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Traffic Signal Priority Control Based on Traffic Wave Theory

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Abstract

With the continuous growth in vehicle ownership, urban traffic congestion has become increasingly severe. Traditional transportation systems and urban road expansion are no longer sufficient to alleviate congestion or meet the mobility needs of residents. In recent years, the rapid development of the Internet of Vehicles (IoV) and vehicle–infrastructure cooperative technologies has opened new avenues for intelligent traffic management. In particular, how to effectively utilize the real-time information from connected vehicles and smart infrastructure to control the movement of connected buses and optimize traffic signal phases at intersections has become a key strategy for improving urban traffic efficiency.

This study focuses on signal timing optimization at connected signalized intersections. First, a vehicle waiting time prediction method based on traffic wave theory is introduced to estimate queue dynamics more accurately. Then, a connected transit signal priority (TSP) control model is developed, aiming to minimize the weighted waiting time of both connected buses and general traffic. The model is solved using a genetic algorithm to obtain the optimal signal timing strategy, thereby achieving effective signal priority control for connected buses.

Keywords: Connected Buses, Signal Priority Control, Genetic Algorithm

1. Introduction

With the continuous growth of the global population and the accelerating pace of urbanization, the demand for urban mobility is increasing rapidly, accompanied by significant changes in travel modes. For public transportation systems, signal priority strategies are generally categorized into spatial priority and temporal priority. The introduction of dedicated bus lanes effectively combines both, and has proven to be one of the most cost-effective solutions for improving transit services. Since the first Bus Rapid Transit (BRT) line was established in Brazil in 1974, BRT systems and dedicated bus lanes have been widely adopted worldwide. Spatial priority is achieved by physically separating buses from general traffic, thereby ensuring unimpeded passage. In contrast, temporal priority is implemented through signal control systems at intersections, which adjust traffic signal phases in real time to provide buses with additional green time or reduced red time, thereby reducing bus delays and improving service reliability.

Transit Signal Priority (TSP) is a traffic signal control strategy first introduced in the early 1960s in Paris, France. In 1967, Wilbur and his colleagues at the Los Angeles Highway Department formally proposed the concept of TSP, granting transit vehicles certain levels of right-of-way priority. Today, TSP systems are widely deployed in major cities such as Seattle, Los Angeles, Oakland, Chicago, and Vancouver, where studies have reported reductions in bus travel time ranging from 9% to 50%.

Signalized intersections are critical components in any transit priority system. By employing various signal control strategies, traffic performance at intersections can be significantly improved under different traffic conditions. Common signal control methods include fixed-time control, actuated control, adaptive control, and manual intervention. Fixed-time control uses predetermined phase sequences and cycle lengths based on historical traffic patterns, and is suitable for intersections with relatively stable traffic volumes or isolated intersections without network connectivity. Actuated control relies on detectors (e.g., loop coils) to adjust signal timings in response to real-time traffic conditions, and is suitable for environments with random vehicle arrivals and fluctuating volumes. Manual control is used in special cases where human intervention is required. Adaptive control dynamically adjusts signal plans based on real-time traffic data collected from sensors or connected vehicles, making it particularly effective in modern, data-rich intelligent traffic environments.

With the rise of Vehicle-to-Everything (V2X) technologies, recent research has focused on integrating intelligent connectivity with transit signal priority systems. Technologies such as Dedicated Short-Range Communication (DSRC) and Cellular V2X (C-V2X), including LTE-V and 5G NR-V2X, enable real-time bidirectional communication between buses and infrastructure. Equipped with On-Board Units (OBUs), connected buses can share location and speed data with Roadside Units (RSUs), which in turn transmit signal phase and timing information back to the buses. This enables dynamic adjustment of signal phases to facilitate smoother transit vehicle passage.

The integration of autonomous driving with connected transit systems further enhances the ability to plan and control bus movements in real time. Through the coordinated operation of "intelligent vehicles" and "smart infrastructure," a new model of urban mobility is being formed—one that addresses both service efficiency and system-level coordination. This concept, known as Cooperative Vehicle-Infrastructure Systems (CVIS) or vehicle-road collaboration, forms the foundation of next-generation Intelligent Transportation Systems (ITS).

However, existing research in the field of TSP under connected environments still faces several limitations. First, many studies focus only on either spatial or temporal aspects of bus priority, without integrating both to maximize performance. Second, the impact of TSP on non-transit (private) vehicles is often overlooked, even though excessive priority given to buses may increase delays, induce sudden stops, and exacerbate congestion for other road users.

To address these gaps, this paper proposes a novel control method for connected transit signal priority and speed planning under cooperative vehicle-infrastructure environments. The method fully leverages shared data between vehicles and infrastructure to improve transit efficiency while also considering the impacts on surrounding traffic. By integrating traffic wave theory with adaptive signal control, and optimizing control decisions using genetic algorithms, the proposed strategy provides a balanced and intelligent solution for modern urban traffic management.

