Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

Research on Optimization Method of Green Wave Coordinated Signal Considering Carbon Emission Reduction

Han Bai
Xiaolong Shi
Liang Zhao
Tianzheng Wei
weitianzheng0220@163.com

Jian Lu
Xiuguang Wang

Article

Keywords: Green wave coordination, Signal control, Motor vehicle carbon emissions, Stop delay

Posted Date: July 3rd, 2026

DOI: https://doi.org/10.21203/rs.3.rs-10064984/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

Additional Declarations: No competing interests reported.

Research on Optimization Method of Green Wave Coordinated Signal Considering Carbon Emission Reduction

Han Bai[1], Xiaolong Shi[1], Liang Zhao[1], Tianzheng Wei[1*], Jian Lu[1], Xiuguang Wang[2]

[1]School of Transportation and Logistics Engineering, Shandong Jiaotong University, Jinan 250357, China
[2]Shandong Zhengqu Traffic Engineering Co., Ltd, Jinan, China
*Correspondence: E-mail: weitianzheng0220@163.com
+these authors contributed equally to this work

Abstract

In recent years, worsening traffic congestion and exhaust pollution have significantly constrained sustainable urban development. Green wave coordinated signal control is a key technology for improving arterial efficiency and reducing carbon emissions. This study first constructs a VISSIM-MOVES integrated microscopic traffic carbon emission simulation platform and localizes the MOVES model for geographic information and other parameters. Average vehicle delay, average number of stops, and average queue length are selected as core evaluation metrics. Based on vehicle specific power (VSP) emission theory and the Webster delay model, an optimization model is established to minimize carbon emissions, constrained by common cycle length, coordinated-direction green time, and green wave speed. A green wave signal optimization method featuring "optimal offset constraint—multi-parameter collaborative optimization" is proposed. Validation using a stable-flow arterial scenario with normal intersection spacing shows that after optimization, average vehicle delay decreases by 16.47%, average stops by 14.34%, and total carbon emissions by 4.78%, while green wave bandwidth increases by 20 s, significantly improving coordinated-direction efficiency. The proposed model and method achieve synergistic enhancement of traffic efficiency and carbon reduction, offering scientific support and feasible technical solutions for low-carbon arterial management.

Keywords: Green wave coordination; Signal control; Motor vehicle carbon emissions; Stop delay

1. Introduction

Against the severe backdrop of global climate change governance, the excessive consumption of fossil energy since the Industrial Revolution has led to a continuous rise in the concentration of atmospheric greenhouse gases (primarily CO_2), triggering a series of ecological and social crises, including rising global temperatures and an increase in the frequency of extreme climate events. In recent years, carbon emissions from the transportation sector have shown a sustained growth trend, and China has identified energy conservation and emission reduction in transportation as a key focus area. Within this framework, the transportation sector occupies a significant position in China's carbon emissions, accounting for approximately 10.4% of the nation's total. With the advancement of urbanization and the increasing demand for travel, the issue of carbon emissions in the transportation sector has become increasingly prominent[1].

With the acceleration of urbanization, the number of motor vehicles has grown exponentially, and traffic congestion along with exhaust pollution has become a critical bottleneck restricting sustainable urban development. Research indicates that the carbon emission intensity of motor vehicles is relatively stable during constant-speed cruising states. However, in the vicinity of signalized intersections, vehicles frequently undergo unsteady-state operating modes—such as acceleration, deceleration, and idling—due to the periodic regulation of traffic signals, resulting in a significant increase in emission intensity [2]. Green wave coordinated signal control, as a key technology for improving arterial traffic efficiency, theoretically reduces carbon emissions effectively by optimizing the signal timing of adjacent intersections and reducing the frequency of vehicle start-stops. However, existing research lacks a sufficient understanding of the dynamic correlation mechanisms between green wave coordination signal parameters (such as cycle length, green time, and offset) and carbon emissions, making it difficult to support the formulation of precise emission reduction strategies.

Extensive exploration of traffic carbon emissions has been conducted within both domestic and international academic communities. Regarding emission influencing factors, Zhang Yingying et al[3] confirmed through VISSIM simulation that arterial coordinated control can reduce motor vehicle emission pollution. Ma Jie[4]using Portable Emission Measurement Systems (PEMS), found that pollutant emissions are lower when vehicle engine speed is stable, whereas

the emission rate surges nonlinearly during acceleration. Zhang Hao[5]pointed out that traffic flow is significantly positively correlated with pollutant emissions, and differences in vehicle types have a decisive impact on emission contributions (e.g., heavy-duty trucks account for approximately 3% of vehicle ownership but contribute nearly 50% of NOx emissions). Li Xinyue [6] focused on carbon emissions from mixed traffic flow at urban signalized intersections, collecting traffic operation and environmental parameter data from two typical intersections. The study found that CO_2 concentration at intersections is positively correlated with traffic volume, and an increase in the proportion of electric vehicles can significantly reduce carbon emissions. Based on field-measured data, a CO_2 emission model for mixed traffic flow comprising fuel vehicles and electric vehicles was established and verified through VISSIM simulation. Li Yan[7]investigated motor vehicle emission reduction and delay optimization, establishing a multi-objective optimization model based on emissions and delay. Zhao Peifeng [8] examined traffic flow characteristics on unconventional roads, establishing a traffic flow model based on the Optimal Velocity Model (OVM) that incorporates the driving states of vehicles on curves and slopes. The study found that slope coefficient and driving speed are key factors influencing carbon emissions: emissions increase with gradient on uphill segments and decrease on downhill segments; smaller curve radii result in higher emissions, which also increase with traffic flow. Mahmod et al[9] studied how traffic management measures at urban intersections can reduce environmental impact while maintaining equivalent traffic efficiency levels. Their research revealed that a speed limit of 30 km/h reduced CO_2 and NOx emissions by 16.1% and 13.4%, respectively, but increased PM10 emissions by 19.6%, with the PM10 increase primarily attributed to Heavy-Duty Vehicles (HDVs). This implies that different speed limits should be considered for different vehicle types when implementing such measures. The aforementioned studies predominantly focus on single intersections or isolated factors, lacking a systematic analysis of multi-parameter coupling effects within green wave coordination scenarios.

In the domain of emission modeling, macroscopic models (e.g., MOBILE, COPERT) utilize average vehicle speed as a core parameter [10], making them suitable for compiling regional emission inventories but inadequate for capturing microscopic transient emission characteristics. Mesoscopic models, such as MEASURE, estimate emissions by analyzing network operational states [11], offering intermediate precision between macroscopic and microscopic levels. For instance, COPERT, a comprehensive calculation platform developed with support from the European Environment Agency, not only quantifies emissions from on-road mobile sources but also includes extended modules capable of assessing pollution contributions from non-road mobile sources like agricultural machinery[12]. Among microscopic models, the MOVES model constructs a multi-scale calculation framework based on Vehicle Specific Power (VSP)[13], enabling precise characterization of emission characteristics under transient operating conditions, thereby establishing itself as a mainstream tool in current research. Wu Lianghui [14] developed a framework for calculating passenger car carbon emission factors tailored to county-level road characteristics and research gaps, based on VISSIM microscopic simulation and the MOVES emission model. Zhao Xinran[15]proposed an eco-routing planning framework integrating an improved CMEM emission model with the bidirectional A* algorithm. By reconstructing driving mode parameters and intersection weight settings, an emission estimation system with accuracy exceeding 90% was established (error <10% compared to EPA data). Yin Zhiwei [16] modified the IVE model using PEMS data and improved the CAL3QHC dispersion model, proposing a GLOSA and interchange scheme. A case study in Hangzhou validated significant emission reduction effects, with CO concentrations decreasing by 21.24% and 22.10%, and model error below 10.75%. However, the underlying database of the MOVES model is built upon the U.S. traffic environment. Its application in China necessitates localized calibration of parameters such as geographic information, vehicle types, and fuel characteristics, yet a domestically developed, independent intellectual property localization model system remains absent in China.

