboptimal solution, resulting in premature maturity. For this reason, this paper proposes an improved adaptive PSO algorithm (MPSO) for solving the traffic flow scheduling optimization problem.

1) Optimization of inertia weights. In the PSO algorithm, the inertia weights must be adjusted to change the flight speed of the particles w. w can maintain the balance between the global search capability and the local search capability, and it also determines the future moving direction of the particles. In traditional PSO algorithms, linearly decreasing inertia weights are generally used. Under the influence of linear inertia weights, the particles are favorable to move in the optimal direction due

to their wider distribution, however, this method will make the particles oscillate repeatedly when they are close to the optimal position, which increases the convergence time of the algorithm. Compared to linear inertia weights, nonlinear inertia weights have superior performance. The non-inertial weights are calculated from equation (20):

$$r(t+1) = 4r(t)(1-r(t)) \tag{19}$$

In Eq. (19): $r(0)$ is a random number between 0 and 1.

$$w = r(t)\,w_{\min} + \frac{(w_{\max} - w_{\min})\,t}{Iter_{\max}} \tag{20}$$

In equation (20): $w_{\min}$ is 0.4 and $w_{\max}$ is 0.9.

2) Optimization of velocity and position update mechanism. During each iteration of the PSO algorithm, each particle of the population has to update its own speed and position once, and the speed and position information of the particles is updated according to the information of the previous generation of particles, including the individual speed v, the individual optimum P_{best}, and the global optimum of the population G_{best}. According to the analysis in the previous section, in the late iteration of the PSO algorithm, most of the particles of the population are close to the optimal particles, which makes the population lose the advantage of population diversity. The MPSO algorithm optimizes the speed and position updating mechanism of the PSO algorithm in order to ensure that the particle population still maintains a certain degree of population diversity in the late iteration and avoids falling into the local optimum.

The velocity update formula shown in Eq. (15) has three terms: the first term contains information about the velocity of the previous generation of particles, the second term contains information about the position of the optimal particle taken by the previous generation of individuals, and the third term contains information about the position of the optimal particle of the previous generation of the population. In the second term of Eq. (15), the particle inherits the information of the individual itself and lacks information exchange with the surrounding particles. For this reason, the MPSO algorithm introduces random neighboring particles U_{i-1} and U_{i+1} in the individual update part of the velocity update, U_{best} is the optimal of the two neighboring particles, and compares U with the current individual optimal particle as a new individual, and the selection of the reference particles R_{best}, R_{best} is obtained by Eq. (21), which is an operation that facilitates the communication between the individual particles and other particles:

$$R^t_{best_i} = \begin{cases} U^t_{best_i} & f(U^t_{best_i}) < f(P^t_{best_i}) \\ P^t_{best_i} & \text{otherwise} \end{cases} \tag{21}$$

In Eq. (21): $P^i_{best_i}$ is the individual optimal particle of the t-generation particle i, and $U^t_{best_i}$ is the local optimal particle between $P^t_{best_i}$ and the random particle.

For the third term in the speed update formula (15) communicating with the population, G_{best} represents the best particle in the population, and the speed update learns from the optimal particle in the third term. In the social population, the society is not only influenced by the optimal individuals, but also by the dominant voice of the society. In order to simulate the social phenomenon, the MPSO algorithm uses the average particle of the population M^t_{best} instead of G^t_{best} in the third part of the speed update, and M is generated by equation (22):

$$M'_{best} = mean(P'_{best_1}, P'_{best_2}, \cdots, P'_{best_N}) \tag{22}$$

In Eq. (22), N is the population size, and P^t_{best} is the position of the optimal particle of the ith particle of the trd generation.

Based on the above analysis, the particle velocity update formula of MPSO algorithm can be expressed as Eq. (23):

$$V_i^{t+1} = w^t v_i^t + r_1 c_1 \times (R_{best_i}^t - X_{ij}^t) + r_2 c_2 \times (M_{best}^t - X_{ij}^t) \tag{23}$$

In Eq. (23), r_1 and r_2 are random quantities between 0 and 1, $c_1 = c_2 = 2$.

The variation of nonlinear inertia weights is introduced into the velocity update Eq. (24) in the MPSO algorithm:

$$X_i^{t+1} = w \times X_i^t + (1-w) \times V_i^{t+1} \tag{24}$$

3.2.3. Traffic flow regulation optimization process. Comprehensive analysis of the above, and combined with the actual situation of traffic flow regulation in the urban traffic intersection scenario in this paper, the optimization process of the MPSO algorithm for the traffic flow regulation model can be obtained as follows:

1) Initialize the population parameters, generate particles that meet the requirements according to the number of vehicles in urban traffic and the objective function and constraints of the traffic flow regulation model.
2) Calculate the fitness of all particles and evaluate each particle according to the fitness function.
3) Update the velocity and position of each particle.
4) According to the optimization of the speed and position updating mechanism of the PSO algorithm in the MPSO algorithm, adjust the speed and position of the particles to make them conform to the actual situation of traffic flow regulation.
5) Evaluate each particle in the population.
6) Update the individual optimal particle P_{best} and the global optimal particle G_{best}.
7) Finally, determine whether the iteration is completed or not. If the iteration is completed, output the optimal scheduling scheme G_{best}. If the iteration is not completed, return to step (3) to continue the iteration.