2. Literature Review

Transit Signal Priority (TSP) strategies can be broadly categorized into spatial priority and temporal priority. Temporal TSP mainly focuses on manipulating traffic signal timing to favor buses, and significant research has been conducted on single-intersection priority control schemes. These strategies are typically classified into passive, active, and real-time (adaptive) TSP methods. Passive TSP does not require real-time detection of buses. Instead, it predefines signal timing plans offline to provide general priority to buses without deploying detectors at intersections. However, passive methods lack flexibility and perform poorly under fluctuating traffic conditions. Ma [1] mathematically modeled the relationship among bus departure frequency, signal cycle length, and bus arrival states, proposing a passive control strategy based on signal cycles. Active TSP detects incoming buses and issues priority requests dynamically. Control methods include green extension, early green, phase skipping, phase repetition, bus-exclusive phases, and flexible phase sequences. Liu [2] studied various active TSP methods to maintain coordination while giving buses priority at isolated intersections. Li [3] addressed phase overlaps in corridor-level TSP schemes. Liu [4] proposed a strategy based on real-time bus data to minimize transit delay, excluding stop dwell times. Li [5] at Northeast Forestry University introduced a video-based bus detection algorithm that incorporates passenger delay into the optimization objective while minimizing negative impacts on private vehicles.

Real-time TSP adapts signal timing based on the movement of transit vehicles and the surrounding traffic state. Mykhailo [7] developed an adaptive control system that switches transit phases in real-time, minimizing stop time and vehicle energy consumption. Dong [8] proposed a dynamic TSP control strategy that adjusts signal timing based on the predicted arrival time of buses, balancing the interests of prioritized and non-prioritized vehicles. Ma [9] proposed a real-time corridor-level TSP system that incorporates schedule deviation prediction, priority object selection, critical intersection identification, and recovery strategies. Zhang [10] from Nanyang Technological University developed a pre-signal-based adaptive signal control system, allowing buses to bypass private vehicles upstream of the main intersection, thereby reducing passenger delay and minimizing disruption to general traffic. Jesus [33] optimized user trajectories to reduce platform congestion and improve the performance of connected TSP systems. Shi [11] proposes a method that integrates signal timing and bus trajectory planning to reduce bus travel delays and enhance driving comfort.

However, existing transit signal priority (TSP) strategies often neglect the impact on general traffic. The changes in signal phases made to accommodate transit vehicles can lead to sudden stops for private vehicles, increased intersection delays, and travel time disruptions for other road users. Such trade-offs may compromise the overall efficiency and equity of traffic operations, especially in mixed-traffic urban environments.

Therefore, to address the limitations of traditional TSP strategies—such as single-objective optimization, incomplete information acquisition, and significant negative impacts on general traffic—this study proposes a novel signal priority control method for connected transit systems. The proposed approach leverages vehicle–infrastructure communication to enhance the efficiency of bus operations while simultaneously considering the performance and delay impacts on surrounding non-transit vehicles at signalized intersections.

3. Assumptions

3.1 Roadway and Vehicle Assumptions

This study aims to improve both bus operation efficiency and overall intersection performance by adjusting signal phase timing. The traffic environment is modeled as a four-leg signalized intersection with bidirectional lanes, including a dedicated bus lane on the main road. All non-transit vehicles are assumed to be cars. Lane-changing behavior and pedestrian crossing activities are not considered. A schematic of the intersection scenario is shown in Figure 1.

Connected buses are equipped with vehicle–infrastructure cooperative communication capabilities, enabling real-time acquisition of their location and speed. In contrast, cars are manually driven. Since buses travel on a dedicated lane, lateral movements are ignored, enabling a more effective integration of signal timing to ensure operational efficiency.

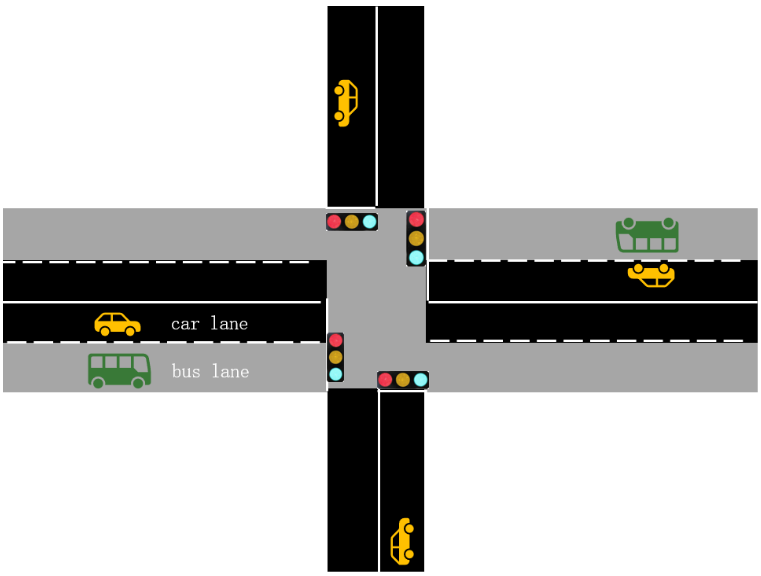

Figure 1. Intersection scenario

3.2 Signal Assumptions

The connected signalized intersection manages conflicting traffic movements via signal phases designed to avoid traffic conflicts. A fixed two-phase signal control scheme is adopted, where signals cycle through red and green states(denoted as p_0 for red and p_1 for green). Each signal cycle C consists of a red duration t_r and green duration t_g, as expressed in Equation 1.