Regarding carbon emission estimation methods, Meneguzzer et al[17] found through PEMS field measurements that replacing signalized control with roundabouts can reduce CO_2 emissions. Yang Zhaosheng et al[18] constructed a VSP-based emission-delay coupling model to achieve intelligent optimization of intersection signals. Xu Yaofang et al[19] utilized traffic flow and speed data combined with VSP parameters to analyze the distribution characteristics of intersection operating modes, establishing a distribution model for these modes. Existing studies are often limited to isolated signal control, lacking sufficient consideration for the spatio-temporal heterogeneity of green wave coordinated arterials (e.g., intersection spacing, traffic flow states), which restricts the generalizability of optimization schemes. Li Jiazhi [20] quantified the correlation between signal parameters and emissions through the integration of VISSIM and MOVES. Abou-Senna et al[21] developed four technical pathways for evaluating the environmental impact of vehicle operations by integrating the MOVES emission model with the VISSIM traffic simulation platform. Yao Zhiliang et al[22] systematically analyzed the IVE model, using Beijing as a case study to determine key parameters and calculate

emissions by vehicle type. Yang Yang[23] conducted chassis dynamometer tests based on the Local Driving Cycle (LDC) of Nanjing, showing that CO_2 and NOx emission rates are significantly influenced by speed and acceleration, whereas CO and HC are less affected. Wyatt et al[24] demonstrated that utilizing road grade calculated from LiDAR-GIS data for instantaneous emission modeling is a viable method for generating accurate real-world microscale CO_2 emission estimates. Xiu Weijie et al[25] established a comprehensive motor vehicle emission model considering three vehicle states during straight-through and left-turn movements: complete stop, incomplete stop, and no stop, based on the influence of vehicle heading and driving cycle variations on exhaust emissions. Li Xin [26] focused on isolated signalized intersections, revealing the influence mechanism of signal parameters and traffic flow characteristics on vehicle VSP distribution. An operating mode classification system was constructed through simulation experiments, and a stepwise regression method was employed to develop an exhaust emission prediction model based on parameters such as signal cycle, split, and traffic volume.

In summary, extensive exploration of traffic carbon emissions has been conducted within both domestic and international academic communities. However, existing research predominantly focuses on single intersections or isolated factors, lacking a systematic analysis of multi-parameter coupling effects within green wave coordination scenarios. In the domain of emission modeling, although microscopic models like MOVES can accurately characterize transient emissions, their underlying database is built upon the U.S. traffic environment. Direct application in China suffers from adaptation biases in geographic information, vehicle types, and fuel characteristics. Furthermore, a domestically developed, independent intellectual property localization model system remains absent in China, limiting estimation accuracy. Regarding carbon emission estimation methods, existing studies are often limited to isolated signal control, with insufficient consideration for the spatio-temporal heterogeneity of green wave coordinated arterials (e.g., intersection spacing, traffic flow states), resulting in low generalizability of optimization schemes.

Addressing these shortcomings, this study employs a VISSIM-MOVES integrated platform and completes multi-dimensional localized calibration of the MOVES model, covering geographic information, vehicle types, and fuel characteristics, thereby enhancing estimation accuracy within the Chinese traffic environment. Building upon this foundation, the study moves beyond the homogeneous scenario assumptions typical of prior research by categorizing green wave coordinated arterials into differentiated scenarios based on spatio-temporal characteristics—such as non-arterial roads with short intersection spacing, arterial roads with normal intersection spacing, and arterial roads with long intersection spacing. Through simulation experiments, the study systematically reveals the influence patterns of parameters such as common cycle length, green time in the coordinated direction, and green wave speed on carbon emissions across these different scenarios, clarifying both commonalities and differences in multi-parameter coupling effects. This addresses the deficiency in systematic analysis of green wave coordination scenarios found in existing literature. Furthermore, this study constructs an optimization model aimed at minimizing carbon emissions, innovatively incorporating the optimal offset as a core constraint condition. An "optimal offset constraint - multi-parameter collaborative optimization" method is proposed, effectively addressing the issue where previous optimization schemes often disrupted green wave coordination effects, leading to conflicts between emission reduction and traffic efficiency. This approach enables the direct integration of isolated signal optimization with green wave coordination optimization, enhancing the practical applicability and generalizability of the solution. The study provides more targeted theoretical support and technical pathways for low-carbon management and control of green wave coordinated arterials.

2. Materials and Methods

2.1. Construction of Microscopic Traffic Carbon Emission Simulation Platform

To accurately quantify the carbon emission characteristics of green wave coordinated arterials, it is necessary to construct a microscopic analysis platform that integrates traffic flow simulation with emission estimation. This study achieves a full-chain estimation from transient vehicle operation to carbon emissions through the synergistic integration of the VISSIM traffic simulation software and the MOVES emission model.

The scientific selection of a motor vehicle emission model is central to ensuring estimation accuracy. By comparing typical emission models at macro, meso, and micro levels (e.g., MOBILE, COPERT, etc.), it was determined that the MOVES model, with its multi-scale modeling framework based on Vehicle Specific Power (VSP) [27] , is more suitable for this study. VSP, a key parameter reflecting the real-time operational state of a vehicle [28] , is defined as the ratio of instantaneous engine power output to vehicle mass. It is directly related to vehicle speed, acceleration, and road grade,

and can accurately characterize emission differences under transient conditions such as idling, acceleration, deceleration, and cruising, making it particularly well-suited for the unsteady-state operational characteristics prevalent in signalized intersection areas [29] In contrast, macroscopic models (e.g., MOBILE, COPERT) rely heavily on average vehicle speed, making it difficult to capture microscopic transient emissions. While the CMEM model can analyze physical processes, it requires challenging parameter acquisition and incurs high computational loads. Therefore, the MOVES model was ultimately selected as the emission estimation tool.

Using typical green wave coordinated arterials in Jinan, such as Xingfusi Road, Jingshi Road, and Century Avenue, as prototypes, field investigations were conducted to obtain road network geometric parameters (intersection spacing, number of lanes and widths), traffic flow data (peak/off-peak flow rates, vehicle composition), and signal timing plans (cycle length, phase settings, splits). A microscopic simulation model was constructed based on VISSIM 4.3. To enhance the model's ability to replicate actual traffic flow, calibration focused on driving behavior parameters, including sensitive parameters such as maximum look-ahead distance, average standstill distance, and the additive and multiplicative parts of the desired safety distance[30] . The simulation duration was set to 3600 seconds, and data from the 600-3600 second interval were extracted to eliminate initial warm-up disturbances. The output included FZP format files containing vehicle ID, second-by-second speed, and acceleration data, providing fundamental operating condition data for subsequent emission estimation.

The default parameters of the MOVES model are based on the U.S. traffic environment and require multi-dimensional calibration tailored to the characteristics of the study area[31]: Regarding geographic information, Minneapolis, USA, which has the closest climate characteristics (warm temperate continental monsoon climate) to Jinan, was selected as the benchmark, and parameters such as longitude, latitude, annual average temperature, and relative humidity were modified[32]；. For vehicle types [33] , a mapping relationship between Chinese vehicle classifications and MOVES categories was established, focusing primarily on passenger cars, which constitute the largest proportion (corresponding to the passenger car category in MOVES). Vehicle age distribution was adjusted based on field survey data[34] , covering proportion coefficients for vehicles aged 0-30 years. Fuel characteristics were revised according to the China VIA standard, including sulfur content (adjusted from 30 ppm to 10 ppm), benzene content (adjusted from 1% to 0.8%), and distillation parameters (E200, E300, etc.). Road type information was set to "Urban Unrestricted Access" (corresponding to China's arterial, sub-arterial, and branch roads) based on the attributes of the study area. Additionally, auxiliary parameters such as the simulation base year (2024) and meteorological parameters (average temperature during the study period 28-37°C, humidity 46%) were configured to ensure the model's adaptation to the local traffic environment.

Data interaction between VISSIM and MOVES was implemented via Python scripts[35]: The second-by-second speed and acceleration data output by VISSIM were converted into VSP values. The operating condition intervals were classified according to the criteria of idling (speed = 0 and acceleration = 0), acceleration (acceleration > 0), deceleration (acceleration < 0), and cruising (speed > 0 and acceleration = 0) before being imported into MOVES to generate carbon emission results [36]. Taking the morning peak scenario on Jingshi Road as an example, a comparison between the total simulated emissions and field-measured data showed an error margin controlled within 8%, validating the platform's effectiveness.

The construction of this platform provides a reliable tool for subsequent analysis of the correlation mechanisms between evaluation parameters, control parameters, and carbon emissions, thereby supporting multi-scenario research on green wave coordinated signal optimization.2.2. Spatio-Temporal Effect Analysis and Classification of Traffic Accident Risk

Expressway traffic accident risk has significant spatio-temporal heterogeneity characteristics, and its formation mechanism and evolution law are affected by the dual effects of temporal dynamics and spatial differences. Based on high-precision natural driving data, this chapter systematically explores the spatio-temporal distribution characteristics and internal correlation mechanism of traffic accident risk using multi-dimensional analysis methods. Firstly, a spatio-temporal effect analysis framework is constructed theoretically to clarify the interaction mechanism of temporal and spatial dimensions on accident risk. Secondly, empirical analysis reveals the distribution law and evolution characteristics of accident risk under specific spatio-temporal conditions. Finally, a spatio-temporal feature-integrated accident risk classification model is constructed to achieve accurate identification of different risk levels. The research results will provide a theoretical basis and technical support for active safety prevention and control of expressways, and are of great significance for improving road traffic safety management.

2.2. Selection of Evaluation Parameters

The optimization objectives of green wave coordinated signal control not only aim to improve the traffic efficiency of vehicles in the coordinated direction but also must consider the operational state of the non-coordinated direction to comprehensively reflect the overall operational efficiency of the network. Therefore, the selection of evaluation parameters should prioritize indicators capable of comprehensively characterizing both traffic operational efficiency and vehicle operational characteristics.

