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Optimization of Urban Traffic Network Signal Scheduling based on Vehicle Delay and Arterial Green Wave

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Abstract

Urban traffic congestion has become increasingly severe due to the rapid growth of vehicle demand, making efficient signal control a critical challenge. Existing traffic signal optimization methods typically focus on either isolated intersections or arterial coordination, lacking a unified framework that balances network-wide efficiency and structured traffic flow. To address this issue, this paper proposes a dual-objective optimization algorithm based on the total delay of vehicles in the road network and the arterial green wave index to coordinate and optimize all intersections in the road network. Experiments are conducted on a real-world urban road network in Guangzhou Province, China. Results show that the proposed method achieves comparable delay performance to state-of-the-art approaches while significantly improving arterial coordination. Specifically, the arterial green-wave index is improved by 44.9% and 46.5% compared with TRANSYT and SYNCHRO methods, respectively. Finally, simulation results based on SUMO demonstrate that the proposed method outperforms baseline approaches in terms of average delay, queue length, and number of stops, validating its effectiveness in realistic traffic scenarios.

Keywords: Traffic optimization and schedule, signal timing optimization, vehicle delay, arterial green wave coordination

1 Introduction

Urban traffic congestion has become increasingly severe with rapid urbanization and the continuous growth of vehicle demand. Improving traffic efficiency without costly infrastructure expansion has made traffic signal control a critical and practical solution for urban traffic management. However, due to the inherent spatiotemporal correlations in traffic flow, congestion at one intersection can propagate across the network, making isolated optimization strategies insufficient for large-scale urban networks.

Regarding solutions to urban congestion, one approach involves infrastructure renovation for road networks with frequent congestion and heavy traffic flow, aiming to enhance the traffic capacity of road segments. However, this method is prohibitively expensive and cannot fundamentally address the issue of road network coordination. Another approach is to optimize the timing plan of traffic lights at intersections within the road network, making the timing plan more aligned with the current flow characteristics of the traffic network. Advances in big data collection and processing technology have supported the development of adaptive traffic signal scheduling optimization, providing a more effective and versatile strategy for alleviating traffic congestion [1]. Therefore, optimizing the timing plan for the road network is an effective means to improve traffic efficiency, enhance the traffic environment, and increase the throughput of the road network [2].

Existing traffic signal optimization methods can generally be categorized into three types: single-intersection control, arterial coordination, and regional network optimization. Single-intersection methods focus on local performance but fail to capture network-level interactions. Arterial coordination methods, such as green-wave control, improve traffic progression along specific corridors but often lead to imbalanced resource allocation, degrading performance in non-arterial directions. Regional optimization approaches aim to improve overall network efficiency; however, they typically overlook structured traffic progression along major arterials [3][4]. However, if only the coordination control of arterial roads is implemented, it may lead to extreme imbalance in phase resource allocation, resulting in poor traffic performance at other intersections or in non-arterial directions at arterial intersections. Therefore, additional constraints need to be imposed on the arterial green wave model to avoid monopoly of green phase resources. The last type of regional coordination control focuses on the overall performance of the road network, including the performance of arterial resources and intersections, so that the entire road network can be in a coordinated and efficient state as much as possible.

Based on the discussion of the above optimization scenarios, the optimization model constructed in this paper aims to establish a dual-objective optimization model that improves the performance of arterial roads in the road network while simultaneously balancing the traffic performance at each intersection. The evaluation metric of vehicle delay is employed to optimize the green phase resources at each intersection, thereby enhancing the traffic efficiency at each intersection. Additionally, a second indicator, the comprehensive green wave bandwidth of arterial roads, is introduced to improve the collaborative traffic efficiency of several core arterial roads in the road network. The optimization algorithm utilizes the NSGA-II dual-objective optimization algorithm to optimize the two objectives, and obtains a set of near-optimal solutions

based on a selection strategy from the final Pareto front solution set, ensuring the balance between the two optimization objectives and the overall performance of the road network.

The main contributions of this paper are summarized as follows:

In the second section, we will organize and analyze the current research status in the field of traffic dispatch optimization.

The research methodology of this article is described in detail in Section 3.

In the fourth section, the experimental part of this paper will be discussed and the data indicators will be quantitatively analyzed.

In Section 5, the optimization results are verified using the SUMO simulation platform.

In Section 6, the main content of this article is summarized, and directions for future research are proposed.

2 Related work

Traffic signal optimization is a complex computational problem due to the stochastic and dynamic nature of traffic flow in urban road networks, traditional analysis and control methods have been proven insufficient to address the signal timing optimization problem in real-world traffic scenarios. Traditional methods cannot effectively solve the traffic signal timing scheduling problem due to the nonlinear and stochastic data in traffic network scenarios. Therefore, a large number of studies have investigated the effectiveness of intelligent optimization methods in improving traffic signal systems. These algorithms can solve for high-quality signal timing schemes within an acceptable time frame [5].

The traffic signal timing and scheduling problem aims to provide safe and efficient traffic flow capacity for the transportation network by defining the cycle length, the green time allocation ratio of each phase, and the absolute offset of intersections.

Swarm-based computational intelligence algorithms [6], such as genetic algorithms [7][8], harmony search algorithms [9], cross-entropy algorithms [10], and particle swarm optimization [11] have been widely used to generate signal timing settings with varying levels of adaptability.

Urban traffic signal timing strategies can be broadly categorized into three types based on their control methods: fixed time cycle strategies, traffic responsive strategies, and adaptive control strategies [12]. The Fixed Time Cycle Strategy (FTCS) [13] is widely adopted due to its simplicity, but this control strategy struggles to cope with the dynamic changes in traffic flow [14]. By utilizing real-time traffic flow data obtained from sensors in the road network, traffic response strategies can effectively adjust traffic signal configurations in real time [15]. However, this control strategy relies too heavily on the real-time performance of sensors, and its coordination performance is limited in road network scenarios with multiple intersections [16]. The adaptive control strategy dynamically adjusts the signal timing plan by combining historical traffic flow data with real-time data [17]. Currently, SCOOT, SCATS, and TRANSYT are the most typical adaptive control systems in urban traffic systems, which can optimize and solve scheduling schemes based on road segment flow and intersection queue length [18].

Signalized intersections serve as the fundamental units of urban road networks, and research on intersection signal timing and scheduling is the foundation for optimizing urban traffic systems. According to the scope of control, signal control can be divided into single-point control, arterial control, and regional coordinated control. Single-point control refers to the control of isolated intersections or relatively independent road junctions in the road network, without considering the coordination with adjacent intersections, in order to minimize vehicle delays at intersections. It is also the basic scenario of traffic control systems [19]. The arterial control strategy is used to manage the signal timing scheme of urban traffic arteries with multiple intersections. The control schemes of each intersection on the artery need to be coordinated, ensuring that vehicles entering the artery can achieve the effect of no or reduced stopping times while maintaining a certain speed. On the other hand, regional coordinated control is used to manage the signals of several intersections within a whole area of the urban traffic network. Based on data such as traffic flow, it optimizes and solves the traffic signal timing of each intersection within the area, aiming to achieve the overall optimal performance of the regional traffic network [20].

1)Isolated intersection:

Literature [21] focuses on an intersection in Wuhan, China, and employs a GA algorithm combined with the Urban Traffic Microscopic Simulation Model (UTMSM) and the International Emissions Vehicle (IEV) model to reduce intersection capacity and vehicle emissions. It also converts the multi-objective model into a single-objective optimization model through weighting for solution. Literature [22] also focuses on a single intersection and employs the NSGA-II algorithm to optimize oversaturated traffic intersections. The two optimization objectives are to maximize the vehicle throughput at the intersection and minimize the vehicle queue length at the intersection. In [23], a single intersection is used as the simulated environment, with the effective green phase duration of each stage of the traffic signal as the control variable. The GA algorithm is employed to minimize the vehicle delay index at the intersection under oversaturated conditions.

Reference [24] proposes a Pareto-front multi-objective PSO algorithm for real-time traffic signal control, with the optimization objectives of minimizing vehicle delay time and minimizing the number of stops. The algorithm requires selecting the optimal solution with a balanced performance from the final Pareto-front solution set. In [25], a hybrid algorithm combining PSO (Particle Swarm Optimization) and Tabu Search is employed to address adaptive traffic control issues. During the optimization process, solutions found by PSO are stored in the Tabu list to minimize the risk of getting stuck in local optima. The optimization model aims to minimize the total vehicle delay and focuses on optimizing the signal timing plan for the Bab Zaer intersection in Rabat, Morocco. [26] proposes a multi-objective PSO algorithm that takes a single intersection as the research object, with average vehicle delay, vehicle emissions, and intersection capacity as multiple optimization objectives, to solve for the signal cycle and green time of each phase at the intersection. This algorithm was ultimately applied at a four-way controlled intersection in Jinzhou, China.

Reference [27] focuses on the application scenario of isolated intersections. By using real-time data, it takes the average vehicle delay as the optimization objective, employs

the PSO algorithm to optimize and solve the traffic signal scheduling problem, and utilizes the SUMO traffic simulator to evaluate the true performance of the solution. In [28], a multi-objective optimization model for traffic signal timing is established for the scenario of a single intersection under oversaturated conditions. The Pareto boundary is solved and the optimal solution is selected using a multi-objective particle swarm optimization algorithm. Finally, traffic simulation is conducted in Paramics to evaluate the scheduling performance of the proposed method. In [29], a traffic flow state equation is established for an isolated intersection, and an optimization model is constructed with the objective function of minimizing average delay and average number of stops. The optimization model is solved based on an adaptively improved artificial fish swarm algorithm, achieving the optimization of urban traffic intersection signal schemes.