4. Simulation analysis

4.1. Simulation Scene Setting

In order to analyze and verify the scheduling performance of different algorithms under the intersection, the algorithm of this paper is compared and verified with the following algorithms by jointly using VisSim and MATLAB software, which are described as follows:

1) Dijstra's algorithm (Method 1): an algorithm that traverses the weights of nodes and nodes and finds an optimal path with the minimum total weight.
2) Elite Ant Colony Algorithm (Method 2): additional pheromone enhancement in the original ACO algorithm to find the optimal path to improve the convergence speed.
3) Reinforcement learning algorithm based on convolutional neural network (Method 3): a two-dimensional map of paths is used as input, and a convolutional neural network is used for training, and finally a possible optimal path is output.
4) Improved particle swarm algorithm (MPSO): on the basis of particle swarm algorithm, the inertia weights and the optimization of speed and position updating mechanism are carried out, which can dynamically adapt to the urban traffic environment and search out the optimal path for traffic flow regulation.

In order to realize a fair comparison of the algorithms' performance in intersection scheduling, the following indicators are defined to verify the performance of the above algorithms respectively:

1) Average stopping delay. The delay time incurred by each vehicle that is at a standstill for some reason. In this paper, an intelligent traffic information management system is used to obtain the total

stopping delay time $y(s)$ under each traffic volume in the conflict area of the intersection and the total intersection traffic volume n (vehicles). The average stopping delay is derived using Equation y/n.

2) Conflict rate. The probability of conflict with other vehicles when each vehicle passes through the intersection conflict area. Using the obtained total number of stops in the conflict area S (times), the total intersection traffic volume n (vehicles), the conflict rate is derived after Equation $S/n \times 100\%$.

3) Total vehicle passing time. Fixed number of vehicles, the time taken by all vehicles to pass through the conflict area.

4) Deviation value: the difference between the final travel path and the initial optimal path under the optimal scheduling of MPSO algorithm. Provide that the number of grids in the path is m, the grid coordinates are expressed as (X,Y), and its corresponding deviation grid coordinates are (X_i,Y_i), the deviation value can be expressed as:

$$\frac{\sum\sqrt{(X_i-X)^2+(Y_i-Y)^2}}{\sum_{a=2}^{m}\sqrt{(X_a-X_{a-1})^2+(Y_a-Y_{a-1})^2}}\times 100\% \tag{25}$$

In establishing the simulation experiment scene, VisSim software is utilized to construct a two-way six-lane intersection model, and the results are shown in Fig. 2. The area of its intersection area is 100 m×100 m, and at the middle intersection is the intelligent roadbed unit RSU with the following hardware parameters: 12-24 V DC power input (supporting the optional 220 V AC input), interactive information storage capacity d>100,000, support for the network port, RS485 communication, external I/O input/output communication, and four PSAM interface. Considering the size scale of the actual vehicle, the size of the grid is defined as 5 m×5m, i.e., the conflict area of the intersection is divided into a 25×25 grid map. Set the average traffic flow of the intersection as 15 vehicles/min (this average traffic flow is the average traffic flow in the conflict area of the intersection), and can be dynamically adjusted according to the simulation needs. Vehicles in the conflict area are sensing nodes, collecting the surrounding physical information and their own vehicle parameters, path selection and uploaded to the convergence node (RSU), the convergence node will broadcast the information to other vehicles, to achieve the vehicle information interaction.