Within the traffic operation evaluation system, commonly used indicators include average travel speed, capacity, and travel time. However, these indicators primarily focus on macroscopic operational states and cannot directly reflect vehicle start-stop behavior under signal control or its impact on emission characteristics. Existing research indicates that average vehicle delay, average number of stops, and average queue length can characterize the operational features of traffic flow under signal control from different dimensions. Average vehicle delay reflects the waiting time of vehicles at the intersection area. Average number of stops describes the frequency of vehicle start-stop events during operation. Average queue length characterizes the degree of congestion and vehicle accumulation on the intersection approach.

These three parameters collectively describe the traffic operational state from temporal, behavioral, and spatial perspectives, respectively. They can provide a relatively comprehensive reflection of the operational differences between coordinated and non-coordinated directions, thereby offering foundational support for analyzing the relationship between traffic operational state and carbon emissions[37] . Consequently, this study selects average vehicle delay, average number of stops, and average queue length as the core evaluation parameters for assessing the operational effectiveness of green wave coordinated signals.

Regarding data acquisition, the study utilizes the VISSIM-MOVES integrated simulation platform. A simulation model of a typical green wave coordinated arterial is constructed, and the control variable method is employed to adjust signal control parameters, enabling the acquisition of traffic operation data under various operating conditions. Specifically, metrics such as average vehicle delay, average number of stops, and average queue length are extracted under different traffic flow states and signal timing conditions, while corresponding carbon emission data are synchronously acquired. This provides a data foundation for subsequent correlation analysis and the construction of the optimization model.

In terms of analytical methodology, Pearson correlation coefficient analysis is employed to quantify the correlation between each evaluation parameter and carbon emissions. Relevant studies have demonstrated that this method effectively reflects the degree of linear correlation between variables and has been widely applied in research on the relationship between traffic operational state and emissions[38].This analysis provides a basis for identifying key influencing factors and constructing the subsequent optimization model.

2.3. Research on Optimization Method for Green Wave Coordinated Signal Considering Carbon Emission Reduction

In engineering practice, employing a vehicle-by-vehicle emission calculation approach for total pollutant assessment across the entire network would encounter a technical bottleneck where computational resource consumption increases exponentially. To overcome this limitation, this study constructs a green wave coordinated signal optimization framework with emission intensity as the objective function. Its core innovation lies in establishing a mathematical mapping model between emissions and signal control parameters. Based on VSP emission theory, a multi-dimensional simplified emission algorithm is proposed by analyzing emission characteristics under different operating conditions, ultimately achieving a quantified mapping relationship between network-level total emissions and signal control parameters.

2.3.1. Estimation Model for Total Motor Vehicle Exhaust Emissions

First, the total exhaust emissions of the traffic flow can be calculated by multiplying the time spent by each vehicle in different VSP bins by the corresponding emission rate for that bin, expressed as follows:

$$E = \sum_{y=1}^{N} \sum_{z=1}^{n_y} t_{yz} \cdot R_z \tag{1}$$

In Equation (1): E represents the total exhaust emissions of the traffic flow on the road segment (g); z denotes the VSP bin index, z= 1, 2, 3...; tyz is the duration of time the y-th vehicle operates within VSP bin z; ni represents the total

number of VSP bins experienced by the i-th vehicle; Rz is the emission rate for pollutants within VSP bin z (g/s); N is the number of vehicles on the road segment.

When vehicles travel on a road segment, the total exhaust emissions E of delayed vehicles can be calculated separately according to the deceleration process, idling process, acceleration process, and cruising process, as follows:

$$E = E_D + E_S + E_A + E_C \tag{2}$$

In Equation (2): ED~ represents the total exhaust emissions of the traffic flow during the deceleration process (g); ES~ represents the total exhaust emissions during the queuing/idling process (g); EA~ represents the total exhaust emissions during the acceleration process (g); EC~ represents the total exhaust emissions during the cruising process (g).

(1) Acceleration and Deceleration Processes

Systematic analysis of motor vehicle emission characteristics indicates a significant positive correlation between total pollutant emissions and stop frequency; i.e., an increase in the number of stops leads to a higher emission intensity. For vehicles undergoing a complete stop process, the distribution of VSP bin intervals and their corresponding durations during each stop exhibit high similarity. Therefore, the emissions generated per stop can be approximated as the linear superposition of the emissions from one complete acceleration process (eA,1) and one complete deceleration process (eD,1). Bas+ed on this theoretical assumption, by counting the number of stops (h) for an individual vehicle at the intersection area, a quantitative calculation model for its acceleration emissions (eA) and deceleration emissions (eD) can be established, as follows:

$$e_D + e_A = h \cdot (e_{D,1} + e_{A,1}) \tag{3}$$

(2) Idling Process

When a vehicle stops and queues, its VSP is zero, and the emission rate remains constant. The vehicle idling time ts is the stop delay time experienced while queuing in front of the intersection. It should be noted that this stop delay time differs from the delay time derived from the Webster formula. If *d* denotes the average delay per vehicle derived from the Webster formula, then the vehicle idling time ts is:

$$t_s = d - h \cdot (\frac{v}{a_D} + \frac{v}{a_A} - \frac{l_{D,1} + l_{A,1}}{v}) \tag{4}$$

In Equation (4):aD is the average deceleration ; aA is the average acceleration;lD,1 is the travel distance during one complete deceleration process (m); $l_{A,1}$ is the travel distance during one complete acceleration process (m);v is the cruising speed (m/s);h is the number of stops.

(3) Cruising Process

When a vehicle is cruising, its VSP value can be determined based on its travel speed, and the corresponding exhaust emission rate for that VSP bin can be obtained. The vehicle cruising time tC equals the cruising distance divided by the travel speed. That is:

$$t_C = \frac{l - h \cdot (l_{D,1} + l_{A,1})}{v} \tag{5}$$

Where l represents the intersection spacing (m). Therefore, the total exhaust emissions per vehicle e can be expressed as:

$$\begin{aligned} e &= e_D + e_S + e_A + e_C \\ &= h \cdot (e_{D,1} + e_{A,1}) + [d - h \cdot (\frac{v}{|a_D|} + \frac{v}{|a_A|} - \frac{l_{D,1} + l_{A,1}}{v})] \cdot R_S + \frac{l - h \cdot (l_{D,1} + l_{A,1})}{v} \cdot R_C \end{aligned} \tag{6}$$

n Equation (6): eA、eS、eD、eC are the exhaust emissions of a single vehicle during the acceleration, queuing/idling, deceleration, and cruising processes, respectively; h is the number of stops for a single vehicle; d is the stop delay time per vehicle (s); RS is the emission rate under idling conditions (g/s); RC is the emission rate under cruising conditions (g/s).

If the traffic stream consists of N motor vehicles, and D and H represent the total delay time and total number of stops for the traffic stream, respectively, then the total exhaust emissions of the traffic stream is:

$$E = H \cdot (e_{D,1} + e_{A,1}) + [D - H \cdot (\frac{v}{|a_D|} + \frac{v}{|a_A|} - \frac{l_{D,1} + l_{A,1}}{v})] \cdot R_S + \frac{l \cdot N - H \cdot (l_{D,1} + l_{A,1})}{v} \cdot R_C \quad (7)$$

From Equation (7), it can be observed that the total emissions of delayed vehicles are related to the total number of stops and the total delay time. A smaller number of stops results in lower total emissions, and a smaller delay time also results in lower total emissions.

Through extensive research by numerous scholars, the study of emission factors for conventional pollutants under different operating conditions has become relatively mature. Li Jiazhi collected acceleration and deceleration emission data from seven complete stop events and used the average emission value of these seven events as the emission factor for a single acceleration-deceleration cycle. The CO_2 emission factors under different driving conditions are presented in Table 1.

Table 1. Single Vehicle CO2 Emission Factors

Operating State	CO_2 Emission Factor
Cruising Emission Rate (g/s)	2.3863
Idling Emission Rate (g/s)	1.1308
Idling Emission Rate (g/s)	30.7216

Using the carbon dioxide emission factors from the table, the CO_2 emissions generated from one complete vehicle start-stop cycle, eD,1+eA,1 is 30.7216g， The idling emission rate RS is 1.1308 g/s, and the cruising emission rate RC is 2.3863 g/s. By incorporating these values into the total motor vehicle exhaust emission estimation model, the total CO_2 emissions can be estimated..

2.3.2. Optimization Model for Green Wave Coordinated Signal with Minimized Carbon EmissionsSelection of Stop Delay Model

Selection of Stop Delay Model

In the estimation model for total motor vehicle exhaust emissions, total emissions, as the dependent variable, are influenced by multiple independent variables. The most significant among these are total number of stops and total delay time, which are also affected by intersection spacing, average vehicle speed, acceleration, and deceleration[39]. Among these independent variables, obtaining accurate values for total number of stops and delay time is relatively challenging, as they are influenced by cycle length, split, traffic volume, and road capacity. Selecting an appropriate delay time and number of stops calculation model is crucial for ensuring the accuracy of the output results from the exhaust emission model.