2)Arterial road district:

Document [30] focuses on the control objects of urban arterial roads. By constructing average delay models, average queue length models, total vehicle delay models, and exhaust emission models as the optimization models for this paper, it combines fuzzy control theory with the Fuzzy Adaptive Sequencing Mutation Multi-Objective Differential Evolution Algorithm (FASM-MDEA) as the optimization algorithm. In [31], urban trunk roads are taken as the research target, and the Particle Swarm Optimization (PSO) algorithm is used as the optimizer to optimize traffic signal timing plans. Each traffic signal timing solution consists of cycle length, green split, and offset. Simultaneously, VISSIM is employed for simulation, and the performance indicators output by the simulation software are used as evaluation metrics for each solution to guide the optimization algorithm's iterative process. The research in Document [32] focuses on a trunk line consisting of three intersections and proposes an improved Genetic Algorithm (GA) to optimize a series of intersection timing schemes on the trunk line. The control variables include not only the green phase allocation time at each intersection, but also the absolute phase difference between intersections, in order to achieve coordinated control and green wave travel on the trunk line.

In [33], the phase difference between adjacent intersections is calculated based on traffic flow information to advance the offset of signal timing, and the signal timing plans for the current intersection and downstream intersections within the current cycle are adjusted and updated. [34] focuses on the field of arterial coordination control and proposes an extended integrated green wave control method. This method considers green time constraints, ensuring the necessary passage time for vehicles on branch roads and the passage time for pedestrians. Therefore, while ensuring the performance of the arterial road, the performance of the branch roads is simultaneously optimized and adjusted to achieve balanced and matched performance.

To enhance the traffic efficiency of oversaturated arterial roads, [35] introduces a coordinated control model for bidirectional oversaturated arterial roads. This model consists of a throughput maximization model and a delay minimization model. The throughput model improves the throughput of the arterial road by optimizing the cycle length and green split ratio of the main road, while the delay model constructs coordination among consecutive intersections on the arterial road by optimizing the offset. In response to the travel efficiency issue of long arterial roads, [36] proposes a

mixed-integer linear programming model, MaxBandLAM, which aims to optimize the arterial road zoning scheme and signal coordination scheme by targeting the weighted sum of bidirectional green bandwidth on arterial links. [37] focuses on a group of arterial intersections and proposes an optimal traffic signal control method that utilizes real-time traffic information provided by sensors to minimize fuel consumption. The optimization objective is solved by weighting evaluation indicators such as total vehicle traffic volume, total vehicle speed, vehicle waiting time, and road preference, using genetic algorithm (GA) as the global optimization method. In Document [38], the research focuses on a collection of arterial roads within multiple urban road networks. The objective is to construct a regional comprehensive arterial green wave coordination index for optimization. Signal timing parameters, including phase time, phase center point, offset, and cycle length, are selected as optimization variables. The optimization of these variables is carried out using Gurobi.

3)Network area

In Document [39], a cellular transmission model is employed to macroscopically model the traffic network. The objective is to maximize system throughput, minimize travel delay, enhance traffic safety, and avoid overflow. These four indicators are used to construct a multi-objective optimization problem, and the control variables, including signal type, cycle time, signal offset, and green phase time for each phase, are solved using Genetic Algorithms (GA). [40] proposes an adaptive Memetic Algorithm (MA) that combines the advantages of Genetic Algorithms (GAs) with the capabilities of local search algorithms to accelerate the search process and generate high-quality solutions. This algorithm utilizes traffic flow information obtained from loop detectors to construct an average vehicle delay based on unit distance as the optimization objective, and schedules and optimizes the signal timing of intersection nodes in real-world urban road networks. [41] focuses on transportation networks and proposes a bi-level optimization framework to address optimal traffic signal optimization problems. The upper-level framework is used to determine signal timing to minimize the average travel time of vehicles, while the lower-level structure aims to achieve performance balance among nodes in the network using the solutions calculated by the upper level.

In Document [42], the NSGA-II algorithm is employed to construct a bi-objective optimization model, using average delay time and average stop time as evaluation metrics, to address the traffic signal optimization problem in road network scenarios. In [43], the PSO algorithm is utilized to optimize indicators such as vehicle waiting to exit, vehicle entry, travel distance, and delay time for the Oe-Enro highway network in Kumamoto City, Japan. The control parameters include the cycle length, absolute offset, and green time allocation for each phase at each intersection in the road network. In [44], the road network is taken as the research object, and ACO and SGA are employed to address the issue of oversaturated traffic networks. By maximizing the throughput of traffic vehicles, the algorithm seeks solutions for the green phases at various intersections while optimizing the ideal offsets for each intersection. The algorithm was ultimately validated through experiments conducted on a hypothetical model based on a one-way traffic network with 20 signals, as well as another real-world model based on the downtown traffic signal network of Fort Worth, Texas.

[45] focuses on road network areas and introduces a novel hybrid method combining clustering analysis and genetic algorithms to optimize the green time of each node in the road network, aiming to minimize vehicle delay indicators. [46] focuses on the scheduling problem of large-scale urban traffic signals and constructs a centralized model to describe the mathematical model of the road network. In this model, the flow of each road segment is modeled as a nonlinear hybrid logic switch function that incorporates source link density, target link density, capacity, and potential psychological reactions of drivers. The optimization objective is to minimize the total delay time of vehicles within a time window. The optimization algorithm part implements three meta-heuristic optimization algorithms, named Jaya algorithm, Harmony Search (HS), and Water Cycle Algorithm (WCA), to solve the problem. In [47], a mathematical model for urban traffic signal scheduling is constructed using the CTM cell transmission model. High-quality solutions are generated through an improved EA algorithm based on an eight-phase control strategy, combined with a Back Propagation Neural Network (BPNN) and a meta-heuristic algorithm.

[48] proposes two separate meta-heuristic algorithms, the Tabu Search Algorithm (TSA) and the Genetic Algorithm (GA), for scheduling optimization of traffic signal strategies in road networks with multiple intersections. [49] proposes an optimized signal control algorithm that combines prediction and coordination at urban intersections. The algorithm first utilizes an LSTM network to predict traffic condition information for subsequent time steps. Subsequently, based on the motion wave theory and flow density diagram, it constructs a mathematical description model of the road network. By dynamically adjusting signal timing, cycle length, and phase segmentation, it seeks the global optimal solution that minimizes network delay. In [50], the offset of each intersection in the entire road network is optimized to coordinate and synchronize the timing of traffic signals across the network, thereby enhancing traffic flow and reducing stops and delays. In this paper, by modeling traffic flow as a sine wave, the offset optimization is formulated as a continuous optimization problem without integer variables. [51] proposes a dynamic regional traffic signal coordination and optimization control method for road networks. This method combines prediction results with an improved whale optimization algorithm to solve scheduling schemes with the average vehicle delay in regional traffic as the optimization objective.

3 Methodology

3.1 Problem outline

The ultimate goal of scheduling optimization for urban road networks is to obtain a set of superior performance timing plans, which includes the signal cycle, cycle start offset, and green phase allocation time for each phase at all nodes in the road network. Typically, a four-phase control strategy is adopted for the phased control of signal lights in the road network, as shown in Fig. 1. The four phases are: straight ahead in the north-south direction, left turn in the north-south direction, straight ahead in the east-west direction, and left turn in the east-west direction.

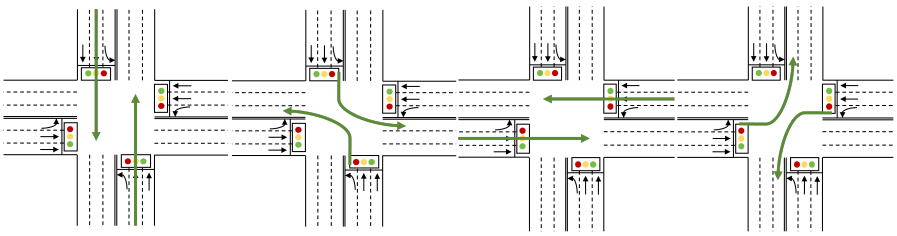


Fig. 1 Schematic diagram of four-phase traffic signal control

The core solving process of the timing plan is shown in Fig. 2. It is usually solved using intelligent optimization methods, so it is necessary to establish evaluation indicators and objective functions to assess the performance of each set of solutions. Common evaluation indicators include: vehicle delay, number of stops, queue length, traffic throughput, fuel consumption, etc. The calculation of these evaluation indicators requires not only the solution of the timing plan, but also the traffic flow information of each road segment in the road network at the current moment and the inherent structural information of the road network. By utilizing the road network structural information, real-time traffic flow information, and the solution of the timing plan, a traffic optimization model can be constructed to solve the optimization objective. At the same time, optimization algorithms are used to continuously iterate and optimize the solution set according to the fitness value of the optimization objective corresponding to each solution, in order to obtain the final timing plan.

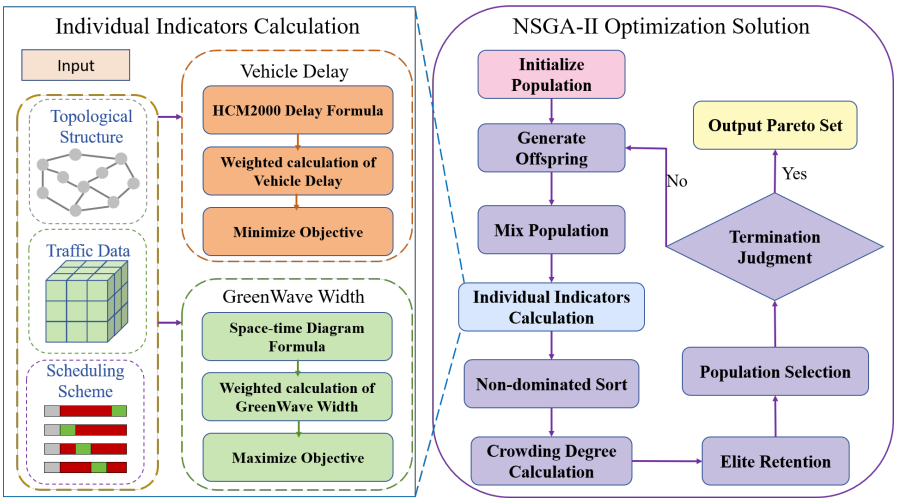


Fig. 2 Core solving process of traffic signal scheduling scheme

In summary, the core of the traffic signal scheduling problem in transportation networks lies in correlating traffic performance indicators such as vehicle delay time and queue length with traffic control parameters (e.g., cycle length, green phase allocation time, and intersection offset). Establishing such a correlation typically requires

macro modeling of the traffic network or solving using empirical calculation formulas for indicators.