$$C = t_r + t_g \tag{1}$$

Left-turn and through movements share the same signal phase, while right-turn movements are governed by a separate phase. Figure 2 illustrates the two-phase signal control and corresponding vehicle movements.

Phase within a signal cycle（C）/ Control the direction of traffic flow	P_0 phase 1（φ_1）	P_1 phase 2（φ_2）
east–west direction	right-turn movement	through and left-turn movement
north–south direction	through and left-turn movement	right-turn movement

Figure 2. Intersection scenario

According to the national standard Road Traffic Signal Control Methodology, the signal cycle should range from 30 to 150 seconds under unsaturated traffic conditions, and up to180 seconds under saturation. The minimum green time for major roads should not be less than 15 seconds, and for minor roads not less than 8 seconds. The maximum red light duration should not exceed 120 seconds in unsaturated flow or 150 seconds in saturated conditions.

3.3 Signal Assumptions

The TSP system operates within a connected vehicle environment capable of real-time, dynamic, and continuous data exchange between buses and infrastructure. The system supports the following functions:

Data Acquisition: The signal controller collects information including current signal phase status, bus trajectory data, and general traffic flow characteristics.

Data Processing: The controller simultaneously considers transit efficiency and social vehicle performance to optimize phase switching times.

Data Distribution: Optimized signal phase instructions are sent to traffic lights.

3.4 Detector Assumptions

Traffic data are primarily collected through inductive loop detectors and video-based detectors.

Inductive Loop Detectors operate on electromagnetic induction principles. As vehicles pass over embedded loops, their presence is detected, allowing extraction of traffic parameters such as volume, average speed, occupancy, average vehicle length, and headway.

Video Detectors use image processing technologies to detect traffic parameters and events. Comprised of field cameras, transmission equipment, and processing units, they capture continuous footage of the roadway and extract information such as queue lengths and lane occupancy at intersections.

4. Signal Control Model for a Single Connected Intersection

4.1 Vehicle Waiting Time Prediction Algorithm Based on Traffic Wave Theory

Traffic wave theory, a fundamental branch of traffic flow theory, describes the dynamic evolution of traffic conditions on roadways through the relationship between traffic density and vehicle speed. By modeling the propagation of traffic waves—such as shockwaves caused by signal changes or traffic disruptions—this theory enables the prediction of key traffic parameters in both space and time.

Specifically, kinematic wave theory can be applied to forecast vehicle queue lengths at signalized intersections at future time points, based on current traffic flow patterns. By accurately estimating queue evolution, it becomes possible to determine the vehicle waiting time over a given time interval, which is critical for signal control and bus priority strategies in connected environments.

Figure 3 illustrates the propagation process of traffic waves, where the backward-forming and forward-dissipating shockwaves reflect the changes in traffic states during signal transitions.

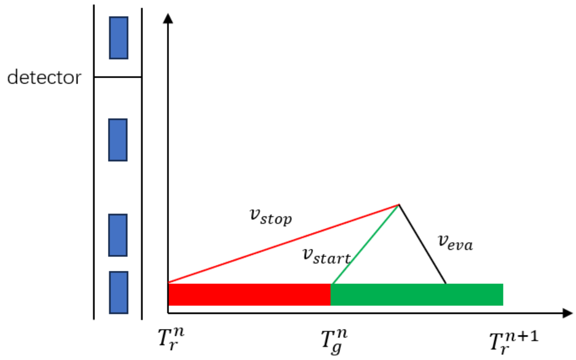

Figure 3. The propagation process of traffic waves

During the red signal phase, a stopping wave propagates backward with a velocity v_{stop}, while during the green signal phase, a starting wave moves backward with a velocity v_{start}. Typically, the dissipation of queues occurs faster than their formation. The interaction point of the two waves occurs at time T^{en}. If this moment precedes the beginning of the next red phase $T^{en} < T_r^{n+1}$, a discharge wave (or evacuation wave) is generated, propagating backward with a velocity v_{eva}. The calculation formulas for the wave speeds of stop waves, start waves, and discharge waves, as well as the encounter time T^{en} between the start wave and the stop wave, are as follows:

$$v_{stop} = \frac{0 - q_0}{\rho_0 - \rho_j} \tag{2}$$

$$v_{start} = \frac{q_c}{\rho_c - \rho_j} \tag{3}$$

$$v_{eva} = \frac{q_c - q_0}{\rho_c - \rho_0} \tag{4}$$

$$T^{en} = \frac{v_{start} * T^{r,j}}{v_{start} - v_{stop}} \tag{5}$$

Let *j* denote the index of the intersection approach, where for a four-leg intersection *j*=1,2,3,4. If the initial queue length at the beginning of the cycle is q_0, the vehicle queue length $q(t)$ at time t can be predicted as follows,

$$q(t) = \begin{cases} q_0 + v_{con} * (t - T^r) & if \quad T_r^n \leq \mathrm{t} \leq T^{en} \\ q_0 - v_{start} * (t - T^{en}) & if \quad T^{en} \leq \mathrm{t} \leq T_r^{n+1} \end{cases} \tag{6}$$

$$Q_j(\mathrm{t}) = \begin{cases} Q_j(\mathrm{t}-1) & if \quad a_v = 0 \\ q_j(t) & if \quad a_v = 1 \end{cases} \tag{7}$$

If the predicted queue length is smaller than the road segment length, the road segment length is taken as the predicted queue length.

The vehicle waiting time, defined as the total red-light waiting time experienced by all vehicles within a given time sequence at the intersection, can be obtained by summing the number of vehicles waiting at the red light at each time step over the time sequence.

In the following, the waiting times for private vehicles and connected buses at the intersection are predicted separately.

The total waiting time of general traffic at intersections is estimated by predicting the queue lengths based on kinematic wave theory and integrating vehicle delay over a control cycle.

$$q_{max} = q(T^{en}) \tag{8}$$

$$T = \frac{q_{max}}{(v_{stop} - v_{start})} \tag{9}$$

$$D_c = \sum_{j=1}^{4} D_{j,c} = \sum_{j=1}^{4} \frac{\int_{T_r^n}^{T^{en}} q(t)\, dt}{\bar{L}} \tag{10}$$

The delay experienced by connected buses depends on the signal phase state, signal switching time, and current bus speed. Within the prediction interval [Tst,Tend], the waiting time is computed as follows:

$$t_i^b = \frac{D}{v_i^b} \tag{11}$$

$$D_{i,b} = \begin{cases} T_s - t_i^b & if \;\; t_i^b < T_s \; and \; p(t) = 0 \\ T_{end} - t_i^b & if \; t_i^b > T_s \;\; and \;\; p(t) = 1 \end{cases} \tag{12}$$

$$D_b = \frac{\sum_{i=1}^{N} D_{i,b}}{N * w_b} \tag{13}$$

D denotes the distance between the connected bus and the intersection, v_i^b represents the bus speed, and t_i^b is the time when the bus reaches the intersection stop line. T_s denotes the signal phase switching time, and T_{end} represents the end time of the subsequent red phase. The function $p(t)$ indicates the signal status, where p(t)=0 corresponds to a red phase and p(t)=1 corresponds to a green phase. w_b denotes the average number of passengers per bus. N is the total number of buses

4.2 Signal Control Model for a Single Connected Intersection

Within the prediction horizon, signal priority control is applied to connected buses to improve their operational efficiency. On one hand, by granting priority passage at intersections, connected buses are more likely to traverse the intersection during green phases, significantly reducing their stop delays. On the other hand, signal priority strategies must also account for the impact on surrounding non-bus traffic, minimizing additional delays imposed on general vehicles due to phase adjustments.

To achieve a balanced optimization, the model considers both bus and general traffic efficiency. Particularly, when using average per capita delay as the objective function, granting excessive priority to buses at intersections with high traffic volumes may lead to significant overall traffic inefficiencies. Therefore, a traffic flow ratio is introduced as a weighting factor to reflect the relative importance of general vehicle throughput in the optimization process.

In summary, the connected bus signal priority control model is as follows：

$$minF = \sum_{t=T_{st}}^{T_{end}} \sum_{j=1}^{L} \sum_{i=1}^{N} \frac{(1-\beta) D_{i,j,b}(t) w_b + \beta D_{i,j,c}(t) w_c}{w_b + w_c} \tag{14}$$

4.3 Constraints

(1) Signal Phase Constraints

The signal phases operate in a cyclic manner, and the cycle length of the intersection should be selected according to the traffic volumes in different directions. If the cycle length is too short, heavy traffic flow may result in congestion. Conversely, if the cycle length is too long, the corresponding red phase duration will increase, leading to greater time losses. In this study, the cycle length of the intersection is determined using Webster's signal timing method.

To prevent potential collision risks arising from conflicting vehicle movements, the intersection signal settings must satisfy the non-conflict condition of traffic flows.

In the two-phase signal model established in this study, the following conditions must be met:

The through and right-turn movements in the east–west direction must not conflict with the left-turn movements in the north–south direction.

The left-turn movements in the east–west direction must not conflict with the through and right-turn movements in the north–south direction.