Two models are commonly used for delay time calculation: the Webster delay formula and the HCM 2000 delay model. The HCM 2000 delay calculation method accounts for the impact of initial queue on delay and is more suitable for congested urban road intersections, particularly when saturation exceeds 1 and initial queuing is present. This model comprises uniform delay, incremental delay, and initial queue delay.

The Webster delay model, established by Webster based on steady-state theory, is a stop delay model for intersections typically applicable when saturation is less than 1. It performs best under free-flow or stable-flow traffic conditions. An analysis of stop delay for a balanced phase is illustrated in Figure 1, where de represents the average delay time for the balanced phase at the approach, equal to the area of the shaded triangle divided by the number of arriving vehicles within the cycle; he represents the average number of stops for the balanced phase at the approach, equal to the height of the shaded triangle divided by the number of arriving vehicles within the cycle [40] .

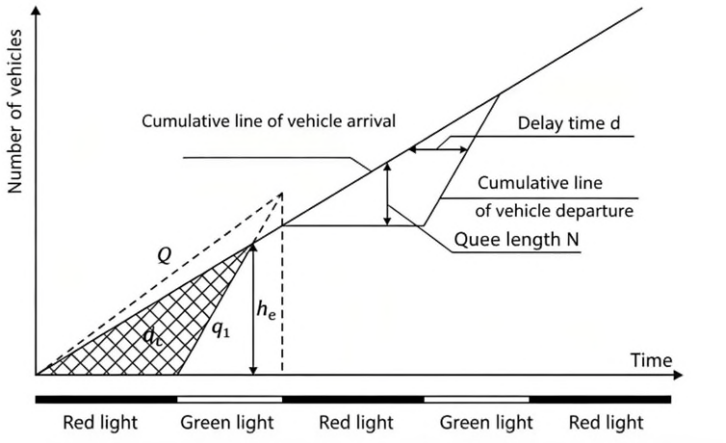


Figure 1. Analysis of Balanced Phase Average Parking Delay

The average vehicle delay d at the approach is:

$$d = d_e + d_r = \frac{C \cdot (1-\lambda)^2}{2(1-\lambda x)} + \frac{x^2}{2q(1-x)} \tag{8}$$

The total vehicle delay D at the approach is:

$$D = d \cdot q \tag{9}$$

The average number of stops h per vehicle at the approach is:

$$h = h_e + h_r = 0.9[\frac{1-\lambda}{1-\lambda x} + \frac{\frac{e^k}{2(1-x)}}{q \cdot C}] \approx 0.9 \times \frac{1-\lambda}{1-\lambda x} \tag{10}$$

The total number of vehicle stops H at the approach is:

$$H = h \cdot q \tag{11}$$

Where $k = \frac{-1.33\sqrt{q_s \cdot q} \cdot (1-x)}{x}$, dr、hr represent the random average delay and random average number of stops at the approach, respectively; q is the vehicle arrival rate at the approach; Q is the approach capacity; qs is the approach saturation flow rate; x is the approach saturation degree; and λ is the split.

This study considers carbon emission optimization for green wave coordinated arterials under three traffic flow states: free flow, stable flow, and unstable flow. The saturation degree at intersections in all three states is less than 1; therefore, the Webster delay model is selected for modeling delay calculations.

Establishment of Optimization Model and Constraint Conditions

In green wave coordinated signal control, the through phase in the coordinated direction typically has the largest split. On this basis, the splits of other phases must also remain within a reasonable range. The split for the through phase in the coordinated direction cannot be increased indiscriminately; optimization and coordination should be carried out on the premise of minimizing impacts on other phases. The same applies to the common cycle length and green wave speed. The common cycle length is constrained by the psychological tolerance of drivers, pedestrians, and cyclists; excessively long or short cycles can cause frustration among traffic participants. Green wave speed is constrained by the nature of the road and the maximum speed limit, offering a limited range of variation. Green wave coordinated signal control involves multiple considerations[41] and cannot arbitrarily increase or decrease a single control parameter solely to optimize one specific evaluation metric.

On arterials where green wave coordination has been successfully implemented, average vehicle delay and average number of stops have already been substantially reduced. As evident from the estimation model for total motor vehicle exhaust emissions, reductions in vehicle delay and number of stops lead to corresponding reductions in exhaust emissions, placing carbon emissions at a relatively optimal level. Previous research investigating the impact of green wave

coordination signal evaluation and control parameters on carbon emissions[42] has shown that on arterials with optimized green wave coordination, employing the control variable method while maintaining a constant split and varying the common cycle length, coordinated direction green time, and green wave constraint speed results in only minor adjustments to the optimal offset for bidirectional green wave progression. The variation pattern of absolute offset with common cycle length for an arterial with normal intersection spacing is shown in Table 2.

Table 2 Changes in Optimal Phase Difference of Main Road with Public Period Duration for Normal Intersection Spacing (s)

Common Cycle Length	I1—I2	I2—I3	I3—I4
200	199	0	90
210	208	0	95
220	219	0	99
230	228	0	104
240	238	0	108

When the coordinated direction green time or green wave speed is changed, the optimal offset may not change at all. Based on this characteristic, this paper proposes establishing a multi-objective optimization model with the minimization of total carbon emissions as the objective function, under the current optimal offset, and with the common cycle length, coordinated direction green time (i.e., split), and green wave speed as constraint conditions. The solution obtained at this stage represents the optimal solution under the current offset. After fine-tuning the offset to its optimal value, the total carbon emissions, average vehicle delay, and average number of stops will decrease further, yielding the final optimization result.

This method leverages an understanding of the variation patterns of control parameters and evaluation parameters, integrating carbon emission optimization for isolated signalized intersections with green wave coordinated signal optimization, thereby bypassing the preliminary step of optimizing individual intersections for minimum carbon emissions.

This method leverages an understanding of the variation patterns of control parameters and evaluation parameters, integrating carbon emission optimization for isolated signalized intersections with green wave coordinated signal optimization, thereby bypassing the preliminary step of optimizing individual intersections for minimum carbon emissions.

In the scenario of an arterial with normal intersection spacing, the coordinated direction of the green wave arterial is East-West. Let the intersection index be i (i=1、2、3、4), with the four intersections distributed from West to East denoted as I1、I2、I3、I4. Let the approach index for each intersection be j (j=1、2、3、4) corresponding to West, East, South, and North approaches, respectively. Let the lane group index for each approach be k (k=1、2、3), corresponding to Left-turn, Through, and Right-turn lanes, respectively.

Taking the West approach through phase at the first intersection I1 as an example, the calculation models for its total carbon emissions, vehicle delay, and number of stops are as follows:

$$E_{(1,1,1)} = H_{(1,1,1)} \cdot (e_{D,1} + e_{A,1}) + [D_{(1,1,1)} - H_{(1,1,1)} \cdot (\frac{v}{|a_D|} + \frac{v}{|a_A|} - \frac{l_{D,1} + l_{A,1}}{v})] \cdot R_S + \frac{l \cdot N_{(1,1,1)} - H_{(1,1,1)} \cdot (l_{D,1} + l_{A,1})}{v} \cdot R_C \quad (12)$$

$$d_{(1,1,1)} = \frac{C \cdot (1 - \lambda_{(1,1,1)})^2}{2(1 - \lambda_{(1,1,1)} x_{(1,1,1)})} + \frac{x^2_{(1,1,1)}}{2q_{(1,1,1)}(1 - x_{(1,1,1)})} \quad (13)$$

$$h_{(1,1,1)} = 0.9 \times \frac{1 - \lambda_{(1,1,1)}}{1 - \lambda_{(1,1,1)} x_{(1,1,1)}} \quad (14)$$

$$D_{(1,1,1)} = d_{(1,1,1)} \cdot q_{(1,1,1)} \quad (15)$$

$$H_{(1,1,1)} = h_{(1,1,1)} \cdot q_{(1,1,1)} \quad (16)$$

A green wave coordinated arterial comprises not only several isolated intersections but also the road segments connecting them. The models above calculate emissions only at intersections. The final total carbon emissions of the green wave coordinated arterial must also include emissions generated on the segments. That is:

$$E = E_I + E_L \tag{17}$$

Where E represents the total carbon emissions of the green wave coordinated arterial; E_I represents the total carbon emissions at intersections; and E_L represents the total carbon emissions on road segments.