3.2 Optimization object

Urban road networks are typically composed of a grid of signalized intersections. Therefore, optimizing the traffic performance of the entire road network requires considering the performance of all nodes within the network and incorporating them into the solution space.

However, nodes in the road network exhibit spatiotemporal correlation, thus it is not feasible to merely superimpose the performance of individual nodes. Instead, it is necessary to incorporate the connections between nodes into the control process. This paper constructs a trunk line set by identifying several consecutive intersections with high traffic volume in the road network, and introduces them as control objects into the optimization model. The upstream and downstream relationships between nodes are addressed and evaluated through the structure of the trunk lines and corresponding evaluation indicators. Additionally, this paper also considers trunk line scenarios involving left turns, to accommodate more complex real-world urban road network situations. The specific meaning of trunk lines is illustrated in Fig. 3.

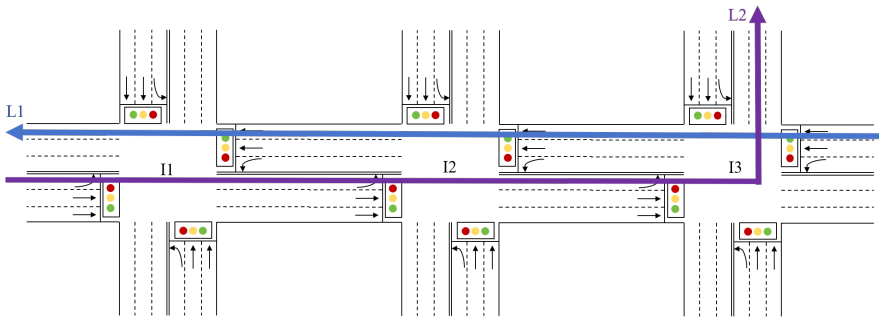


Fig. 3 Schematic diagram of the definition of transportation mainline links

This paper takes the set of trunk lines, which are composed of various nodes in the road network and intersections with high traffic volume, as the optimization object for problem research. Simultaneous optimization of various nodes in the road network will significantly enhance the overall traffic capacity of the road network. Trunk line coordinated control focuses more on the traffic capacity among a series of intersections, but it will also improve the overall traffic performance of the road network. At the same time, due to the potential sharp decline in the performance of non-trunk line nodes in the road network during trunk line coordinated control, comprehensive performance optimization of each node in the road network can prevent traffic resources from being monopolized by trunk lines. Therefore, introducing the set of trunk lines as a research object while comprehensively optimizing road network nodes can make the performance of the traffic road network more balanced and more in line with the green wave traffic strategy in real-life situations.

3.3 Performance measure

3.3.1 Vehicle delay

For each traffic node in the road network, this paper evaluates the performance of solutions using the indicator of vehicle delay. HCM2000, also known as the Highway Capacity Manual, is a professional manual compiled by the Transportation Research Board of the United States for analyzing the capacity and level of service of roads and transportation facilities. This model considers various factors, including traffic flow, signal cycle, and green-to-red ratio, to calculate the average delay time of vehicles at intersections. The specific empirical formula is as follows: The total average delay (per vehicle) is:

$$d = d_1 \times PF + d_2 + d_3 \tag{1}$$

Where d represents the average delay per vehicle, encompassing start-up delay, queue delay, and random delay. d_1 denotes uniform delay, representing the periodic delay caused by red lights under ideal conditions. PF is an incremental factor, dimensionless, indicating the impact of traffic flow coordination on delay. It is set to 1.0 for isolated intersections and can drop to 0.65-1.0 for well-coordinated intersections. d_2 signifies incremental delay, representing the additional queue delay caused by traffic demand nearing or exceeding capacity, typically due to random fluctuations. d_3 stands for initial queue delay, representing the extra delay brought by vehicles left over from the previous cycle, which is usually set to 0 for stable traffic flow, i.e., initial queues are ignored.

$$d_1 = \frac{C(1 - g/C)^2}{2(1 - \min(1, X) \cdot g/C)} \tag{2}$$

Where C represents the cycle length of the signal, g denotes the phase green time of the current phase in the direction of vehicle traffic. X signifies the saturation level of traffic flow on the current road segment, v stands for the actual flow rate on the current road segment, and c indicates the maximum traffic capacity limit of the current road segment.

$$X = \frac{v}{c} \tag{3}$$

$$d_2 = 900\,T \left[(X - 1) + \sqrt{(X - 1)^2 + \frac{8\,k\,I\,X}{c\,T}} \right] \tag{4}$$

Where T represents the analysis cycle length, typically set at 0.25 or 0.5. X denotes the traffic flow saturation of the road segment at the current moment, c signifies the traffic capacity of the road segment, k stands for the incremental delay factor, reflecting the impact of signal timing on delay, and I represents the upstream signal influence factor, usually set between 0.6 and 0.9 for intersections under coordinated control.

$$d_3 = \frac{1800\,P\,\left(\frac{v}{c}\right)\left(1 - \frac{r}{C}\right)}{c\,T} \tag{5}$$

Where P represents the number of queued vehicles at the end of the previous cycle, r denotes the effective red light time, and under stable traffic conditions, assuming no initial queue, d_3 is set to 0.

3.3.2 Mainline green wave

For a main route, in addition to knowing a series of intersections on the route, it is also necessary to understand the driving directions at each intersection, and some intersections also have the requirement for left-turning on the main route. The main means of coordinated control for the main route is green wave control, which involves adjusting the green phase length and cycle offset at each intersection on the main route, so that the scheduling plan and deviation between intersections can better match the arrival characteristics of vehicles at a set speed, achieving the effect of passing through the main route area without stopping or reducing the number of stops. Therefore, this paper adopts the public green wave bandwidth at each intersection on the main route as the evaluation index for the main route.

This article utilizes a spatiotemporal diagram to merge and solve the public green wave bandwidth intervals of multiple intersections. Additionally, for green phases that cross cycle boundaries, multiple intervals are superimposed to ultimately calculate the sum of green wave bandwidth, which represents the total width of the time window during which vehicles can be in green phases at all intersections. The calculation method is explained below through a two-intersection arterial road scenario.

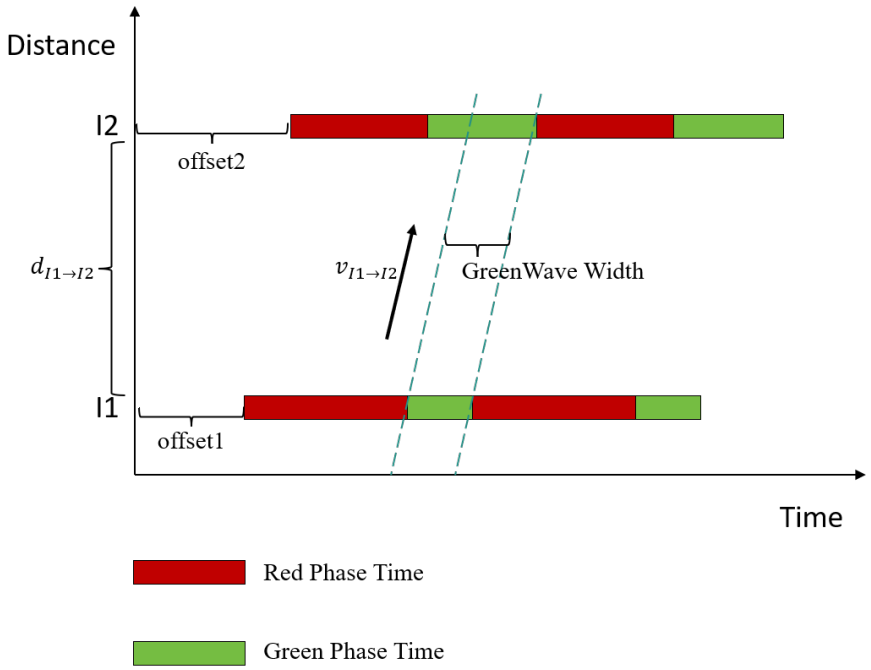


Fig. 4 Schematic diagram of green wave speed of mainline vehicles

Vehicles traveling on the main line need to adhere to certain speed standards to potentially form a green wave. As shown in Fig. 4, the distance that a vehicle needs to travel from the upstream intersection to the downstream intersection is d. If the vehicle

travels at the current set speed v of the main line, it will take d/v seconds to reach the downstream intersection. Therefore, when superimposing time windows later, the offset caused by this travel time needs to be eliminated first. The specific approach is to "advance" the downstream intersection's scheduling scheme by d/v seconds in the time dimension (if there are more than two intersections on the main line, then traverse the intersections one by one, calculate the travel time and accumulate it, and shift the timing scheme of each intersection forward according to the travel time).