Figure 6 illustrates the traffic movement scheme of the intersection, in which each movement is assigned a specific movement ID. Table 1 describes the signal phase status serving lane

$l \in L$ and the corresponding traffic movements it controls. Let k denote the time sequence, and signal phase status is denoted by $p(k)$. $p(k)$=0 represent the signal phase status serving lane $l \in L$ at time k. $p_l(k) = 0$ indicates that the signal phase for lane l at time step k is red, while pl(k)=1 indicates that it is green. For traffic flows with conflicting movements, their signal states must not be green or red simultaneously. Therefore, the signal status must satisfy constraint (15).

$$p_l(k) + p_{l'}(k) \leq 1 \tag{15}$$

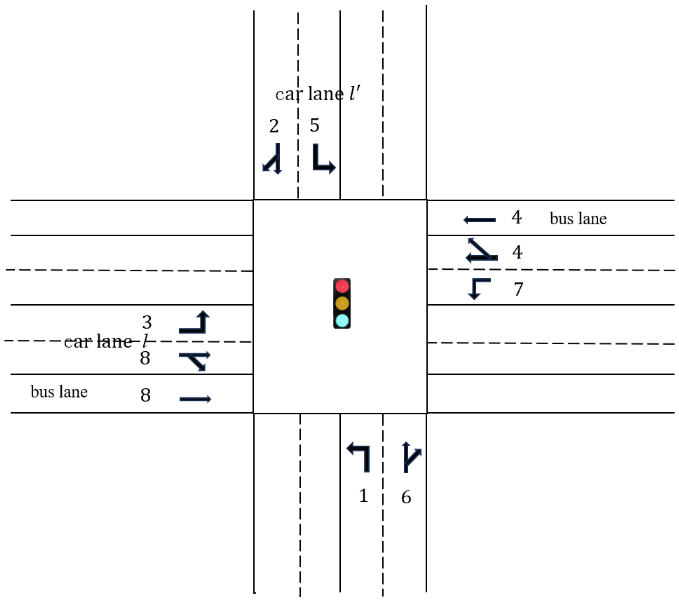

Figure 6. Traffic Movement Diagram of the Signalized Intersection

Table 1. Description of the traffic movement states served by the signal phase control for lane $l \in L$.

Phase Status	Permitted Traffic Movements
Red Light	2, 3, 6, 7
Green Light	1, 4, 5, 8

Within a phase cycle $[T_{st}, T_{end}]$, assuming the cycle starts with a red phase and T_s denotes the phase switching moment, the phase allocation time must satisfy constraints (16) and (17). Constraint (16) ensures that the green phase duration assigned to lane $l \in L$ does not exceed the maximum allowable green time $t_{g,max}$, while constraint (17) ensures that it is not less than the minimum allowable green time $t_{g,min}$. The phase cycle assigned to lane $l \in L$ should contain exactly one red phase and one green phase, meaning that the signal phase should switch exactly once within each cycle. Constraint (18) ensures that the signal state variable takes integer values of either 0 or 1.

$$\sum_{t=T_{st}}^{T_{end}} p_l(t) \leq t_{g,max}, \quad p_l(t) \in \{0, 1\}, \quad \forall l \in L \tag{16}$$

$$\sum_{t=T_{st}}^{T_{end}} p_l(t) \geq t_{g,min}, \quad p_l(t) \in \{0, 1\}, \quad \forall l \in L \tag{17}$$

$$\sum_{t=T_{st}}^{T_{end}} s(t) = 1 \tag{18}$$

(2) Bus Position Constraints

In the connected bus signal priority control system, signal optimization is performed in a rolling horizon manner, with one of the objectives being the minimization of the average passenger waiting time for buses. When calculating bus delay, the distance between the bus and the intersection must be considered. If, within the optimization horizon, the time for the bus to reach the intersection at its maximum allowable speed exceeds one signal cycle, the resulting delay is considered zero.

In the extreme case where the bus travels at a very low speed and cannot reach the green phase within the current cycle, it may still catch the green phase in the subsequent cycle. Therefore, the optimal detection position for bus delay calculation should satisfy the following conditions:

The travel time for the bus to reach the intersection at its maximum speed is less than one signal cycle. The travel time for the bus to reach the intersection at its minimum operational speed is less than two signal cycles. These constraints ensure that the priority request is evaluated in a time window where the bus has a realistic opportunity to benefit from signal adjustment without causing excessive disruption to the traffic flow.