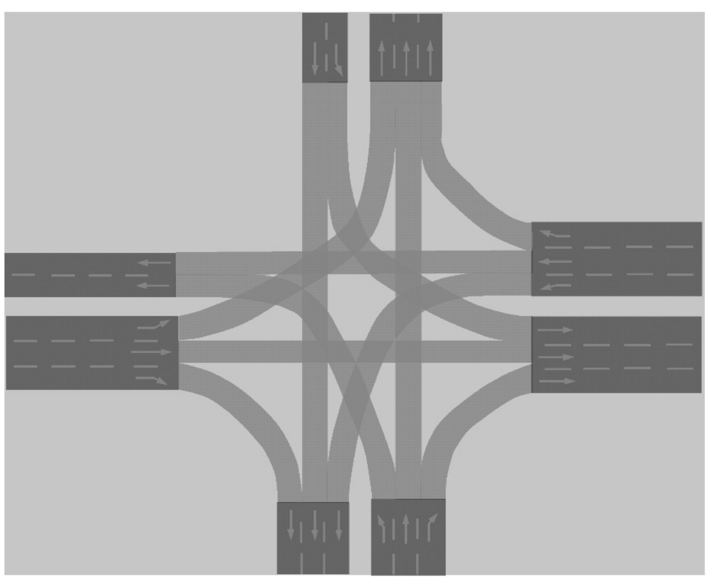


Fig. 2. Intersection model drawing

4.2. *Traffic Scheduling Performance Analysis*

4.2.1. Average parking delays. The four algorithms are shown in Table 1 and Fig. 3, where t indicates the time of vehicle entering the intersection, T indicates the time of vehicle exiting the intersection, and d indicates the time of vehicle delay. According to the data in the table and Fig. 3, it can be seen that the average delay time of vehicles under the optimized traffic flow control model of four algorithms, MPSO, Method 1, Method 2 and Method 3, are 0.22s, 1.42s, 2.01s and 2.05s, respectively, and the total delays are 3.26s, 21.36s, 30.20s, 30.73s, respectively.The MPSO algorithm used in this paper is similar to the Method 1 algorithm and the Method 3 algorithm. MPSO algorithm reduces the average vehicle delay significantly compared with the traffic flow control model optimized by Method 1, Method 2 and Method 3 algorithms. Meanwhile, the vehicle delays of the model in this paper are more concentrated, with 25%~75% of the data distributed in the interval of 0~0.25s. The vehicle delays of the other three models are more dispersed, and 25%~75% of the data are distributed in the intervals of 0.05~2.46s, 0.28~2.75s, and 0.85~2.97s, respectively, which demonstrates that this paper's optimization model of traffic control based on the MPSO algorithm is able to reduce the vehicle delays effectively.

Table 1. Results of 4 methods for comparing

	MPSO			Method 1			Method 2			Method 3		
	t /s	T /s	d /s	t /s	T /s	d /s	t /s	T /s	d /s	t /s	T /s	d /s
1	2.89	2.89	0.00	2.97	4.19	1.22	2.68	4.57	1.89	2.85	5.64	2.79
2	5.08	5.08	0.00	4.33	6.11	1.78	4.74	7.95	3.21	3.23	6.69	3.46
3	4.95	4.95	0.00	3.53	5.99	2.46	4.84	5.07	0.23	2.36	5.63	3.27
4	3.06	3.06	0.00	4.35	4.38	0.03	2.06	4.53	2.47	3.29	5.34	2.05
5	3.86	3.94	1.06	2.54	4.28	1.74	4.75	5.93	1.18	2.91	4.45	1.54
6	3.37	3.39	0.46	3.45	6.06	2.61	5.53	5.81	0.28	3.53	6.16	2.63
7	3.18	3.18	0.00	3.87	5.29	1.42	4.42	4.51	0.09	4.89	5.54	0.65
8	2.61	2.61	0.00	4.02	4.33	0.31	3.78	5.09	1.31	3.32	3.71	0.39
9	3.23	3.28	1.05	5.33	5.39	0.06	3.26	6.01	2.75	3.02	4.98	1.96
10	2.74	2.89	0.25	4.12	4.43	0.31	4.32	4.33	0.01	3.51	4.36	0.85
11	5.81	5.92	0.11	3.33	7.56	4.23	2.19	8.13	5.94	5.35	6.72	1.37
12	5.91	5.91	0.00	3.63	7.51	3.88	4.11	7.68	3.57	3.05	7.02	3.97
13	3.81	3.83	0.12	4.51	4.54	0.03	3.29	5.96	2.67	3.71	6.08	2.37
14	3.41	3.42	0.21	5.96	6.01	0.05	2.65	5.1	2.45	5.41	5.87	0.46
15	2.47	2.47	0.00	2.02	3.25	1.23	3.19	5.34	2.15	2.57	5.54	2.97

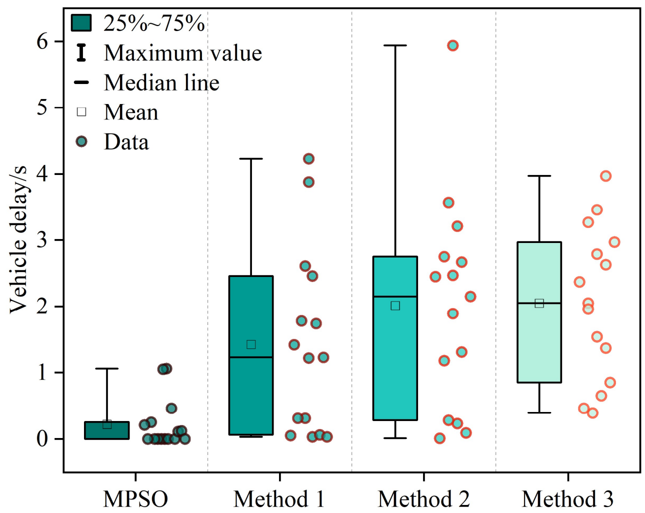


Fig. 3. Comparison of average vehicle delays

Further comparing the individual vehicle delays under this paper's model with the other three models, the results are shown in Fig. 4. From the scatter plot, it can be seen that the maximum vehicle delays in the MPSO, Method 1, Method 2, and Method 3 models are 1.18s, 4.23s, 5.94s, and 3.97s, respectively, and the maximum vehicle delays in this paper's model are reduced by 72.10%, 80.13%, and 70.28%, respectively, when compared with the other three models. Meanwhile, the kite diagram shows that this paper's model significantly reduces the average vehicle delay and the fluctuation amplitude of the delay by optimizing the traffic flow control model using the MPSO algorithm, which proves the effectiveness of this paper's model in traffic flow control in urban intersections.