After excluding deviations in travel time, the time intervals of the green phase can be directly superimposed in the vertical dimension. Furthermore, since time is periodic, there may be situations where the green phase time interval of a certain intersection, denoted as $dep_start > dep_end$, spans the boundary of a cycle. In this case, the interval needs to be split into two segments: from *dep_start* to the end of the cycle and from the beginning of the cycle to *dep_end*. When the cross-cycle green phase is split into the beginning and end of the cycle, and when superimposing the intervals with the green phases of other intersections, both segments of the phase need to be superimposed. Finally, the superimposed results are summed to obtain the final green wave width of the main line.

3.4 Model optimization

The previous section introduced the calculation method for the vehicle delay index of a single vehicle at a single intersection, and also presented a spatiotemporal graphical method for calculating the green wave bandwidth of a trunk road. In this section, a dual-objective optimization model will be constructed based on these two indicators, aiming to minimize the total average delay of vehicles in the regional road network and maximize the total bandwidth of green wave on the trunk roads of the road network.

The goal of minimizing the total average delay of vehicles in the regional road network involves simultaneous optimization of all intersections within the network. On the other hand, maximizing the green wave effect on main roads focuses on several main roads with high traffic volume in the network, aiming to enhance the green wave passing capacity of vehicles on these main road links. The improvement in the passing capacity of main roads will further enhance the traffic performance of the entire road network. Additionally, the goal of minimizing the total average delay of vehicles in the regional road network also prevents the optimization of main roads from falling into local optima, thereby ignoring the basic passing capacity of non-main intersections.

To achieve coordinated optimization control of regional traffic signals, constraints need to be imposed on control parameters such as signal cycle length, initial offset at each intersection, and green time for each phase at each intersection:

$$T_{\min} \leq T_i \leq T_{\max}, \quad i \in L_{\text{insecs}} \tag{6}$$

$$T = T_i = T_j, \quad i \in L_{\text{insecs}},\ j \in L_{\text{insecs}} \tag{7}$$

$$0 \leq \text{OFFSET}_i \leq T, \quad i \in L_{\text{insecs}} \tag{8}$$

$$g_{\min} \leq g_{i,j} \leq g_{\max}, \quad i \in L_{\text{insecs}},\ j \in L_{\text{phases}} \tag{9}$$

$$\sum_{j}^{L_{\text{phases}}} g_{i,j} = T, \quad i \in L_{\text{insecs}},\ j \in L_{\text{phases}} \tag{10}$$

Formula 6 indicates that the cycle lengths of all intersections must adhere to the constraints of upper and lower limits, where Linsecs represents the set of all intersections in the road network. Formula 7 states that the signal cycle lengths of all intersections in the road network must be consistent, as consistency in cycle length is a prerequisite for coordinated green wave control on arterial roads. Formula 8 suggests that the starting offsets of all intersections in the set must be less than the common cycle length of the current solution. Formula 9 demonstrates that the green light duration of each control phase at all intersections must adhere to preset upper and lower limit constraints. Furthermore, for each intersection, the sum of green light durations for all control phases must equal the common cycle length, a relationship reflected in Formula 10.

3.4.1 Minimize the total average delay of vehicles in the regional road network

The minimization model in this section aims to establish a regional average vehicle delay model, facilitating the coordinated optimization of regional traffic signals. Vehicle delay refers to the time loss incurred by vehicles in motion due to other vehicles and traffic control facilities, and this indicator is also the most commonly used evaluation metric in traffic signal control. Based on the delay index calculation formula mentioned above and the constraints of the model, a regional average vehicle delay model is constructed. The specific formula is as follows:

$$DO = min(\sum_{i}^{L_{\text{insecs}}} \sum_{j}^{L_{\text{phases}}} flow_{i,j} \cdot delay_{i,j}) \tag{11}$$

Where DO represents the optimization objective function for minimizing vehicle delay, i denotes the index of an intersection within the set of regional intersections, and j represents the index subscript of the current phase within the set of four-phase control strategies. $flow_{i,j}$ signifies the traffic flow information of intersection i in the $j-th$ phase direction, while $delay_{i,j}$ stands for the vehicle delay value of a single vehicle at intersection i in the $j-th$ phase direction. By accumulating the delay information across all control phases of all intersections, we can obtain the overall delay metric of the road network.

3.4.2 Maximize the total bandwidth of green wave on arterial roads in the road network

The maximization model in this section aims to establish a green wave coordination model for arterial road networks, achieving coordinated optimization of a series of intersections within the arterial area. Green wave width refers to the maximum time span during which vehicles can travel through a series of intersections without stopping at a preset speed on the arterial road. This indicator is also the most commonly used evaluation metric in arterial coordination control.

Based on the spatiotemporal graphical method for calculating the green wave bandwidth of arterial roads mentioned above and the constraints of the model, a road

network arterial green wave bandwidth model is constructed. The specific formula is as follows:

$$GO = min(\sum_{w}^{L_{\text{waves}}} flow_w \cdot width_w) \tag{12}$$

Where L_{waves} is the set of trunk lines selected based on areas with high traffic flow in the regional road network, $flow_w$ is the average traffic flow of vehicles on the trunk line with index w, and $width_w$ is the sum of the interval green wave widths calculated using the spatiotemporal graph method under the current scheduling solution for the current trunk line.

Therefore, the GO objective is to sum the green wave indicators based on flow weighting for the set of arterial roads within the area. Solving this objective function will result in a more balanced distribution of green wave resources among the arterial roads in the road network. Arterial roads with relatively higher traffic flow will receive more green wave resources, but this objective also ensures green wave performance for arterial roads with lower traffic flow, avoiding extreme imbalance in the distribution of green wave resources in the road network.

3.5 Encoding and decoding scheme

Due to the nonlinear, time-varying, and lagging nature of the transportation system, it is difficult to obtain satisfactory results using traditional control methods. When using intelligent optimization algorithms to solve the aforementioned optimization model, each set of scheduling schemes will be constructed as a multi-dimensional solution vector, which includes the common cycle of the scheduling scheme, the starting offset of each intersection, and the green light passing time of each intersection during each control phase. Therefore, the dimension of each solution vector can be calculated using the following formula:

$$dimension = 1 + N + N \cdot phases) \tag{13}$$

Where 1 represents a universal public cycle length, N is the number of intersections in the regional road network, and each intersection requires a starting offset to be solved. $phases$ is the number of control phases of the currently adopted control strategy, which is uniformly a four-phase control strategy in this paper.

To ensure that the solution, after undergoing mutation and crossover operations during the solving process, still satisfies the constraints set by the optimization model, and to facilitate the interpretation of the solution, this paper adopts binary encoding and decoding.

In the encoding stage, each dimension of the solution vector is encoded as an 8-bit binary value, with the specific format shown in Table 1.

Where c represents the binary variable of the public signal cycle, φ_i represents the binary variable of the starting offset at the ith intersection, and $\theta_{i,j}$ represents the binary variable of the green light passing time at the jth control phase at the ith intersection.

When it is necessary to evaluate the solution vector, that is, to calculate various evaluation indicators based on the solution vector, the binary solution needs to be decoded back into a meaningful decimal solution first. Corresponding decoding

Table 1 Structure diagram of encoding and decoding scheme

Traffic signal timing for the intersections			
Cycle Time	Offsets	Intersection 1	···
Dim(0)	Dim(1-N)	Dim(N+1) to Dim(N+phases)	···
Cycle:c	φ_i	$\theta_{i,j}$	···
8 bits	8 bits	8 bits* phases	···

Source: This is a solution structure description used to describe the optimization model encoding and decoding scheme.

schemes are designed for three types: signal common period, starting offset, and green phase duration. The specific formulas are as follows:

$$cycle_time = T_{min} + c\frac{T_{max} - T_{min}}{255} \tag{14}$$

$$offset_i = \varphi_i \frac{cycle_time}{255}) \tag{15}$$

$$g_{i,j} = g_{min,j} + \frac{\theta_{i,j}}{\sum_{j=1}^{phases}\theta_{i,j}}(cycle_time - \sum_{j=1}^{phases} g_{min.j})) \tag{16}$$

Firstly, the *cycle_time* is decoded, and the interval where the upper and lower bounds of the cycle lie is mapped to an interval with a length of 255. c represents the proportion of this interval, and finally, this proportion is reflected back into the upper and lower bounds of the cycle, plus the shortest cycle time.

When decoding the initial offset of each intersection, the interval $(0, cycle_time)$ is mapped to an interval with a length of 255. The binary variable φ_i represents the proportion occupied in this interval. Multiplying this proportion by the cycle time yields the actual value of the initial offset of the current intersection.

When decoding the green light allocation time for each phase at each intersection, $\theta_{i,j}$ does not represent the binary proportion of the *cycle_time* occupied by each phase, but rather the green phase margin after deducting the minimum passing time of each phase from the *cycle_time*. This margin allocation scheme ensures that all decoded green phase times in the solution set meet the minimum time constraint. $\theta_{i,j}$ requires summing the binary variables of each phase at the current intersection to obtain the proportion of green time that can be allocated to the current phase from the cycle margin. To avoid monopolistic allocation of the cycle margin by a certain phase, a proportional upper limit threshold is set to prevent extreme situations. Green light resources exceeding the proportional upper limit are allocated to the remaining control phases in an average manner.

3.6 Optimization algorithm

Traffic signal control methods are typically implemented through optimization processes, with genetic algorithms (GAs) being widely and successfully applied in this

field [52][53][54]. However, the Genetic Algorithm (GA) is a single-objective optimization algorithm, often used to solve single-objective optimization problems or to transform multiple interrelated optimization objectives into a single-objective optimization problem for solution. The two optimization objectives selected in this paper exhibit mutually exclusive characteristics. The regional vehicle delay model will enable iterative solution of cycle time with a gradually decreasing trend, while the arterial green wave bandwidth model will enable solution of cycle time with a gradually increasing trend. Therefore, the optimization model proposed in this paper needs to seek a compromise solution between these two conflicting optimization objectives, in order to achieve a balanced and excellent performance for both optimization indicators. Such problems cannot usually be solved by transforming them into a single objective function, as optimizing one objective often leads to the deterioration of the other. Therefore, this paper adopts a multi-objective optimization algorithm for solution. NSGA-II is currently one of the most classic and widely used multi-objective evolutionary algorithms.