Let d_i denote the distance between bus iii and the intersection. Based on the intersection phase status and the remaining time of the current phase, the estimated arrival time window of the connected bus at the stop line, the travel distance, and the speed–acceleration constraints, the feasible signal window for the bus to arrive at the intersection can be determined 808080. The calculation of the signal window range $[T_{min}, T_{max}]$ is given by Equations (19) and (20).

$$T_{min} = \left(d_i + \left(v_{max}^b - v_{min}^b\right)^2 / (2a_{max}^b)\right) / v_{max}^b \tag{19}$$

$$T_{max} = \left(d_i + \left(v_{max}^b - v_{min}^b\right)^2 / \left(2a_{min}^b\right)\right) / v_{min}^b \tag{20}$$

Let d_q denote the distance between the bus and the intersection stop line at the time when the algorithm is initiated. Within the allowable speed limits, the bus travel time from position d_q to the intersection should fall within the range $[T_{min}, T_{max}]$. Therefore, signal adjustment and speed planning are triggered when the bus is located at a certain distance from the intersection. When calculating bus delays, the bus position must satisfy the constraint specified in Equation (24).

$$d_{i,min} = t_{g,min} * v_{max}^b - 2a_{max}^b / \left(v_{max}^b - v_{min}^b\right)^2 \tag{21}$$

$$d_{i,max} = (T^C - t_{g,min}) * v_{min}^b + 2a_{min}^b / \left(v_{max}^b - v_{min}^b\right)^2 \tag{22}$$

$$d_{i,min} \le d_q \le d_{i,max} \tag{23}$$

$$\begin{gathered} if \quad d_{i,max} - d_{i,min} < v_{max}^b \\ then \quad d_{i,max} = d_{i,max} + \mathrm{a} \\ a = min\{A, A \in d_{i,max} - d_{i,min} + a - v_{max}^b < 0\} \\ d_{i,max} - d_{i,min} \ge v_{max}^b \end{gathered} \tag{24}$$

4.4 Genetic Algorithm Design and Implementation for the Proposed Optimization Problem

To solve the proposed optimization problem, a genetic algorithm (GA) is designed with the following steps:

(1) Initialization of the Population:

The algorithm begins by generating an initial population, i.e., a set of feasible solutions. The quality of the initial population directly affects the efficiency of the algorithm and the quality of the final solution. A well-constructed initial population can significantly accelerate convergence and facilitate the search for a global optimum.

To ensure global search capability, feasible solutions are randomly and uniformly distributed across the initial population. The population size is set to 100.

Feasible solutions are selected according to the following principle:

For an optimization problem defined as $P = (U, f)$, where U represents the feasible search space, $f: U \to F$ denotes the objective function defined in Equation (14), a solution vector $S = \{u_1 \dots, u_r, \dots u_N\}$is formed. Each individual solution u_r in the population must satisfy the constraint:

$$\begin{cases} T_s \in [T_{st}, T_{end}], \ \ s(T_s) = 1 \\ t \in [T_{st}, T_s) and (T_s, T_{end}], \ \ s(t) = 0 \end{cases} \tag{25}$$

(2) Determination of Decision Variable Boundaries:

The decision variables in the model correspond to the phase switching time points within a signal cycle, which can be equivalently expressed as the duration of green phases. These variables are sorted chronologically within the cycle. Let u_1 denote the lower bound and u_N the upper bound of the decision variables.

(3) Fitness Evaluation and Termination Criteria:

The fitness function evaluates the performance of each chromosome (solution candidate) with respect to the objective function defined in Equation (14). This function quantifies how well an individual adapts to the optimization objective, and it is used to compute the probability of selection for each individual in the population.

After computing the fitness of all individuals, the algorithm checks whether the termination criterion is satisfied. If so, the optimal solution is output and the algorithm stops.

(4) Genetic Operators – Selection, Crossover, and Mutation:

If the termination condition is not satisfied, the algorithm proceeds with the following evolutionary operators:

Selection Operator: Individuals with higher fitness values are more likely to be selected for reproduction. A selection mechanism (e.g., roulette wheel or tournament selection) ensures that high-performing chromosomes are retained for the next generation.

Crossover Operator: Selected parent chromosomes are recombined to generate new offspring. This operator allows the algorithm to explore new regions of the solution space.

Mutation Operator: With a predefined mutation probability, random mutations are introduced to some offspring to enhance population diversity and avoid premature convergence.

These steps are iteratively repeated until the termination condition (e.g., a maximum number of generations or convergence threshold) is met.

The algorithm is implemented using the geatpy library in Python, which provides robust tools for population initialization, fitness evaluation, and genetic operations tailored for multi-parameter optimization problems.

5. Simulation and Analysis

To verify the effectiveness of the proposed signal priority control algorithm, a simulation platform is built based on Simulation of Urban Mobility (SUMO).

5.1 Simulation Environment Setup and Experimental Case Design

(1)The intersection road network is created in SUMO using the netedit tool. The network includes the intersection layout, traffic signals, general-purpose lanes, and dedicated bus lanes. A schematic diagram of the constructed network is shown in Figure 7. Upon completion, the road network is exported as a .net.xml file.