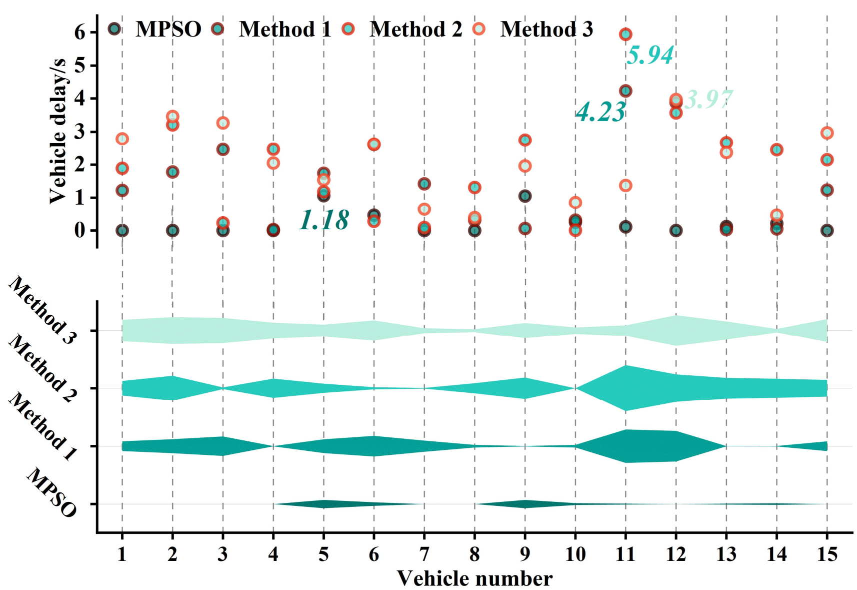


Fig. 4. Comparison of vehicles' delay of different models

4.2.2. Conflict rate. Fig. 5 shows the conflict rate (CR) of vehicle route intersections in intersections and the comparison of conflict rate computation time under the four models using MPSO, Method 1, Method 2 and Method 3. According to the data in the figure and its distribution, it can be seen that in the conflict rate calculation time, the traffic flow regulation model optimized by the MPSO algorithm in this paper requires the least calculation time, indicating that the model has the best computational efficiency. In the conflict rate index, the average values of vehicle conflict rate achieved by the four algorithm-optimized traffic flow regulation models are 13.06%, 37.89%, 53.99%, and 67.23%, respectively. Compared with other algorithms, the model optimized by the MPSO algorithm in this paper for urban intersection traffic flow control can achieve the reduction of vehicle conflict rate of 24.83%, 40.93% and 54.17%, respectively. And the reduction of conflict rate can realize the saving in the process of resource scheduling, which helps to save resources and improve the execution efficiency of vehicles.

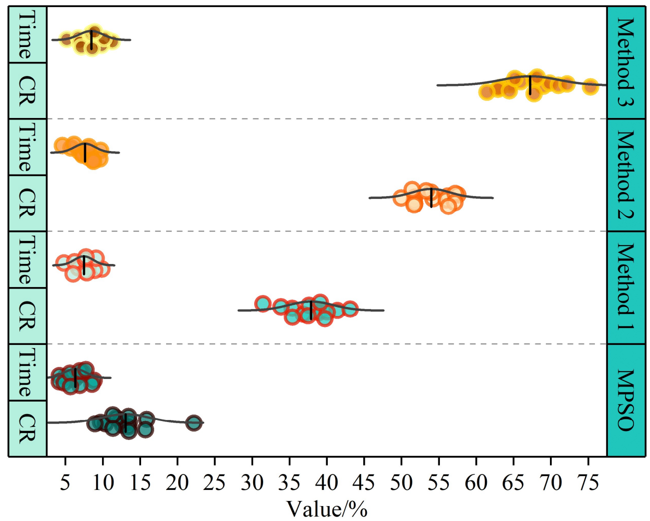


Fig. 5. Vehicle route intersection conflict rate

4.2.3. Total vehicle travel time. In this section of the experiment, the effects of different traffic flows on the total vehicle travel time under the above four vehicle flow regulation methods are considered. Although the density of vehicle distribution cannot be directly controlled in the scheduling model, the vehicle reach rate (a) can be set in VisSim software to indirectly set different traffic environments. In the experiment, according to the total number of vehicles put into the experiment, five different vehicle reach rates are set to simulate traffic states with different degrees of congestion, in order to analyze and compare the performance of the four intersection flow scheduling methods under different traffic states.

Fig. 6 shows the total vehicle passing time for the four methods with different vehicle reach settings. From the figure, it can be seen that the total vehicle passing time of all the four traffic scheduling methods increases as the traffic flow increases. When the traffic flow is small and the degree of traffic congestion is low, in the Method 1 algorithm as well as the vehicle scheduling model optimized by the MPSO algorithm, the vehicles are basically unaffected by other vehicles when they pass through the intersection, so the difference in the total vehicle passing time of these two methods is small. With the increase of traffic flow and the increase of vehicle congestion, the gap between the two methods gradually increases. The advantage of the traffic scheduling method proposed in this paper compared with Method 1 method is that Method 1 method emphasizes the safety distance between vehicles and the safety distance between vehicles in different road sections affects the total number of vehicles that can be accommodated at the intersection. The vehicle scheduling method proposed in this paper, on the other hand, takes advantage of the temporal characteristics of urban traffic, so that as long as the vehicles do not have trajectory conflicts at the intersection, the vehicles are able to exist at the intersection area at the same time, and therefore the intersection area is able to schedule more vehicles at the same time than the scheduling model based on the Method 1 algorithm. The scheduling under Method 2 and Method 3 algorithms, on the other hand, is limited by signal phasing, and the intersections lead to stopping and waiting of vehicles even if there are no other vehicles, so it is the least efficient.