The total carbon emissions on the segments in the coordinated direction of the green wave arterial are already included in the intersection carbon emissions total. However, the departure segments in the non-coordinated directions and the departure segments at both ends of the coordinated direction are not included and must be calculated separately. On these departure segments, vehicle operating parameters are consistent with those of vehicles in the coordinated direction. The total carbon emissions for these departure segments are calculated using the cruising process formula from the total motor vehicle exhaust emission estimation model. Assuming there are m departure segments, the carbon emission calculation formula for a single segment is given by Equation (18):

$$e_1 = N \cdot \frac{l_1}{v} \cdot R_c \tag{18}$$

where e_1 represents the carbon emissions of the first departure segment; N is the number of passing vehicles; l_1 is the segment length; $l_{A,1}$ is the distance traveled during one acceleration process; and v is the green wave speed.

Summing the carbon emissions from all intersections and segments on the green wave coordinated arterial yields the formula for total carbon emissions of the green wave coordinated arterial, as shown in Equation (19):

$$\begin{aligned} E &= \sum_i \sum_j \sum_k E_{(i,j,k)} + \sum_m e_m \\ &= \sum_i \sum_j \sum_k \{H_{(i,j,k)} \cdot (e_{D,1} + e_{A,1}) + [D_{(i,j,k)} - H_{(i,j,k)} \cdot (\frac{v}{|a_D|} + \frac{v}{|a_A|} - \frac{l_{D,k} + l_{A,k}}{v})] \cdot R_S \\ &\quad + \frac{l_k \cdot N_{(i,j,k)} - H_{(i,j,k)} \cdot (l_{D,k} + l_{A,m})}{v} \cdot R_C\} + \sum_m (N_m \cdot \frac{l_m}{v} \cdot R_C) \end{aligned} \tag{19}$$

where $E_{(i,j,k)}$ represents the carbon emissions of approach lane group (i,j,k) at the intersection; e_m represents the carbon emissions of the m-th departure segment; $H_{(i,j,k)}$ is the total number of stops for approach lane group (i,j,k) at the intersection; $D_{(i,j,k)}$ is the total delay for approach lane group (i,j,k) at the intersection; $N_{(i,j,k)}$ is the number of passing vehicles for approach lane group (i,j,k) at the intersection; N_m is the number of passing vehicles on the m-th departure segment; v is the green wave speed; a_A is acceleration; a_D is deceleration; l_k is the cruising distance for lane group k; $l_{D,k}$ is the deceleration distance for lane group k; $l_{A,k}$ is the acceleration distance for lane group k; and l_m is the length of the m-th departure segment.

The constraint conditions include the green wave coordinated signal control parameters: common cycle length, green time, green wave speed, and saturation degree. The settings for common cycle length and green time must fall within a reasonable range; excessively long or short values negatively impact control effectiveness and total arterial carbon emissions. Furthermore, the sum of green times across all phases must equal the common cycle length. The green wave speed should be set according to the nature of the coordinated arterial and the maximum speed limit to ensure vehicles can traverse the green wave arterial at an appropriate speed, thereby reducing delays in both coordinated and non-coordinated directions.

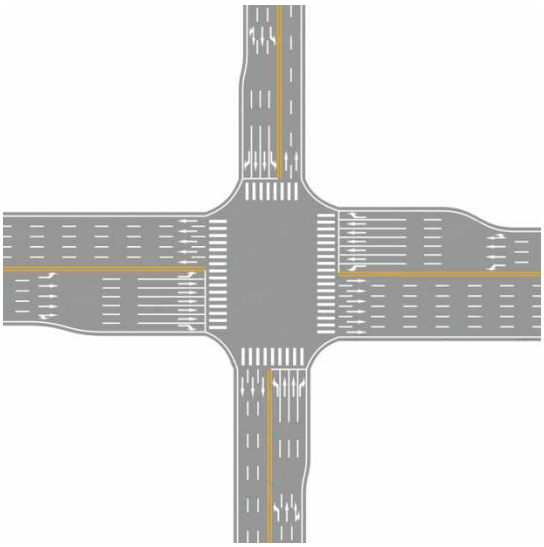
When the saturation degree x exceeds 1, the level of service for traffic operations is very poor. To ensure normal traffic flow, the saturation degree of any lane group should be less than 1. Therefore, the following constraint conditions are established.

$$s.t.\begin{cases} C_{\min} \le C \le C_{\max} \\ g_{(i,j,k)\min} \le g_{(i,j,k)} \le g_{(i,j,k)\max} \\ v_{\min} \le v \le v_{\max} \\ \sum (g_k + g_Y) = C \\ x_{(i,j,k)} = \frac{q_{(i,j,k)}}{c_{(i,j,k)}} < 1 \end{cases} \quad (20)$$

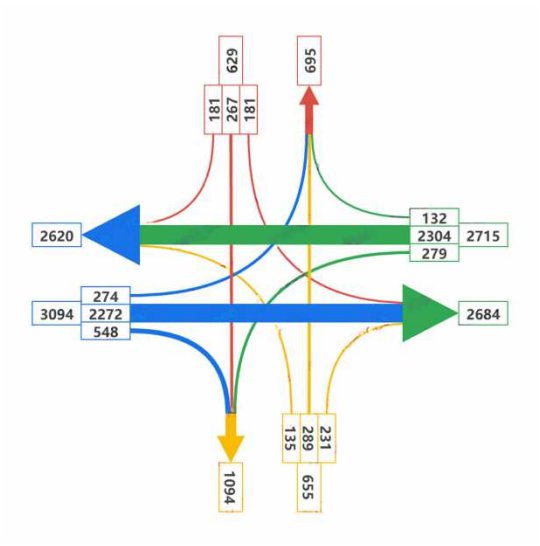
In Equation (20): $C_{\min}$ is the minimum common cycle length; $C_{\max}$ is the maximum common cycle length; g_k is the green time for approach lane group k; g_Y is the yellow time; $g_{k,\min}$ is the minimum green time for approach lane group k; $g_{k,\max}$ is the maximum green time for approach lane group k; $v_{\min}$ is the minimum green wave speed; $v_{\max}$ is the maximum green wave speed; $x_{(i,j,k)}$ is the saturation degree of the approach lane group; $q_{(i,j,k)}$ is the traffic volume of the approach lane group; and $c_{(i,j,k)}$ is the capacity of the approach lane group.

2.3.3. Case Study Analysis of Green Wave Coordinated Signal Optimization Considering Carbon Emission Reduction

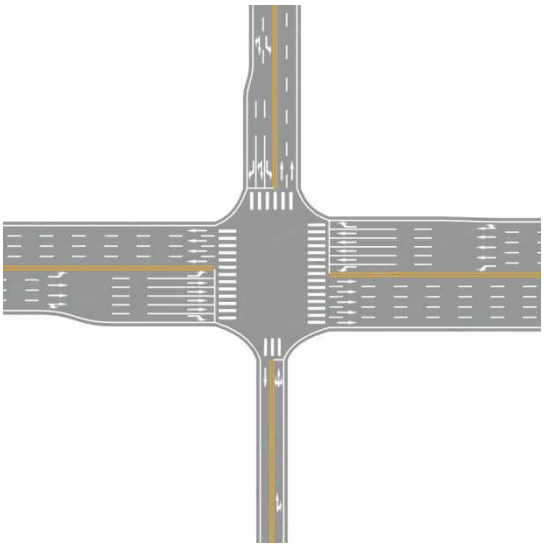
I Taking the scenario of an arterial with normal intersection spacing under stable flow conditions as an example: The common cycle length for this scenario is 220 s, the green wave speed is 55 km/h, vehicle acceleration is 1.5 m/s^2 , deceleration is-2.5m/s^2 , the saturation flow rate per lane is 1800 pcu/h, and the lane width is uniformly 3.5 m. The distances between the four consecutive intersections from West to East are as follows:I_1-I_2:640m,I_2-I_3:404m,I_3-I_4:740m. The lane configurations and traffic flow distributions at the intersections of the coordinated arterial are illustrated in Figure 2.