For a typical multi-objective optimization problem, it can be abstracted as follows:

$$\min_{x \in \Omega} F(x) = (f_1(x), f_2(x), , f_k(x) \tag{17}$$

Where x is the decision variable vector, also known as the solution vector, which in the context of the regional traffic signal timing optimization problem studied in this paper refers to the cycle length, starting offset, and green phase allocation time. $F(x)$ is the objective function vector, containing k objective function indicators for the current solution vector x, and Ω is the space of all feasible solutions for the solution vector x.

Due to the conflicts often existing among multiple objectives, there is usually no single solution that can simultaneously minimize all objectives. Therefore, the concept of Pareto optimal solution set needs to be introduced to evaluate the actual performance of various solutions.

Assuming there are currently two solutions, denoted as x_1 and x_2, with their corresponding objective function vectors being $F(x_1)$ and $F(x_2)$, x_1 is said to dominate x_2 when the following conditions are met, mathematically denoted as $x_1 < x_2$. Specifically, for all objective functions, x_1 is not inferior to x_2, and at least in one performance metric, it is superior to x_2. Only in this case can we say that x_1 is better than x_2, which is referred to as x_1 dominating x_2 in the field of multi-objective optimization.

$$f_i(x_1) \leq f_i(x_2), i = 1, 2, k \tag{18}$$

$$f_i(x_1) < f_i(x_2), \exists i \in \{1, 2, k\} \tag{19}$$

If there is no feasible solution in the Ω feasible solution space that can dominate the current solution x, meaning that x cannot improve any objective without compromising certain indicators, then x becomes a Pareto optimal solution.

The set consisting of all objective function vectors corresponding to Pareto optimal sets is called the Pareto frontier, denoted as:

$$PF = \{F(x)|x \in ParetoOptimalSolution\} \tag{20}$$

For a bi-objective optimization problem, the Pareto frontier is a two-dimensional curve in the objective space. For three-dimensional or higher-dimensional optimization problems, the Pareto frontier will exist in the form of a surface or hypersurface, representing all possible optimal boundaries.

The NSGA-II algorithm addresses the issues of computational complexity and insufficient diversity in the solution set of the initial NSGA. By leveraging the core logic of selection, crossover, and mutation in genetic algorithms, it combines three mechanisms: Fast Non-dominated Sorting, Crowding Distance, and Elitism, to search for the Pareto front solution set in multi-objective optimization problems.

The rapid non-dominated sorting mechanism stratifies all individuals in the population according to their dominance relationships, establishing a priority hierarchy. During the initialization phase, it is necessary to record the number of times each individual is dominated by other individuals, as well as the set of other individuals that each individual can dominate. Subsequently, the individuals in the population are traversed pairwise to determine their dominance relationships and update the dominated quantity and dominance set of each individual. Finally, a stratification operation is performed, where all individuals are stratified according to their dominated quantity and dominance set, to quickly identify the superior solutions in the population.

To avoid the accumulation of solutions and ensure the diversity of the solution set, a congestion calculation index is introduced to measure the spatial congestion degree of a solution in its current dominance layer. The higher the congestion degree of an individual solution, the sparser the surrounding space of the solution, indicating greater exploration potential. Therefore, individuals with higher congestion degrees are more likely to be retained during subsequent selection. The congestion degree of an individual is calculated using a formula.

The set consisting of all objective function vectors corresponding to Pareto optimal sets is called the Pareto frontier, denoted as:

$$crowd_k = crowd_k + \frac{f_i(k+1) - f_i(k-1)}{f_i^{max} - f_i^{min}} \tag{21}$$

The elite retention strategy preserves the inheritance of high-quality solutions by merging the parent population and the offspring population. The parent population generates the offspring population through crossover and mutation, and then the two populations are merged and subjected to a rapid non-dominated sorting process to hierarchically sort the individuals in the merged population. The hierarchical priority and individual crowding degree indicators are combined to construct the final solution set for the next generation.

3.7 Selection of equilibrium solution

The final output of the NSGA-II algorithm is a set of solutions on the Pareto frontier, rather than a single solution. All solutions in the Pareto frontier set are non-dominated, meaning that no additional solution can outperform these solutions in all evaluation dimensions. Therefore, it is necessary to specify a solution selection strategy to choose the final reasonable compromise solution, so that multiple optimization objectives are in a balanced and relatively superior state.

Taking the dual-objective optimization problem of urban road network signal timing and scheduling studied in this paper as an example, the Fig. 5 shows the Pareto front solution set obtained through the NSGA-II algorithm. The two indicators, vehicle delay and arterial green wave bandwidth, are mutually inhibitory. Traversing through each solution in the Pareto front solution set, it is found that when the green wave bandwidth indicator increases, the vehicle delay indicator corresponding to the current solution also rises. Therefore, a compromise solution needs to be chosen to ensure superior vehicle delay indicators while simultaneously increasing the length of the arterial green wave time.

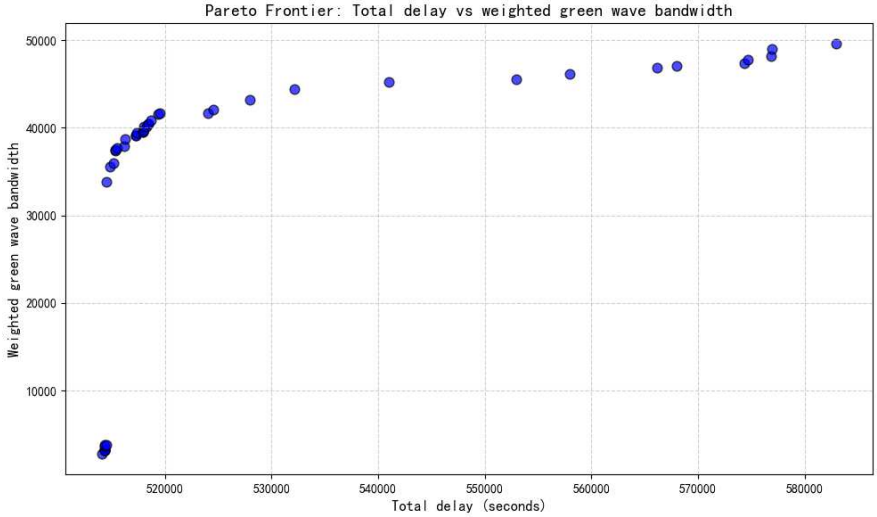


Fig. 5 Schematic diagram of Pareto front solution set distribution

The core of the Pareto frontier lies in the trade-off between objectives, where enhancing the performance of one objective inevitably leads to a decline in the performance of other objectives. A commonly used method to select an ideal solution from the Pareto frontier solution set is the knee point identification method. This method locates the critical point where marginal benefits undergo a sudden change on the Pareto frontier, considering it as the solution with the maximum benefit, thus possessing higher decision-making value. For instance, in the research scenario presented in this paper, the specific meaning of the knee point refers to the inflection point where

sacrificing a minor amount of vehicle delay metrics can significantly increase the length of arterial green waves, or the inflection point where sacrificing a minor amount of arterial green wave bandwidth can significantly reduce the vehicle delay metrics in the road network.

Making decisions and selecting solutions through knee points can ensure that the performance of each optimization objective is not excessively extreme, while minimizing the cost of trade-offs.

The underlying logic of the knee point identification method is to calculate the position where the target trade-off ratio undergoes a drastic change. In the context of bi-objective optimization, the trade-off ratio represents the amount of cost required to reduce one unit of target B by target A, which can be mathematically represented by the absolute value of the derivative. Therefore, curvature analysis is commonly used in bi-objective optimization problems for knee point identification. The core process of curvature analysis is as follows:

1) Data preprocessing: Remove duplicate and outlier solutions from the Pareto solution set, arrange the solution set in ascending order according to one of the optimization objectives to form a continuous broken line, and apply interpolation methods and other techniques for smoothing to obtain the Pareto front curve.

2) Curvature calculation: Calculate the first and second derivatives of each solution individual on the Pareto front curve, and compute the curvature of each point using the provided formula. A higher curvature indicates a steeper curve.

$$K(f_i) = \frac{\left|f''(f_{1i})\right|}{\left[1 + (f'(f_{1i})^2)\right]^{3/2}} \tag{22}$$

3) Locating knee points: Traverse the curvature values of all points, find the point with the maximum curvature, and verify whether there is a significant difference in curvature before and after this point.

4 Experimental Analysis

4.1 Raw dataset

A set of real road networks in Guangzhou, Guangdong Province, China, was selected as the research object for optimization model modeling and scheduling scheme solving. The road network structure is shown in Fig. 6. The road network consists of three roads in the north-south direction and two roads in the east-west direction. There are a total of eight signalized intersections in the road network that require signal timing scheduling optimization.

Based on traffic survey results, the Table 2 provides real-world traffic flow data for each intersection and direction in the current urban road network. The data is presented in pcu/h, representing the number of vehicles passing through the road segment within an hour. Specifically, "northbound straight" refers to the traffic flow coming from the north of a certain intersection and heading south in a straight direction. Similar definitions apply to other fields.