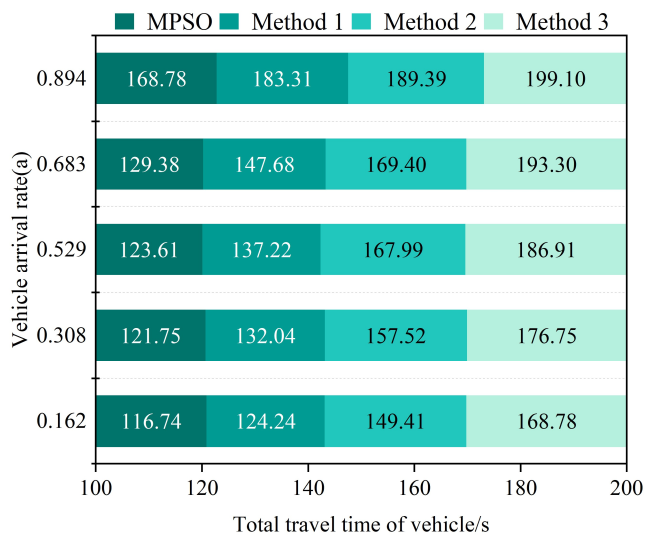


Fig. 6. Total travel time of vehicles

Figure 7 shows the comparison of the variance of the total vehicle passing time of the four vehicle scheduling methods under different traffic flows. Since the smaller the value of the variance of the total vehicle passage time, the smaller the difference in the total passage time between vehicles, and the closer to the average value, the higher the fairness of the traffic flow scheduling. As can be seen from the figure, the variance of total vehicle passing time is higher in the regulation model under Method 3 and Method 2 algorithms, which is because even though the traffic environment is not congested, the cyclic scheduling of signal phases leads to the fact that vehicles on some road sections are able to pass through the intersection directly due to encountering a street light, whereas vehicles on the other road sections are forced to wait due to encountering a red light, leading to a larger difference in the total passing time of the intersection between the vehicles, and thus the two algorithms are more equitable. There is a large difference between the total intersection passage time between vehicles due to the red light and the total intersection passage time between vehicles due to the red light and the total intersection passage time between vehicles due to the red light. Method 1 and MPSO algorithms overcome the defects of signalized scheduling methods, which significantly reduces the variance of the total vehicle passing time and ensures the fairness of vehicle scheduling. However, the variance value of total vehicle passing time of all methods increases with the increase of vehicle reaching rate, indicating that the fairness of vehicle scheduling in more congested scenarios has decreased.

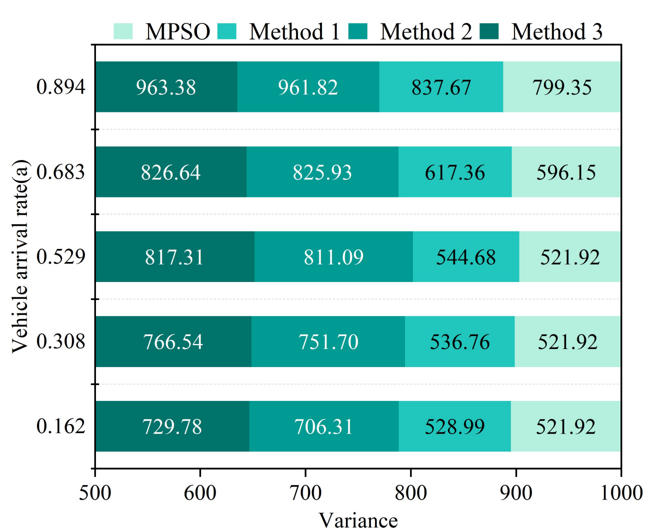


Fig. 7. Variance of total vehicle travel time

4.2.4. Deviation values. Table 2 shows the deviation values of the vehicle regulation paths from the initial optimal path under the scheduling of the four algorithms. The smaller the deviation value, the higher the fit between the regulation path and the initial optimal path, and the lower the difficulty coefficient of the implementation of the regulation method. As can be seen from the table, this paper MPSO algorithm under the control of the vehicle control path and the initial optimal path of the difference between the three algorithms compared to the other three algorithms is significantly reduced, the average control difference of 15 vehicles is 8.89, compared with the other three algorithms were reduced by 40.09%, 64.07%, 74.75%. It shows that the traffic flow regulation model optimized by MPSO algorithm can have stronger adaptability to regulate the traffic flow at urban intersections.