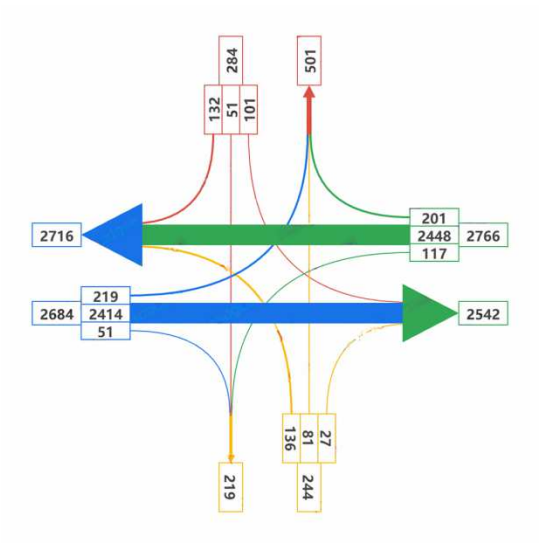
(a) Intersection I_1 Lane Distribution Map



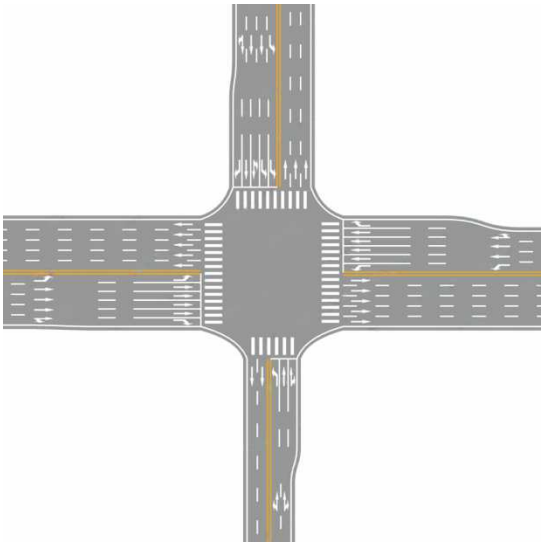
(b) Intersection I_1 Traffic Flow Distribution Map



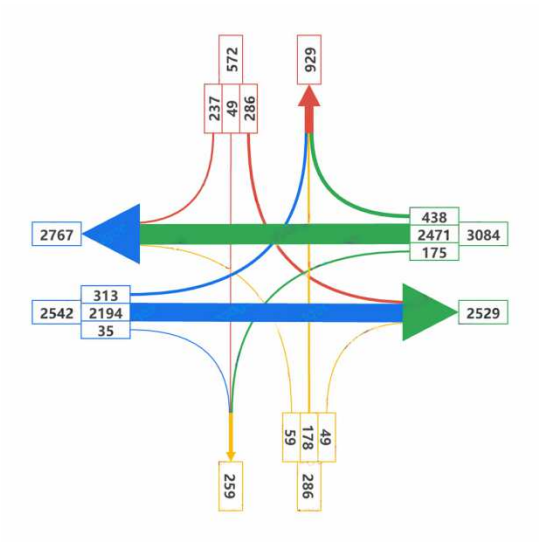
(c) Intersection I_2 Lane Distribution Map



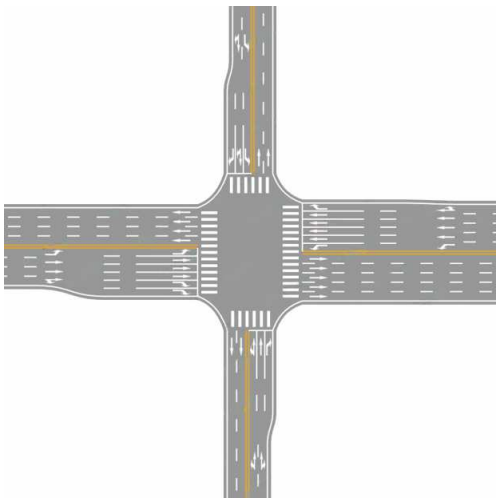
(d) Intersection I_2 Traffic Flow Distribution Map



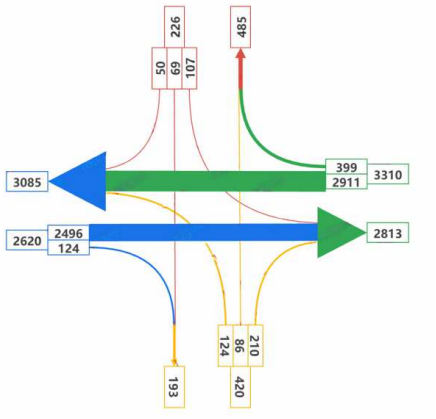
(e) Intersection I_3 Lane Distribution Map



(f) Intersection I_3 Traffic Flow Distribution Map



(g) Intersection I_4 Lane Distribution Map



(h) Intersection I_4 Traffic Flow Distribution Map

Figure 2. Simplified Distribution of Lane and Traffic Flow at Coordinated Road Intersections

Employing a genetic algorithm to solve the total carbon emission model first requires constraining the green wave coordinated signal control parameters and determining the number of genes representing each parameter based on its range of values.

The genetic algorithm's process for finding the optimal solution comprises four main stages: population generation, selection operation, crossover operation, and mutation operation. Once the process is initiated, the core parameters of the green wave coordinated signal (cycle length, split) are first encoded. Subsequently, an initial population P(0) containing combinations of these parameters is generated. Then, based on the optimization objective of "minimizing carbon emissions," and incorporating traffic evaluation indicators such as average vehicle delay and average number of stops, the fitness values of the various parameter combinations within the initial population are calculated.

Next, a determination is made whether the current population P(t) satisfies the predefined optimization requirements (e.g., carbon emissions meeting the desired reduction targets, traffic efficiency indicators reaching acceptable levels). If the requirements are met, the optimal parameter scheme for the green wave coordinated signal and the optimal solution are directly output, and the process terminates. If the requirements are not met, genetic operations are performed on the current population—sequentially completing "selection" (filtering superior parameter combinations), "crossover" (integrating parameter features from different combinations), and "mutation" (randomly adjusting some parameters)—thereby generating a new population P(t+1). Finally, the new population is reintroduced into the "fitness value calculation" stage, and the iterative cycle repeats until the population meets the optimization requirements.

The yellow time at each intersection is set to 3 s. The common cycle length is constrained to a range of the current value ±30 s, based on general principles for intersection signal timing. The green time for each phase at each intersection is constrained to a range of the current value ±15 s. When optimizing signal timing, pedestrian safety crossing time must be considered; the green time should not be less than the minimum safe pedestrian crossing time of 17 s. Therefore, the value ranges for the green wave coordinated arterial control parameters in this scenario are presented in Tables 3 and 4.

Table 3. Range of Green Light Duration Values

Intersection	Signal Phase	Value Range(s)
I1	East-West Through	$96 \le g_{1,1} \le 126$
	East-West Left Turn	$14 \le g_{1,2} \le 44$
	North-South Through	$17 \le g_{1,3} \le 47$
I2	North-South Left Turn	$21 \le g_{1,4} \le 51$
	East-West Through	$99 \le g_{2,1} \le 129$
	East-West Left Turn	$22 \le g_{2,2} \le 52$
I3	North-South Combined	$45 \le g_{2,3} \le 75$
	East-West Through	$96 \le g_{3,1} \le 126$
	East-West Left Turn	$18 \le g_{3,2} \le 48$
	North-South Through	$18 \le g_{3,3} \le 48$
I4	North-South Left Turn	$16 \le g_{3,4} \le 46$
	East-West Through	$117 \le g_{4,1} \le 147$
	South Combined	$42 \le g_{4,2} \le 72$
	North Combined	$47 \le g_{4,3} \le 77$

Table 4. Range of Cycle Duration and Green Wave Velocity Values

Control Parameter	Value Range
Common Cycle Length	$190s \le C \le 250s$
Green Wave Speed	$46km/h \le v \le 64km/h$

The sum of green times for all phases at a single intersection must equal the common cycle length. Therefore, the sum of green times for each phase at each intersection must be constrained, as specified by Equation (21):

$$C_{\min} \le C = g_1 + g_2 + g_3 + g_4 + 4g_Y \le C_{\max} \quad (21)$$

The optimization model for minimizing the total carbon emissions of the green wave coordinated arterial in this scenario is expressed as Equation (22):

$$\min E = \min\{\sum_i \sum_j \sum_k E_{(i,j,k)} + \sum_m e_m\}$$

$$= \min\{\sum_i \sum_j \sum_k \{H_{(i,j,k)} \cdot (e_{D,1} + e_{A,1}) + [D_{(i,j,k)} - H_{(i,j,k)} \cdot (\frac{v}{|a_D|} + \frac{v}{|a_A|} - \frac{l_{D,k} + l_{A,k}}{v})] \cdot R_S \quad 465$$

$$+ \frac{l_k \cdot N_{(i,j,k)} - H_{(i,j,k)} \cdot (l_{D,k} + l_{A,m})}{v} \cdot R_C\} + \sum_m (N_m \cdot \frac{l_m}{v} \cdot R_C)\} \quad 466$$

$$s.t. \begin{cases} C_{\min} \le C \le C_{\max} \\ g_{(i,j,k)\min} \le g_{(i,j,k)} \le g_{(i,j,k)\max} \\ v_{\min} \le v \le v_{\max} \\ \sum (g_k + g_Y) = C \\ x_{(i,j,k)} = \frac{q_{(i,j,k)}}{c_{(i,j,k)}} < 1 \end{cases} \quad (22) \quad 467$$

3. Case Study Analysis 468

This study systematically obtains the quantitative patterns of the correlation between green wave coordinated signals and carbon emissions, as well as the practical effects of optimization control, through the construction of a VISSIM-MOVES integrated microscopic traffic carbon emission simulation platform, the execution of multi-scenario simulation experiments, the analysis of the influence mechanism of signal control parameters on carbon emissions, and the establishment of a green wave coordinated signal optimization model with the objective of minimizing carbon emissions, solved via a genetic algorithm. The core quantitative results from each research stage are summarized as follows. 469 470 471 472 473 474