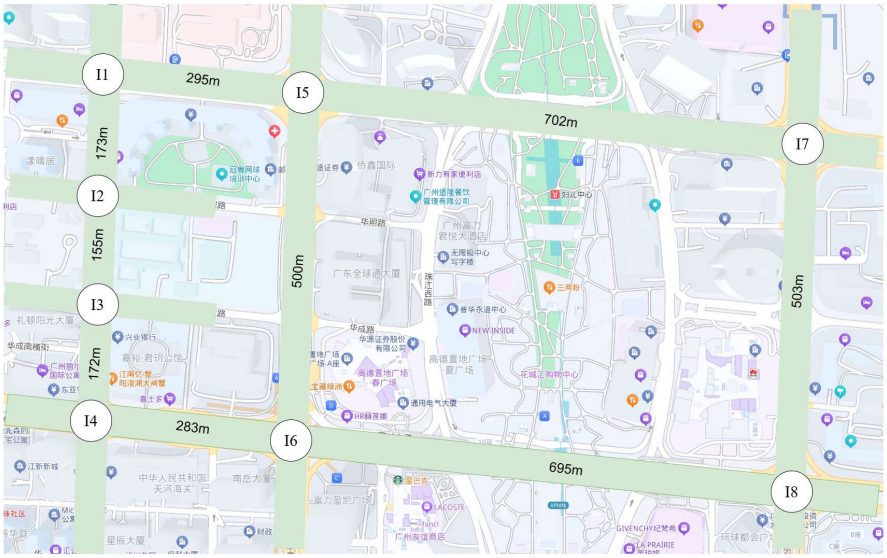


Fig. 6 Guangzhou Road Network Structure Map

Table 2 Traffic flow data of various intersections and directions in the urban road network

Direction of Travel	Traffic flow at each intersection(pcu/h)							
	I1	I2	I3	I4	I5	I6	I7	I8
North straight	320	390	377	330	390	228	247	355
North turn left	30	145	76	50	210	385	376	0
North turn right	38	26	43	38	92	89	88	78
South straight	316	382	382	325	383	393	0	440
South turn left	40	176	176	85	225	218	476	0
South turn right	52	38	38	50	68	48	138	98
East straight	567	80	94	495	450	300	273	467
East turn left	240	36	34	256	216	276	296	276
East turn right	75	57	22	89	79	78	97	125
West straight	550	100	90	500	461	378	300	440
West turn left	270	37	36	276	220	290	276	296
West turn right	67	38	28	78	68	64	118	112

Source: This is a table used to describe the real traffic flow data of the current urban road network.

Based on road network traffic control and actual traffic flow data, it can be concluded that at intersection I7, direct southbound traffic is not allowed to pass through the intersection; at intersection I8, northbound traffic is not allowed to turn left, and southbound traffic is also not allowed to turn left; normal traffic is allowed in all directions at other intersections.

Based on the coordinated control requirements of the arterial roads in the road network, four node links with high traffic flow data were selected as the target arterial roads for study. The specific arterial roads are described in Table 3.

Table 3 Description of core trunk lines in urban road network

Arterial Road	Node Link	Direction Description	Speed Limit
L1	I1,I2,I3,I4	I1 NS,I2 NS,I3 NS,I4 NS	30km/h
L2	I8,I7,I5,I1	I8 SS,I7 SL,I5 ES,I1 ES	50km/h
L3	I8,I6,I4	I8 ES,I6 ES,I4 ES	50km/h
L3	I6,I5	I6 SS,I5 SS	50km/h

Source: This is a table used to describe the core trunk lines in urban road networks.

4.2 Model solution

Based on the structure of the road network, traffic flow data, trunk line setting information, and the dual-objective regional traffic network signal optimization model constructed in this paper, the NSGA-II algorithm is employed for solving. Additionally, the knee point identification method is adopted to select the final equilibrium solution from the Pareto front solution set as the output solution of the algorithm.

The optimization algorithm is written in Python 3.9 and solved on a computer equipped with an i9-13900HX processor and an RTX 4060 graphics card, with a population size of 200 and 300 generations.

This paper will employ the following baseline models to construct comparative experiments, in order to verify the superiority of the dual-objective optimization algorithm for urban transportation networks proposed in this paper.

1. Fixed Uniform Timing: This algorithm is one of the most basic post-admission control strategies. All intersections adopt a common signal cycle, with each control phase receiving equal green light time. The starting offset for all intersections is set to 0. It is an egalitarian timing strategy that does not consider actual traffic distribution.

2. Flow-Weighted Timing: This method incorporates a flow-sensing mechanism on the basis of fixed-cycle timing. It allocates green light time according to the total flow ratio of each phase, with a fixed cycle of 120 seconds and an offset set to 0 for each intersection. Therefore, it represents a simple adaptive control concept based on proportion.

3. Webster Optimal Cycle Timing: This algorithm is a relatively classic single-intersection signal timing theory in the field of traffic control. Its core is to calculate an optimal cycle, with the principle shown in Equation 22. Here, Copt represents the optimal cycle to be calculated, L is the total loss time per cycle (usually 2 times the number of phases), and Y is the flow saturation rate of the critical phase. Under a unified cycle, the flow weighting method is used to allocate green light time to each

phase.

$$C_{opt} = \frac{1.5L + 5}{1 - Y} \tag{23}$$

4. TRANSYT-like multi-objective weighted optimization: TRANSYT is a classic network signal coordination optimization software developed by the Transport and Road Research Laboratory in the UK. Its core principle is to simulate the propagation of traffic flow using a continuous model. The performance indicators inherit vehicle delay and number of stops, and search for the optimal cycle, offset, and green time allocation through the hill-climbing method.

5. SYNCHRO-like coordinated green wave control: SYNCHRO is a commercial signal timing software developed by Trafficware, which is widely used in North America. Its core principle integrates HCM analysis, Webster cycle calculation, and coordination optimization. It maximizes green wave bandwidth by manually or automatically setting offsets, requiring iterative adjustments until the optimization objectives are met.

6. Regional vehicle delay single-objective optimization algorithm (delay-single): This method utilizes the single-objective optimization algorithm constructed based on the model for minimizing the total average delay of vehicles in the regional road network proposed in this paper, and employs the GA algorithm for solving. Its evaluation indicators and optimization objectives are consistent with those of the dual-objective optimization algorithm presented in this paper.

7. Mainline Green Wave Single-Objective Optimization Algorithm (greenwave-single): This method utilizes the maximized total green wave bandwidth model for road network mainlines constructed in this paper to develop a single-objective optimization algorithm, which is solved using the GA algorithm. Its evaluation metrics and optimization objectives are consistent with those of the dual-objective optimization algorithm presented in this paper.

The Table 4 below summarizes the common cycle length and the starting offset of each intersection obtained through different methods:

Table 4 Solution results of signal control parameter optimization for various methods

Method	**Cycle(s)**	**Offsets for all intersections(s)**							
		I1	I2	I3	I4	I5	I6	I7	I8
Fixed Uniform	120	0	0	0	0	0	0	0	0
Flow-Weighted	120	0	0	0	0	0	0	0	0
Webster Optimal	100	0	0	0	0	0	0	0	0
TRANSYT-like	114	45	75	83	17	18	110	4	101
SYNCHRO-like	100	8	21	40	70	87	50	36	0
Delay-Single	116	0	0	0	0	0	0	0	0
greenwave-single	130	109	1	22	41	80	41	85	83
Muti-object	115	56	77	96	0	28	98	28	10

Source: This is a table used to calculate the solution results of signal control parameter optimization for various methods.

In the aforementioned methods, since the Fixed Uniform, Flow-Weighted, Webster Optimal, and Delay-Single methods do not pay attention to the offsets at each intersection during the solution process, their offsets are all set to 0 for processing.

The Table 5 and Table 6 present a statistical overview of the traffic light scheduling schemes derived from various methods for each intersection. It displays the scheduling schemes obtained through each method and breaks them down by individual intersections. Since the research focuses on a four-phase control strategy, the timing vector for each intersection comprises four dimensions: north-south through traffic, north-south left turn, east-west through traffic, and east-west left turn.

Table 5 The traffic light scheduling schemes for each intersection solved by various methods(Intersections I1 to I4)

Method	**Timing plan for each intersection**			
	I1	I2	I3	I4
Fixed Uniform	[36,28,28,28]	[36,28,28,28]	[36,28,28,28]	[36,28,28,28]
Flow-Weighted	[33,15,46,26]	[61,28,16,15]	[64,24,17,15]	[34,15,43,28]
Webster Optimal	[27,15,36,22]	[47,23,15,15]	[50,20,15,15]	[28,15,34,23]
TRANSYT-like	[36,15,39,24]	[39,39,21,15]	[39,39,20,16]	[37,15,39,23]
SYNCHRO-like	[27, 5,46,22]	[56,23,14, 7]	[58,20,15, 7]	[28, 7,42,23]
Delay-Single	[29,16,38,33]	[40,35,26,15]	[40,20,40,16]	[20,18,39,39]
greenwave-single	[45,22,41,22]	[46,41,24,19]	[44,25,24,37]	[44,17,43,26]
Muti-object	[39,16,39,21]	[39,38,22,16]	[39,39,22,15]	[39,15,39,22]

Source: This is a table used to calculate the traffic light scheduling schemes for each intersection solved by various methods(Intersections I1 to I4).

Table 6 The traffic light scheduling schemes for each intersection solved by various methods(Intersections I5 to I8)

Method	**Timing plan for each intersection**			
	I5	I6	I7	I8
Fixed Uniform	[36,28,28,28]	[36,28,28,28]	[36,28,28,28]	[36,28,28,28]
Flow-Weighted	[36,20,44,20]	[30,29,33,28]	[15,43,31,31]	[37,15,38,30]
Webster Optimal	[30,18,34,18]	[25,24,28,23]	[15,35,25,25]	[30,15,30,25]
TRANSYT-like	[39,18,39,18]	[29,26,37,22]	[15,39,31,29]	[31,16,39,28]
SYNCHRO-like	[30,18,34,18]	[25,24,28,23]	[12,38,25,25]	[34,2,39,25]
Delay-Single	[39,21,40,16]	[24,33,28,31]	[17,35,25,39]	[40,16,40,20]
greenwave-single	[40,43,32,15]	[24,16,44,46]	[20,43,44,23]	[39,40,36,15]
Muti-object	[36,25,39,15]	[37,15,37,16]	[15,39,29,32]	[39,22,39,15]

Source: This is a table used to calculate the traffic light scheduling schemes for each intersection solved by various methods(Intersections I5 to I8).