Table 2. Deviation values for each algorithm

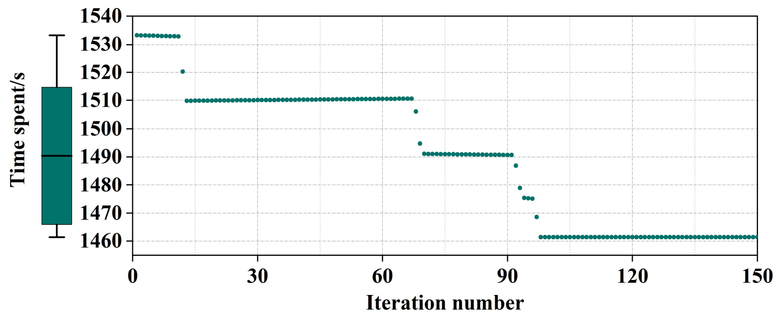
Vehicle number	MPSO	Method 1	Method 2	Method 3
1	9.73	13.46	24.74	37.87
2	9.88	14.15	23.38	35.42
3	9.38	14.13	24.15	35.68
4	8.70	15.83	23.92	33.41
5	8.01	14.84	25.36	34.93
6	9.35	14.43	24.67	37.12
7	9.36	12.66	24.26	33.14
8	9.26	16.57	23.57	33.49
9	8.15	12.85	26.47	35.16
10	8.10	15.58	25.43	35.05
11	9.03	15.90	25.41	36.77
12	8.20	15.89	25.22	37.07
13	8.95	15.44	25.93	34.63
14	9.24	14.91	24.90	33.30
15	8.08	15.97	23.73	35.10
Mean	8.89	14.84	24.74	35.21

Comprehensive analysis of the above four indicators for the average stopping delay can be found that the use of this paper's MPSO algorithm to optimize the traffic flow regulation model, can be achieved in the various indicators of significant advantages in performance. It shows that the use of this paper's method of urban intersection traffic regulation can fully ensure the efficiency and safety of vehicle traffic in the intersection, to solve the problem of vehicle congestion and traffic accidents at intersections has an important application value.

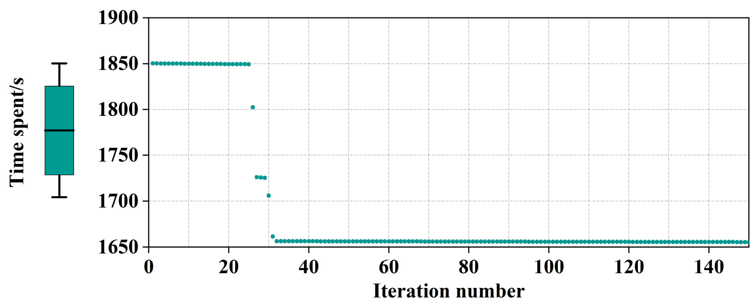
4.3. Analysis of the effectiveness of algorithm improvement

In this paper, before using PSO algorithm to optimize the traffic flow control model, firstly, for the problems of PSO algorithm, such as easy to precocity and easy to fall into the local optimum, the PSO algorithm is improved by optimizing the inertia weights as well as the speed and position updating mechanism. In order to test the effectiveness of the improvement of PSO algorithm in this paper so as to fully solve the problem of optimization of traffic flow control, this section compares the MPSO algorithm with the PSO algorithm in order to illustrate the reasonableness of the improvement strategy of this paper through the experimental results. In the experiment, the maximum number of iterations of PSO algorithm and MPSO algorithm is set to 150 times.

Firstly, traditional PSO algorithm and MPSO algorithm are applied to analyze this simulation experiment, and the iteration results of the two algorithms are obtained as shown in Fig. 8, (a) and (b) are the MPSO algorithm and traditional PSO algorithm respectively. It can be seen through the iteration result graph, when the number of iterations is 150 times, in terms of convergence, the PSO algorithm converges faster at the beginning, but with the increase of the number of iterations, its search efficiency gradually decreases. While the MPSO algorithm converges with higher accuracy than the PSO algorithm and has better convergence results and finally obtains the optimal solution 1461s.