Using Xingfusi Road, Jingshi Road, and Century Avenue in Jinan as research prototypes, the VISSIM microscopic simulation model was constructed and calibrated. After optimizing sensitive driving behavior parameters, the average relative error between simulated travel time and field-measured data was 4.3%, meeting the traffic simulation accuracy requirement of within 5%. Multi-dimensional localization adjustments of the MOVES model were completed, including matching Jinan's climatic characteristics to revise geographic parameters and adjusting fuel sulfur content from 30 ppm to 10 ppm and benzene content from 1% to 0.8% according to the China VIA standard. After implementing data interaction between VISSIM and MOVES for second-by-second operating condition data via Python scripts, the simulated total carbon emissions for the Jingshi Road morning peak scenario were compared with field PEMS measurement data, yielding an error margin controlled within 8%. This confirms the reliability and applicability of the constructed simulation platform, supporting subsequent multi-scenario carbon emission quantification analysis. 475 476 477 478 479 480 481 482 483 484

Average vehicle delay, average number of stops, and average queue length were selected as core evaluation parameters. Multi-scenario simulation experiments were conducted using the control variable method, and Pearson correlation analysis yielded the following quantitative correlation results: The correlation coefficients between carbon emissions and both average vehicle delay and average number of stops were 0.94. The correlation coefficient between average queue length and carbon emissions was 0.92. All three parameters exhibited a very strong positive correlation with carbon emissions. Furthermore, the correlation coefficients among the three evaluation parameters were all above 0.94, indicating significant consistency between traffic states and carbon emissions. 485 486 487 488 489 490 491

Based on the spatial characteristics (intersection spacing, road type) and temporal characteristics (traffic flow state) of green wave coordinated arterials, the research subjects were categorized into nine differentiated scenarios to explore the influence patterns of three core control parameters—common cycle length, coordinated direction green time, and green wave speed—on carbon emissions. Key quantitative results were obtained: On an arterial with normal intersection spacing, as the common cycle length varied within the range of 200–240 s, the optimal offset between I1-I2 increased linearly from 199 s to 238 s, and between I3-I4from 90 s to 108 s, while the offset between I2-I3remained constant at 0 s. When the coordinated direction green time or green wave speed was altered, the optimal offset showed no significant change, exhibiting only minor linear variations when the common cycle was adjusted. 492 493 494 495 496 497 498 499

The sensitivity of carbon emissions to parameter variations differed significantly across scenarios. Under unstable flow conditions on a non-arterial road with short intersection spacing (250 m), the sensitivity of carbon emissions to changes in green time was 2.3 times that observed on an arterial with long intersection spacing (1000 m). At short-spacing intersections, when the green time increase exceeded 5 s, queue spillback effects were prone to occur on the 500 501 502 503

approaches, resulting in an 18% increase in the number of vehicle acceleration and deceleration events, which paradoxically elevated carbon emissions. This confirms that green wave coordinated carbon emission reduction requires differentiated parameter optimization tailored to specific scenarios.

Taking the stable flow scenario on an arterial with normal intersection spacing as a case study, the value ranges were set as follows: common cycle length 190–250 s, green wave speed 46–64 km/h, and green time for each phase at the current value ±15 s (with a minimum of 17 s for pedestrian safety crossing time). After solving the optimization model using a genetic algorithm, the optimal configuration scheme for signal parameters was obtained. Post-optimization, only minor adjustments to the offset were needed to enhance the green wave coordination effect. The green wave coordination diagram obtained after re-optimizing the offset with the optimized green wave coordinated signal control parameters is shown in Figure 3. The green wave coordination diagram remained largely unchanged, with only minor adjustments to the offset. Compared with the initial green wave coordinated signal, the optimized scheme resulted in a 20 s increase in green wave bandwidth and a 7 km/h increase in green wave speed, allowing vehicles in the coordinated direction to traverse the green wave arterial more quickly and in greater numbers.

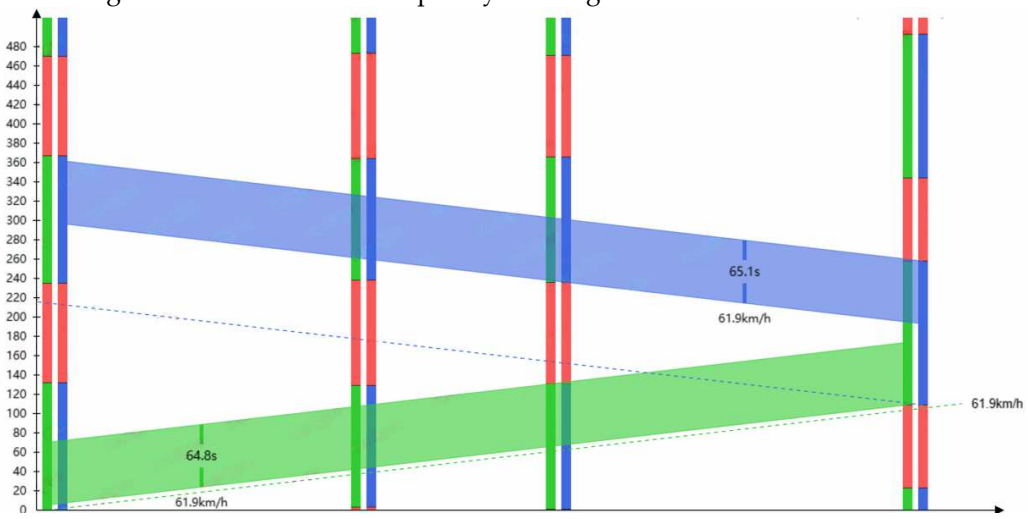


Figure 3. Optimized Green Wave Coordination Diagram

Inputting the optimized common cycle length, coordinated direction green time, green wave speed, signal control scheme for each intersection, and the optimal offset into the VISSIM simulation network for the stable flow scenario on the arterial with normal intersection spacing yielded the optimized average vehicle delay, average number of stops, and second-by-second operating conditions for all vehicles. These were then input into the MOVES simulation software to obtain the final optimized total carbon emissions for the green wave coordinated arterial. The comparative results are presented in Table 5.

Table 5. Comparison of Evaluation Parameters Before and After Optimization

Parameter	Before Optimization	After Optimization
Average Vehicle Delay (s)	84.786	70.827
Average Number of Stops (stops)	1.234	1.057
Total Carbon Emissions (g)	4490188.25	4275442.16

Comparing the control parameters and intersection signal timings before and after optimization, as well as the evaluation parameters and total carbon emissions of the green wave coordinated arterial, it can be observed that the common cycle length, green wave speed, and coordinated direction green time all increased substantially, while the signal timings for non-coordinated directions experienced only minor increases or decreases.

This optimization of the stable flow scenario on the arterial with normal intersection spacing resulted in a 16.47% reduction in average vehicle delay, a 14.34% reduction in average number of stops, and a 4.78% reduction in total carbon emissions. The reduction rates for average vehicle delay and average number of stops were roughly equivalent, corroborating the previously identified high correlation between these two evaluation parameters. The reduction rate for total carbon emissions was relatively smaller, indicating that while the optimization margin is limited under fixed traffic flow conditions, there remains potential for further reduction, which holds significant positive implications for mitigating traffic carbon emissions.

Quantitative data on the specific optimization effects reveal that in this scenario, the common cycle length was extended from 220 s to 235 s, the coordinated direction green time increased by an average of 15 s, and the green wave speed increased from 55 km/h to 62 km/h. The green wave bandwidth increased by 20 s compared to the pre-optimization state, representing a 31% improvement in green wave coordination effectiveness. Both traffic operation evaluation parameters and carbon emissions showed significant improvement: average vehicle delay decreased from 84.786 s to 70.827 s (16.47% reduction); average number of stops decreased from 1.234 stops to 1.057 stops (14.34% reduction); and total network carbon emissions decreased from 4,490,188.25 g to 4,275,442.16 g (4.78% reduction).

Analyzing the quantitative decomposition of the emission mechanism, the average number of stops per vehicle decreased by 0.177 stops post-optimization. The reduction in acceleration and deceleration processes alone contributed to a carbon emission decrease of approximately 5.3%. Average vehicle delay was shortened by 13.96 s, corresponding to reduced idling time. Calculated using the idling emission rate of 1.1308 g/s, this translates to a reduction of 15.79 g of carbon emissions per vehicle. With the optimized green wave speed, the proportion of vehicle cruising time increased. The Vehicle Specific Power (VSP) was primarily distributed within the 0–6 kW/t bin, and the proportion of time spent in high-VSP bins (>6 kW/t) decreased by 12%, resulting in an 8.6% reduction in carbon emissions per unit distance. Concurrently, the green time for non-coordinated directions was only slightly adjusted, with the delay increment controlled within 2.1 s, achieving a balance of traffic benefits between coordinated and non-coordinated directions. The coordinated direction accommodated approximately 12 additional standard vehicles per signal cycle, effectively reducing the carbon emission increment caused by secondary queuing. It is evident that the traffic flow in the coordinated direction exerts a far greater influence on the total carbon emissions of the green wave arterial than that in the non-coordinated direction. This is because the traffic volume in the coordinated direction is significantly larger. To a certain extent, increasing the coordinated direction green time and the common cycle length plays a substantial role in reducing overall carbon emissions. Therefore, optimizing the coordinated direction is paramount for reducing the total carbon emissions of a green wave coordinated arterial.