For the dual-objective optimization algorithm proposed in this paper, a set of Pareto front optimal solutions is ultimately obtained. The equilibrium solution is determined by analyzing the curvature of the curve using the knee point identification method to obtain the solution with the maximum benefit, which serves as the final solution of the algorithm in this paper.

4.3 Indicator analysis

The evaluation metrics for solutions obtained by different algorithms can be derived from the calculation formula of the optimization objective. This section will solve and analyze the vehicle delay metrics, arterial green wave metrics, and actual green wave durations of each arterial route for each solution.

The vehicle delay and arterial green wave indicators are shown in the Table 7:

Table 7 The vehicle delay and mainline green wave indicators corresponding to each method's

Method	Vehicle delay index	Mainline greenwave index
Fixed Uniform	580108.73	0
Flow-Weighted	522017.83	0
Webster-Optimal	518139.43	0
TRANSYT-like	514777.54	29776.92
SYNCHRO-like	494239.85	29459.8
Delay-Single	514834.98	0
greenwave-single	605230.42	50251.75
Muti-object	518127.63	43158.67

Source: This is a table used to calculate the vehicle delay and mainline green wave indicators corresponding to the solutions of various methods.

In terms of vehicle delay, there are significant differences among various optimization methods. The Fixed Uniform method, due to its fixed timing, cannot adapt to changes in traffic flow, thus its vehicle delay is only slightly better than that of the arterial green wave optimization model. The Flow-Weighted method allocates green light time based on the proportion of traffic flow, thereby reducing vehicle delay to some extent. The Webster Optimal method utilizes the optimal cycle formula to allocate green light time for each phase using flow weighting under a unified cycle, thus achieving good results. However, it is only suitable for isolated intersections and cannot perform coordinated control on arterial lines. Both the TRANSYT-like and SYNCHRO-like methods, as core algorithms implemented in two commercial scheduling software, excel in reducing vehicle delay. The SYNCHRO-like method considers more factors and achieves more prominent optimization effects at complex intersections. The Delay-Single method aims to minimize vehicle delay, thus achieving superior delay indicators. However, it cannot guarantee coordinated control between intersections through arterial green waves. The greenwave-single method focuses on arterial

green waves, resulting in a high vehicle delay of 605,230.42, indicating that it sacrifices the right of way for non-arterial roads to some extent. The Multi-object method comprehensively considers multiple objective factors, achieving a vehicle delay of 518,127.63. While balancing multiple objectives, it also significantly improves traffic efficiency.

A comprehensive analysis from the perspectives of two indicators reveals that the TRANSYT-like, SYNCHRO-like, greenwave-single, and the multi-objective method proposed in this paper can optimize vehicle delay indicators across the entire road network while generating green wave time widths on the arterial roads. However, among the four methods, the optimization model proposed in this paper can simultaneously ensure both vehicle delay indicators and arterial green wave indicators. Although the vehicle delay indicators of the dual-objective optimization method in this paper differ by 0.65% and 4.83% from the TRANSYT-like and SYNCHRO-like methods, respectively, they exceed these two algorithms by 44.9% and 46.5% in terms of arterial green wave indicators. The greenwave-single algorithm is designed solely to improve the coordination efficiency of arterial roads, so its arterial filtering indicators should theoretically be higher. This algorithm exceeds the dual-objective optimization algorithm by 16.4% in terms of green wave indicators, but it lags behind by 16.8% in terms of overall road network vehicle delay indicators. Therefore, this paper proposes a dual-objective optimization algorithm for urban regional road networks that is optimal among multiple comparative algorithms when considering both vehicle delay and arterial green wave indicators comprehensively.

The trunk green wave index analyzed above is an index calculated based on the weighted flow of each trunk. Below, we present a statistical analysis of the actual green wave lengths of each trunk, with the data results shown in the Table 8.

Table 8 The true green wave length of each main line corresponding to each method's solution

Method	**GreenWave width(s)**			
	L1	L2	L3	L4
Fixed Uniform	0	0	0	0
Flow-Weighted	0	0	0	0
Webster-Optimal	0	0	0	0
TRANSYT-like	11	30	4	25
SYNCHRO-like	26	0	26	24
Delay-Single	0	0	0	0
greenwave-single	42	25	36	21
Muti-object	37	31	10	28

Source: This is a table used to calculate the true green wave length of each main line corresponding to the solutions of various methods.

Compared with the results obtained by other algorithms, the two algorithms proposed in this paper for optimizing the maximum green wave bandwidth of urban road network trunk lines, namely the greenwave-single single-objective optimization algorithm and the Multi-object regional road network bi-objective optimization algorithm, achieved significant green wave time widths on four trunk lines with high traffic volume. Compared with the other two algorithms capable of green wave coordination control, the two optimization algorithms proposed in this paper can obtain longer green wave travel times, achieve significant green wave bandwidths across multiple trunk lines, and distribute green wave resources more evenly among various trunk lines. For example, the TRANSYT-like algorithm can only achieve a time width of 4 seconds for trunk line L3, while the SYNCHRO-like algorithm cannot allocate any green wave time to trunk line L2 at all.

Upon further analysis of the two green wave coordination algorithms presented in this paper, it is observed that although the Muti-object regional road network dual-objective optimization algorithm yields a reduced green wave width for each arterial road compared to the greenwave-single bandwidth single-objective optimization algorithm, it also takes into account the average vehicle delay at other non-arterial intersections within the road network. In terms of the quantitative indicator of vehicle delay, it is reduced by 14.4% compared to the greenwave bandwidth single-objective optimization algorithm. Since the dual-objective optimization algorithm necessitates simultaneous optimization of the traffic capacity at other non-arterial intersections in the road network, its performance in terms of green wave time indicators may be inferior to optimization algorithms specifically designed for arterial road coordination. However, it still maintains a leading position compared to other comparative algorithms.

5 Simulation analysis

The indicator analysis conducted in the previous section was based on theoretical formulas to theoretically analyze the solutions obtained from various algorithms. Therefore, in this section, we will utilize a traffic simulation platform to construct a road network consistent with the dataset used by the optimization algorithm, and conduct simulations using real traffic flow data to verify the performance indicators of each set of solutions in a real-world road network operating environment.

Eclipse SUMO (Simulation of Urban Mobility) is an open-source microscopic traffic simulation platform developed under the auspices of the German Aerospace Center (DLR). It specializes in the detailed simulation of multimodal traffic flows, including vehicles, pedestrians, and public transportation, within urban road networks. It is widely applied in research areas such as traffic signal control optimization, road network planning, and the verification of Intelligent Transportation Systems (ITS).

This section will cover the process of building a road network using SUMO, configuring traffic flow information, running simulations, and obtaining quantitative indicators after simulation. The quantitative indicators primarily focus on the average delay time and average queue length at each intersection, as well as the average vehicle delay and average number of stops per vehicle.

The simulation road network built by SUMO is shown in Fig. 7. Its road network structure is built according to the dataset information used in the optimization model, and the simulation time is set to one hour.

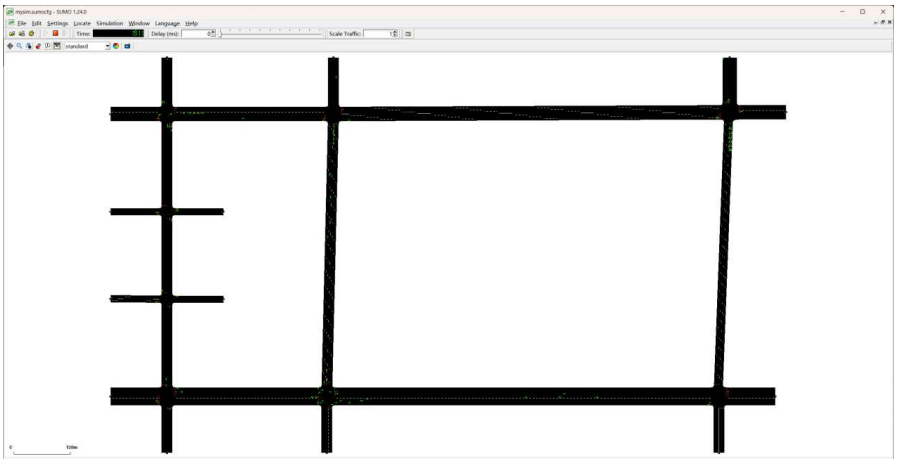


Fig. 7 SUMO simulation platform road network structure

The simulation experiment also conducted simulation analysis on eight sets of solutions obtained from a total of eight algorithms, including the dual-objective optimization algorithm presented in this paper. The quantitative indicators for vehicle dimensions obtained are shown in the Table 9.

Table 9 Quantitative indicators of each method solution in the simulation experimental platform

Method	Average delay time of vehicles (seconds)	Average number of vehicle stops (times)
Fixed Uniform	97.99	1.54
Flow-Weighted	92.39	1.61
Webster-Optimal	85.38	1.25
TRANSYT-like	86.83	1.29
SYNCHRO-like	90.67	1.35
Delay-Single	91.71	1.56
greenwave-single	107.90	1.60
Muti-object	79.17	1.25

Source: This is a table used to calculate the quantitative indicators of various method solutions in the simulation experiment platform.