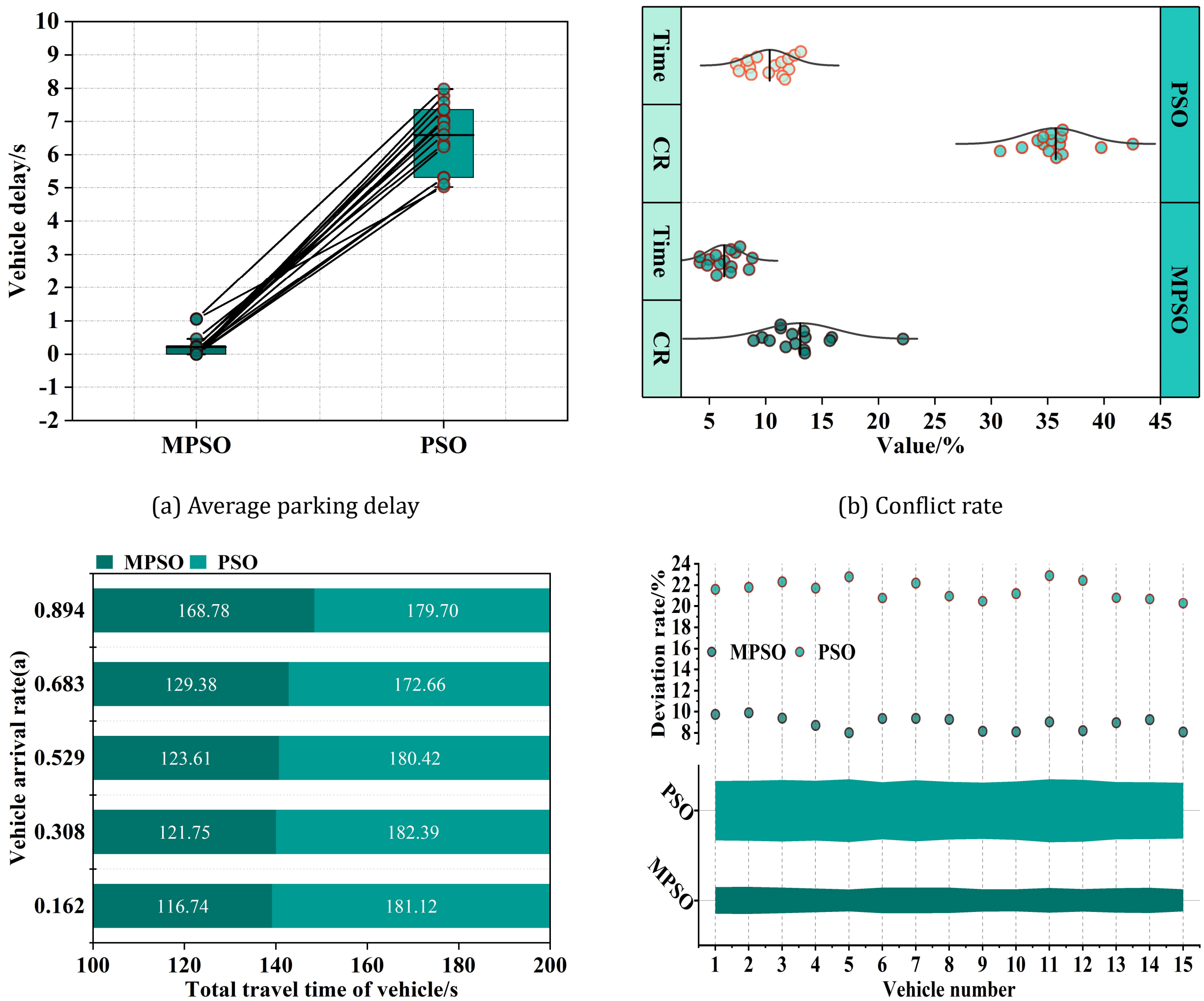
(a) MPSO



(b) PSO

Fig. 8. Algorithm iteration results

In order to further verify the feasibility and effectiveness of the MPSO algorithm optimized by inertia weight, speed and position update mechanism in intersection vehicle control, the results of the average parking delay and other evaluation indicators of the MPSO algorithm and the PSO algorithm are compared and analyzed, and the experimental simulation results are shown in Figure 9, and (a)-(d) represent the average parking delay, collision rate, total vehicle passage time and deviation value solution results, respectively. As can be seen from the figure, in the four indicators, the solution results of the MPSO algorithm are due to the PSO algorithm.Although the PSO algorithm has a stronger search ability, the search process has more ups and downs and fluctuations, and the search process is not stable enough, and it is easy to fall into the local optimal solution. The MPSO algorithm proposed in this paper optimizes the inertia weights and the speed and position update mechanism of the PSO algorithm, thus reducing the dependence of the problem to be optimized on the parameters and improving the versatility of the algorithm, and therefore outperforms the PSO algorithm in all indicators. The experimental results fully demonstrate the feasibility and effectiveness of this paper for the improvement of PDO algorithm.



(a) Average parking delay

(b) Conflict rate

(c) Total traffic time

(d) Deviation rate

Fig. 9. Comparison of experimental simulation results

5. Conclusion

This paper constructs an intelligent traffic information management system and discusses in depth the functional implementation method of the traffic flow scheduling module and the optimization method of the traffic flow scheduling model in the system. Simulation results show that the average parking delay in the traffic scheduling model optimized by MPSO algorithm is significantly lower than that of Dijstra and other algorithms, and the maximum vehicle delay is reduced by 72.10%, 80.13%, and 70.28% compared with that of Dijstra, elite ant colony, and reinforcement learning based on convolutional neural network, respectively. Meanwhile, the vehicle conflict rate, the total vehicle passage time, and the solution deviation rate in the solution of this paper's method are smaller than those of the other three methods. In addition, the improved MPSO algorithm is compared and analyzed with the PSO algorithm, and the results show that the MPSO algorithm has a higher solution accuracy and performs better than the PSO algorithm in various indexes, which fully demonstrates the effectiveness of the improved algorithm in this paper.

Funding

This work was supported by Key Research and Development Project of the Science and Technology Department of Guangxi Province (grant number: 2021AB22121) and Nanning "Yongjiang Plan" "Youth Talent Project" (grant number: RC20240104).

References

[1] Alama, E. T., Aloysius, A., & Ph, T. (2021). Urbanization and transportation crisis in urban centres: the Panacea. J Res Human Soc Sci, 9(6), 7-17.

[2] Pulugurtha, S. S., & Gouribhatla, R. P. (2020). Spatio-temporal variations in energy loss due to traffic congestion. Transportation Letters, 12(1), 9-17.

[3] 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.

[4] Haider, M. Z., & Papri, R. S. (2021). Cost of traffic congestion in Dhaka Metropolitan City. Public Transport, 13(2), 287-299.