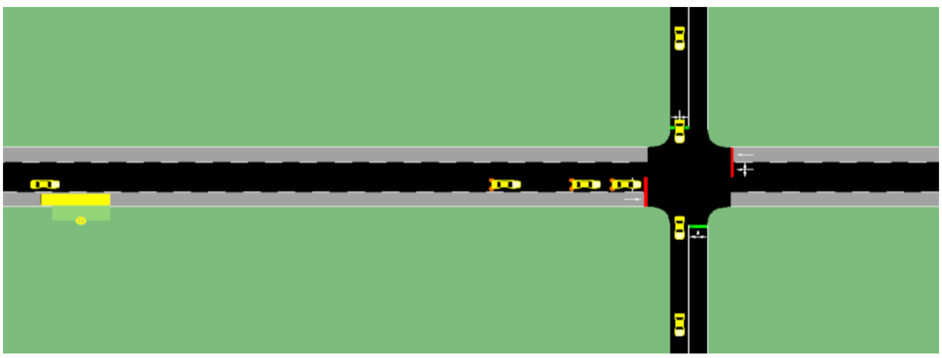

Figure 7. Traffic Movement Diagram of the Signalized Intersection

(2) Parameter Input: According to the simulation requirements, the traffic flow for each road segment is configured, and the corresponding .flow.xml file is generated. To verify the performance of the proposed algorithm under varying traffic demand levels, multiple traffic flow scenarios are designed for simulation experiments. The traffic signal timing parameters and traffic flow parameters are summarized in Table 2.

Table 2. Intersection Test Samples and Input Parameters.

Sample No.	East–West Average Traffic Volume (veh/h)	North–South Average Traffic Volume (veh/h)	East–West Through Green Time (s)	North–South Through Green Time (s)	Cycle Length (s)
1	500	250	35	20	55
2	600	300	48	32	80
3	700	350	70	35	105
4	800	400	117	58	140

(4) Simulation Execution: The algorithm is deployed by utilizing the TraCI interface to acquire real-time traffic data and output control parameters. The simulation is then conducted by setting the simulation duration in the .sumocfg file and executing the simulation to verify the proposed method.

In this study, four simulation scenarios were designed, as illustrated in Table 2. For each scenario, eight datasets were collected across different time periods. Simulations were conducted under both fixed-time signal control and the proposed TSP algorithm. The results were compared and analyzed in terms of average passenger waiting time for buses, average waiting time for social vehicles, and the average queue length of social vehicles at intersections.

5.2 Simulation Results Analysis

(1) Analysis of Average Bus Waiting Time

Tables 3 and 4 compare the statistical characteristics of bus waiting times under fixed-time signal control and the proposed TSP algorithm across different traffic flow rates (500–800 veh/h). Under fixed-time control, the mean waiting time for buses increases significantly with traffic volume, rising from 4.38 s at 500 veh/h to 17.88 s at 800 veh/h. In contrast, with TSP control, the mean waiting time remains substantially lower, ranging from 2.38 s to 8.63 s over the same traffic flow range. This demonstrates the TSP algorithm's ability to mitigate delays even under heavier traffic conditions. The maximum observed bus waiting time is also markedly reduced under TSP control, particularly at high traffic volumes, where it decreases from 70.00 s (fixed-time) to 18.00 s (TSP) at 800 veh/h. The standard deviation values indicate that TSP not only lowers the average waiting time but also reduces variability, suggesting more consistent bus travel times. Additionally, the skewness and kurtosis values show that under fixed-time control, waiting time distributions become more positively skewed and heavy-tailed at high volumes, reflecting occasional extreme delays. In contrast, TSP produces distributions that are more symmetric and less prone to outliers.

Overall, the implementation of TSP results in substantial reductions in average passenger waiting time, with percentage decreases of 41.71%, 50.00%, 59.76%, and 51.75% for traffic flows of 500, 600, 700, and 800 veh/h, respectively. These findings confirm that TSP significantly improves bus service reliability and efficiency, particularly in congested scenarios.

Table 3. Statistical characteristics of bus waiting times under fixed-time signal control.

Traffic volume (veh/h)	500	600	700	800
Minimum (s)	0.00	0.00	0.00	0.00
Maximum (s)	14.00	14.00	23.00	70.00
Mean (s)	4.38	8.00	10.25	17.88
Standard deviation (s)	6.19	6.16	9.27	25.60
Kurtosis	-1.56	-1.98	-1.69	1.55
Skewness	0.82	-0.43	-0.03	1.49

Table 4. Statistical characteristics of bus waiting times under the TSP algorithm

Traffic volume (veh/h)	500	600	700	800
Minimum (s)	0.00	0.00	0.00	0.00
Maximum (s)	14.00	14.00	23.00	70.00
Mean (s)	4.38	8.00	10.25	17.88
Standard deviation (s)	6.19	6.16	9.27	25.60
Kurtosis	-1.56	-1.98	-1.69	1.55
Skewness	0.82	-0.43	-0.03	1.49
Reduction in average passenger waiting time (%)	41.71	50.00	59.76	51.75

(2) Analysis of Average Waiting Time for General Traffic

The statistical characteristics of the per capita waiting time for passengers in general vehicles under fixed-time signal control are presented in Table 5, while those under the TSP algorithm are presented in Table 6.