Among them, under the same traffic simulation data, the solution obtained by the dual-objective optimization algorithm proposed in this paper achieved the best results in both the average delay time and average number of stops in the vehicle dimension,

which were 79.17 seconds and 1.25 times respectively. Compared with the TRANSYT algorithm, it improved by 9.68% and 3.2%, and compared with the SYNCHRO algorithm, it improved by 14.53% and 8%. However, the single-objective optimization algorithm based on vehicle delay proposed in this paper only considered the delay performance at each intersection without considering the collaborative relationship between intersections, so the solution of this algorithm was not outstanding compared with other algorithms. In addition, the single-objective optimization algorithm based on arterial green wave indicators was superior to the one that only focused on the arterial set and completely ignored the traffic performance of non-arterial signal intersections. Therefore, the solution of this algorithm showed extremely poor performance in real-world environments.

The average vehicle delays at each intersection are shown in the Table 10.

Table 10 Simulate the average vehicle delay at each intersection using multiple methods

Method	**Average vehicle delay at each intersection (seconds)**							
	I1	I2	I3	I4	I5	I6	I7	I8
Fixed Uniform	23.34	21.80	17.95	25.33	35.09	36.76	35.28	36.45
Flow-Weighted	21.86	23.99	16.34	21.70	45.76	48.57	40.48	55.74
Webster-Optimal	20.07	20.94	15.82	19.69	27.98	27.66	35.86	34.22
TRANSYT-like	18.36	18.45	12.48	34.06	30.05	36.18	35.33	32.17
SYNCHRO-like	20.34	20.23	14.54	23.14	28.19	26.26	31.01	34.55
Delay-Single	21.75	21.73	18.54	18.40	30.06	33.32	23.61	33.81
greenwave-single	21.36	19.63	11.08	21.54	35.92	34.85	37.94	33.94
Muti-object	18.21	16.27	10.47	20.75	26.21	27.79	28.83	29.44

Source: This is a table used to calculate the average vehicle delay at various intersections simulated by multiple methods.

From the perspective of overall average delay, the solution obtained by the dual-objective optimization algorithm in this paper performs optimally with a mean value of 19.85 seconds, which is 37.6% lower than the worst-performing Flow-Weighted method. The TRANSYT-like and SYNCHRO-like algorithms also exhibit good performance. Furthermore, the traditional Fixed Uniform and Flow-Weighted methods lag far behind multi-objective optimization and arterial coordination methods. Traditional strategies relying solely on fixed timing or flow weighting can no longer meet the control requirements of complex road networks.

Based on quantitative indicators, an analysis was conducted on the dimensions of various intersections, as illustrated in the Fig. 8. Intersection I3 exhibits the lowest delay across all scheduling schemes, which is related to its traffic flow characteristics. On the other hand, Intersection I8 is a concentrated point of high delay within the entire road network. Additionally, Intersections I5, I6, and I7 also generally have high delay values. These intersections are located on multiple main roads in the city and experience generally high traffic flow.

The average queue length at each intersection is shown in the Table 11.

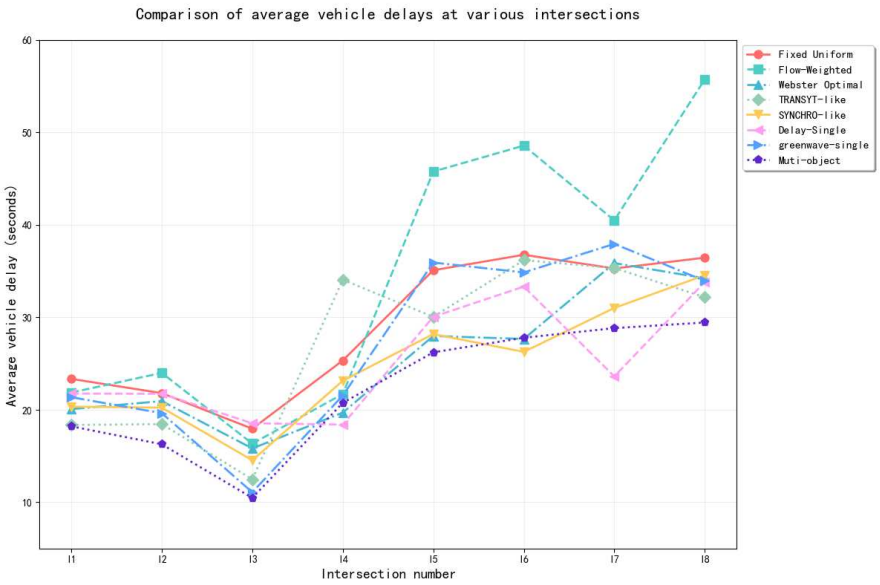


Fig. 8 Comparison of Average Vehicle Delay at Various Intersection Solutions

Table 11 Simulate the average queue length at each intersection using multiple methods

Method	**Average queue length at each intersection (meters)**							
	I1	I2	I3	I4	I5	I6	I7	I8
Fixed Uniform	8.5	6.3	4.3	9.0	9.6	7.2	7.6	6.2
Flow-Weighted	8.5	5.6	3.4	8.3	8.8	9.0	8.6	7.0
Webster-Optimal	8.5	5.5	3.8	7.0	9.1	6.1	6.5	6.7
TRANSYT-like	7.2	5.0	3.7	12.6	9.7	6.7	7.3	7.1
SYNCHRO-like	7.3	4.4	3.0	7.6	7.5	6.1	6.5	5.5
Delay-Single	7.6	4.9	4.0	5.0	7.5	10.4	7.8	6.8
greenwave-single	8.4	6.1	4.6	6.8	10.8	13.8	7.5	9.3
Muti-object	6.9	4.5	3.1	5.3	8.5	6.7	6.1	7.1

Source: This is a table used to calculate the average queue length of various intersections simulated by multiple methods.

Based on the simulation results, an analysis of queue lengths at various intersections is conducted, as illustrated in the Fig. 9. The solution of the dual-objective optimization algorithm proposed in this paper exhibits lower queue lengths at all eight intersections, and demonstrates a more balanced optimization effect compared to other algorithms. In traditional methods, the Fixed Uniform and Flow-Weighted algorithms still lag behind methods that perform collaborative optimization globally in terms of queue length.

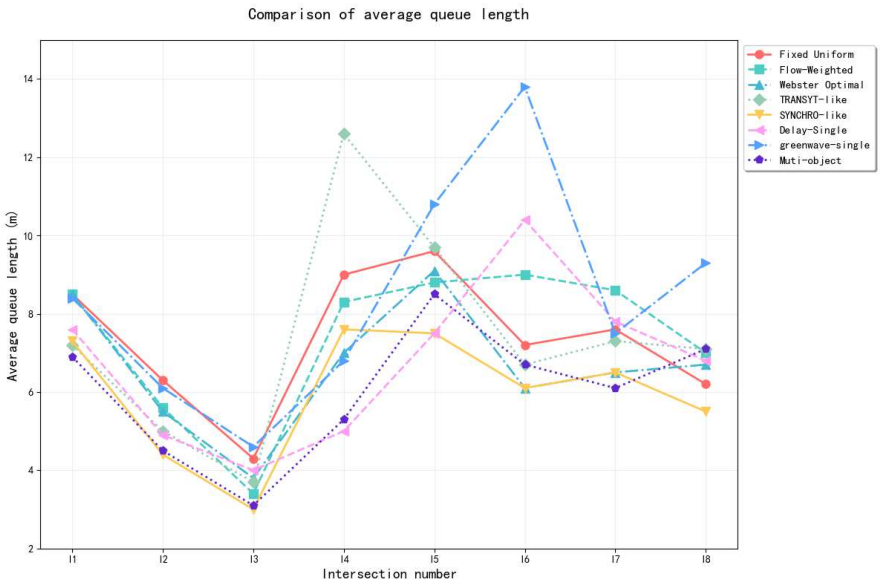


Fig. 9 Comparison of Average Queue Length at Various Intersection Solutions

The intersection I3 remains the node with the shortest queue length among all intersections, which matches the shortest vehicle delay indicator mentioned above. In addition, the average queue length at intersections I4, I5, and I6 is a concentrated point of high values, which is related to their high traffic volume and characteristics of approaching saturation at certain time points.

6 Conclusion and Discussion

This paper investigates the coordinated optimization of urban traffic signal networks, focusing on both the overall regional network and several high-traffic trunk lines. By constructing two optimization objectives: minimizing the total vehicle delay in the regional road network and maximizing the total green wave bandwidth of the road network trunk lines, combined with the constraints of signal control parameters, a bi-objective optimization model is constructed in this paper. The optimization model is solved using the NSGA-II multi-objective optimization algorithm to obtain a set of non-dominated Pareto front solutions. Finally, the solution with the largest marginal benefit mutation in the front solution set is selected as the output of the algorithm based on the knee point identification method.

The effectiveness of the proposed method is evaluated using a real-world traffic dataset from Guangzhou City, Guangdong Province, China, with seven comparative algorithms designed for benchmarking. Experimental results demonstrate that the solution of the dual-objective optimization algorithm proposed in this paper performs optimally in both vehicle delay indicators and arterial green wave indicators, with the arterial green wave indicator improving by 44.9% and 46.5% compared to TRANSYT and SYNCHRO, respectively. Finally, this paper constructs a SUMO simulation road

network and verifies the effectiveness of the algorithm's solution in a real road network operating environment.

In the future, it is planned to introduce additional optimization objectives based on the dual-objective optimization model presented in this paper to achieve a more comprehensive evaluation of indicators. Consideration will also be given to scheduling optimization for traffic scenarios under near-saturated or oversaturated conditions, taking into account sudden accidents and weather factors, to construct a mathematical optimization model with robustness to traffic flow characteristics. Furthermore, the optimization efficiency of the model should be considered to meet the real-time scheduling requirement scenarios of the traffic network.

Declarations

- Conflict of interest
  The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.
- Funding
  This research did not receive funding.

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