[5] Sakr, A., El-Afifi, M. I., & Team, P. (2023). Intelligent traffic management systems: a review. Nile journal of communication and computer science, 5(1), 42-56.

[6] Musa, A. A., Malami, S. I., Alanazi, F., Ounaies, W., Alshammari, M., & Haruna, S. I. (2023). Sustainable traffic management for smart cities using internet-of-things-oriented intelligent transportation systems (ITS): challenges and recommendations. Sustainability, 15(13), 9859.

[7] 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.

[8] Li, Y., Chen, Y., Yuan, S., Liu, J., Zhao, X., Yang, Y., & Liu, Y. (2021). Vehicle detection from road image sequences for intelligent traffic scheduling. Computers and Electrical Engineering, 95, 107406.

[9] Yang, S., Tan, J., Lei, T., & Linares-Barranco, B. (2023). Smart traffic navigation system for fault-tolerant edge computing of internet of vehicle in intelligent transportation gateway. IEEE transactions on intelligent transportation systems, 24(11), 13011-13022.

[10] Alkhatib, A. A., Maria, K. A., AlZu'bi, S., & Maria, E. A. (2022). Smart traffic scheduling for crowded cities road networks. Egyptian Informatics Journal, 23(4), 163-176.

[11] Song, M., & Hou, Z. (2020). Model analysis of traffic emergency dispatching in intelligent transportation system under cloud computing. International Journal of Internet Protocol Technology, 13(1), 46-54.

[12] Vidal, P. J., & Olivera, A. C. (2019). Management of urban traffic flow based on traffic lights scheduling optimization. IEEE Latin America Transactions, 17(01), 102-110.

[13] Kljaić, Z., Pavković, D., Mlinarić, T. J., & Nikšić, M. (2021). Scheduling of traffic entities under reduced traffic flow by means of fuzzy logic control. Promet-Traffic&Transportation, 33(4), 621-632.

[14] Karmakar, G., Chowdhury, A., Kamruzzaman, J., & Gondal, I. (2020). A smart priority-based traffic control system for emergency vehicles. IEEE Sensors Journal, 21(14), 15849-15858.

[15] Nama, M., Nath, A., Bechra, N., Bhatia, J., Tanwar, S., Chaturvedi, M., & Sadoun, B. (2021). Machine learning-based traffic scheduling techniques for intelligent transportation system: Opportunities and challenges. International Journal of Communication Systems, 34(9), e4814.

[16] Kumar, N., Mittal, S., Garg, V., & Kumar, N. (2021). Deep reinforcement learning-based traffic light scheduling framework for SDN-enabled smart transportation system. IEEE Transactions on Intelligent Transportation Systems, 23(3), 2411-2421.

[17] Xu, C., Wang, G., Wei, M., Zhang, P., & Peng, B. (2024). Intelligent transportation vehicle road collaboration and task scheduling based on deep learning in augmented Internet of things. IEEE Transactions on Vehicular Technology.

[18] Peng, Y., Wang, C., Wen, W., Wen, S., & Xiong, X. (2023). An Online Scheduling Framework for Multiple TBD Flows in Intelligent Transportation Systems. IEEE Transactions on Intelligent Transportation Systems, 25(1), 1054-1068.

[19] Younes, M. B., Boukerche, A., & De Rango, F. (2023). SmartLight: A smart efficient traffic light scheduling algorithm for green road intersections. Ad Hoc Networks, 140, 103061.

[20] Liu, Y., Huo, L., Wu, J., & Bashir, A. K. (2023). Swarm learning-based dynamic optimal management for traffic congestion in 6G-driven intelligent transportation system. IEEE Transactions on Intelligent Transportation Systems, 24(7), 7831-7846.

[21] Wang, M., Leng, S., Liao, X., Cao, J., & Zhang, K. (2024, August). Adaptive Scheduling of Traffic Flow and Network Resources for Intelligent Connected Vehicles. In 2024 IEEE/CIC International Conference on Communications in China (ICCC) (pp. 155-160). IEEE.

[22] Hu, W., Wang, H., Qiu, Z., Nie, C., & Yan, L. (2018). A quantum particle swarm optimization driven urban traffic light scheduling model. Neural Computing and Applications, 29, 901-911.

[23] Yan, W., Li, M. J., Zhong, Y. C., Qu, C. Y., & Li, G. X. (2020). A novel k-MPSO clustering algorithm for the construction of typical driving cycles. IEEE Access, 8, 64028-64036.

[24] Tian, D., & Shi, Z. (2018). MPSO: Modified particle swarm optimization and its applications. Swarm and evolutionary computation, 41, 49-68.

[25] Alexey Terentyev,Alexey Marusin,Sergey Evtyukov,Aleksandr Marusin,Anastasia Shevtsova & Vladimir Zelenov. (2023). Analytical Model for Information Flow Management in Intelligent Transport Systems. Mathematics,11(15).

[26] Anonymous. (2014). Massively Parallel Dantzig-Wolfe Decomposition Applied to Traffic Flow Scheduling. NASA Tech Briefs,38(11),71-72.

[27] Zhongxing Li,Zenan Li,Chaofeng Pan & Jian Wang. (2024). Short-term traffic flow prediction based on spatial–temporal attention time gated convolutional network with particle swarm optimization. Applied Intelligence,55(2),214-214.