Low to moderate traffic volumes (500–600 veh/h): The mean waiting time is reduced by approximately 20%, suggesting that TSP adjustments have a relatively significant positive spillover effect on private vehicles in less congested conditions.

High traffic volumes (700–900 veh/h): The reduction rate decreases to around 11–12%, indicating that under heavy congestion, the priority given to buses can slightly limit the benefits for private vehicles, though the overall delay is still lower than under fixed-time control.

Distribution characteristics: Lower kurtosis and skewness values under TSP control indicate a more balanced distribution of delays, implying that extreme waiting times are less frequent compared to fixed-time control. Overall, while TSP primarily targets bus priority, the results demonstrate that it can also yield noticeable efficiency gains for private vehicles, especially in lower congestion scenarios.

Table 5. Statistical Characteristics of Average Waiting Time for Private Vehicles under Fixed-Time Control.

Traffic volume (veh/h)	500	600	700	800
Minimum (s)	12.15	17.46	50.59	65.07
Maximum (s)	13.61	22.28	57.34	82.15
Mean (s)	12.87	20.57	53.72	76.34
Standard deviation (s)	0.45	1.62	2.85	6.49
Kurtosis	0.41	0.74	-1.91	-0.03
Skewness	-0.01	-1.01	0.27	-1.27

Table 6. Statistical Characteristics of Average Waiting Time for Private Vehicles under TSP Control.

Traffic volume (veh/h)	500	600	700	800
Minimum (s)	9.50	16.29	41.12	64.93
Maximum (s)	11.68	17.86	52.25	72.04
Mean (s)	10.73	17.09	48.20	68.39
Standard deviation (s)	0.90	0.53	3.53	2.54
Kurtosis	-1.58	-0.48	1.55	-1.46
Skewness	-0.42	-0.22	-1.20	0.06
Reduction in average passenger waiting time (%)	20.03%	20.37%	11.45%	11.61%

(3) Analysis of Average Queue Length of General Traffic at Intersections

The statistical characteristics of the average queue length at intersections under fixed-time signal control are presented in Table 7, while those for general vehicles under the TSP algorithm are presented in Table 8. The comparison between fixed-time control and the TSP strategy reveals that TSP consistently reduces the average queue length for private vehicles at all traffic volumes.

Reduction magnitude: The decrease ranges from 9.16% to 13.20%, with the highest relative improvement observed at 600 veh/h. This suggests that moderate traffic flow conditions allow TSP to optimize green time allocation more effectively for both buses and private vehicles.

Low traffic volumes (500–600 veh/h): Queue lengths remain short, and the standard deviation is small, indicating stable and predictable traffic performance.

High traffic volumes (700–800 veh/h): While queue lengths are significantly larger overall, TSP still manages to reduce them by nearly 10%, showing its robustness in congested scenarios.

Distribution characteristics: Under TSP, kurtosis and skewness values suggest a more balanced distribution of queue lengths, with fewer extreme cases compared to fixed-time control at certain traffic levels.

Overall, the results confirm that TSP not only benefits bus operations but also helps to alleviate queuing for private vehicles, even under heavy congestion.

Table 7. Statistical characteristics of bus waiting times under fixed-time signal control

Traffic volume (veh/h)	500	600	700	800
Minimum (s)	6.34	11.83	58.34	99.27
Maximum (s)	6.74	14.32	71.43	112.42
Mean (s)	6.49	13.22	64.14	108.67
Standard deviation (s)	0.13	0.92	5.04	4.21
Kurtosis	0.94	-1.55	-1.71	3.96
Skewness	1.10	-0.39	0.54	-1.91

Table 8. Statistical characteristics of bus waiting times under the TSP algorithm

Traffic volume (veh/h)	500	600	700	800
Minimum (s)	5.64	10.37	56.15	90.30
Maximum (s)	5.96	12.55	60.16	108.86
Mean (s)	5.81	11.47	58.26	96.60
Standard deviation (s)	0.12	0.67	1.56	5.92
Kurtosis	-1.59	0.55	-1.81	2.13
Skewness	-0.15	0.19	-0.29	1.30
Reduction in average passenger waiting time (%)	10.39%	13.2%	9.16%	11.11%

6. Conclusion

This study focuses on the signal optimization problem in a single-intersection scenario and proposes a hybrid traffic signal control method integrating traffic wave theory. First, the coupling relationship between traffic flow characteristics and signal control was analyzed. Then, based on traffic wave theory, vehicle delays and queue lengths were predicted, and signal optimization was conducted with the objective of minimizing the weighted average delay of buses and private vehicles. A genetic algorithm was employed to optimize signal phase decisions.

Finally, a typical single-intersection scenario was modeled using the SUMO simulation platform to compare the performance of the proposed signal control algorithm under different traffic conditions. The simulation results indicate that the proposed method achieves notable improvements in reducing bus delays, private vehicle delays, and average queue lengths for private vehicles, thereby validating its effectiveness and feasibility.

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