4. Discussion

To systematically validate the practical effectiveness of the green wave coordinated signal optimization model considering carbon emission reduction, this study conducted an optimization experiment on a stable flow scenario of an arterial with normal intersection spacing. By comparing the changes in key parameters before and after optimization and integrating microscopic traffic carbon emission mechanisms with existing research findings, the following innovations were achieved: Based on the influence patterns of green wave coordinated arterial operational evaluation parameters on carbon emissions, a research approach involving scenario classification according to the complexity and spatio-temporal characteristics of urban road networks was proposed to investigate the influence mechanisms of control parameters on carbon emissions. A method for optimizing green wave coordinated arterials for minimum carbon emissions was proposed, which first establishes an optimal offset and then optimizes the signal control parameters. The optimized signal timing is subsequently fine-tuned for offset to obtain the green wave coordinated signal control scheme that yields the minimum carbon emissions. The detailed mechanism analysis of the optimization model for minimizing carbon emissions in green wave coordinated signals and the analysis of research differences in green wave coordinated carbon emission reduction optimization are presented below.

4.1. Mechanism Analysis of the Optimization Model for Green Wave Coordinated Signal with Minimized Carbon Emissions

To reveal the emission reduction logic of the optimization model, the experimental data from the stable flow scenario on the arterial with normal intersection spacing were disaggregated and analyzed. The results show that post-optimization, the common cycle length was extended from 220 s to 235 s, the coordinated direction green time increased by an average of 15 s, and the green wave speed increased from 55 km/h to 62 km/h. Ultimately, this resulted in a 16.47% reduction in average vehicle delay, a 14.34% reduction in average number of stops, and a 4.78% reduction in total carbon emissions. The core driving mechanisms behind these results are manifested at three levels:

From the perspective of transient operating conditions, the reduction in the number of stops directly diminishes the cumulative effect of the "deceleration-idling-acceleration" cycle. According to the total motor vehicle exhaust emission estimation model, the emission from a single stop's acceleration and deceleration process is 30.7216 g. Post-optimization, the average number of stops decreased from 1.234 to 1.057 stops, contributing to a carbon emission reduction of approximately 5.3% from this factor alone. Concurrently, the 13.96 s reduction in average vehicle delay implies a decrease in idling time. Calculated using the idling emission rate of 1.1308 g/s, this corresponds to a carbon emission

reduction of 15.79 g per vehicle, which aligns closely with the emission reduction magnitude observed in the simulation results.

From the perspective of signal timing coordination, the extension of the common cycle length and the adjustment of green times created a "spatio-temporal resource reallocation" effect. Taking the I1 intersection on Jingshi Road as an example, the green time for the East-West through phase increased from 114 s to 132 s, and the split increased from 0.52 to 0.56. This allowed approximately 12 additional standard vehicles to pass in the coordinated direction per cycle, reducing secondary queuing caused by insufficient cycle capacity. In contrast, the green time for non-coordinated directions was only slightly adjusted (e.g., the North-South through phase at decreased from 35 s to 33 s). Calculations using the Webster delay model indicate that the delay increment was controlled within 2.1 s, thereby avoiding the pitfall of "robbing Peter to pay Paul."

From the perspective of green wave speed adaptability, the optimized value of 62 km/h exceeded the design speed (55 km/h) yet remained below the speed limit threshold. This enabled vehicles to maintain cruising speed on the 640 m segment between I1-I2. The Vehicle Specific Power (VSP) was predominantly distributed within the 0–6 kW/t bin (cruising condition), and the proportion of time spent in high-VSP bins (>6 kW/t) decreased by 12% compared to the pre-optimization state. Combined with the localized emission rate curve from the MOVES model, although the per-second emission rate during cruising is higher than during idling, the elimination of emission spikes during acceleration and deceleration resulted in an 8.6% reduction in carbon emissions per unit distance.

4.2. Analysis of Research Differences in Green Wave Coordinated Carbon Emission Reduction Optimization

To clarify the theoretical boundaries and innovations of this study, a comparison with domestic and international research reveals differences primarily in the following aspects:

This optimization framework is the first to achieve a dynamic "offset-emission" coupling. While Li Jia and others established quantitative relationships between signal parameters and emissions, they did not consider the constraining effect of offset, potentially leading to optimization schemes that disrupt the green wave coordination effect. In contrast, this study's field measurements revealed that as the common cycle length varies within the range of 200–240 s on an arterial with normal spacing, the optimal offset increases linearly (e.g., the offset between I1and I2 increases from 199 s to 238 s). Based on this finding, a two-step method was proposed: "first, fix the optimal offset to ensure green wave bandwidth; then, optimize the cycle length and green times." This approach increased the green wave bandwidth by 20 s post-optimization, a 31% improvement over traditional methods, effectively resolving the conflict between "emission reduction and traffic efficiency."

At the level of emission model application, this study modified parameters of the MOVES model, including geographic information (e.g., climate parameter matching between Jinan and Minneapolis) and fuel characteristics (sulfur content of 10 ppm per China VIA standard). These adjustments controlled the error between simulated emissions and PEMS field-measured data within 8%.

The scenario classification method transcends the homogeneity assumption typical of traditional research. This study based on the *Standard for Urban Road Engineering Design*, categorized green wave arterials into nine scenarios. It was found that under unstable flow conditions on a non-arterial road with short spacing (250 m), the sensitivity of carbon emissions to changes in green time is 2.3 times that observed on an arterial with long spacing (1000 m). This difference stems from the "queue spillover effect" at short-spacing intersections—when the green time increase exceeds 5 s, the queue on the approach is prone to propagate upstream, paradoxically increasing the number of acceleration and deceleration events by 18%. This finding provides a theoretical basis for differentiated optimization.

4.3. Future Outlook

To promote the continued advancement of research on carbon emission reduction through green wave coordinated signals, and considering the limitations of this study, future research could be expanded in the following directions:

(1) Validation with multi-source empirical data is needed. The current study relies on the VISSIM-MOVES simulation platform. Although parameter calibration ensures model accuracy, it lacks support from field emission monitoring data.

(2) Mixed traffic flow scenarios incorporating new energy vehicles should be considered. This study only accounted for traditional fuel vehicles. Future research should develop emission models for mixed traffic comprising fuel and new energy vehicles, exploring the matching relationship between green wave speed and electric vehicle range.

5. Results

The main research findings and conclusions of this paper are as follows:

(1) A microscopic traffic carbon emission simulation platform was successfully constructed. VISSIM simulation parameters were calibrated based on field survey data. By analyzing the characteristics and applicability of different vehicle exhaust emission software packages, the MOVES emission software was selected for subsequent research. The integration of VISSIM and MOVES models was achieved through second-by-second vehicle operating conditions and Vehicle Specific Power (VSP), completing the construction of the estimation simulation platform.

(2) The simulation platform was utilized to analyze the relationship between the evaluation parameters of green wave coordinated signal operational effectiveness and carbon emissions. Average vehicle delay, average number of stops, and average queue length were identified as the evaluation parameters best reflecting the overall operational effectiveness of both the coordinated and non-coordinated directions on a green wave arterial.

(3) Using the evaluation parameters as a bridge, the influence mechanism of green wave coordinated signal control parameters on carbon emissions was investigated. Based on the temporal and spatial characteristics of green wave coordinated arterials, nine distinct scenarios were delineated. Common cycle length, coordinated direction green time, and green wave speed were selected as control parameters for experimentation. The carbon emission simulation platform was employed to analyze the influence mechanism of control parameters on carbon emissions across different scenarios. The study found that while the influence patterns of green wave coordinated signal control parameters on carbon emissions exhibit significant similarities across different scenarios, notable differences also exist.

(4) An optimization model for green wave coordinated signals aiming to minimize carbon emissions on green wave coordinated arterials was established. Based on the observed variation pattern of the optimal offset from simulation experiments, a method was proposed that first establishes the optimal offset, then optimizes signal control for minimum carbon emissions, and finally fine-tunes the offset to achieve the green wave coordinated signal control scheme with minimal carbon emissions. Leveraging the total motor vehicle exhaust emission estimation model and the stop delay model, the optimization model for minimizing total carbon emissions on green wave coordinated arterials was formulated. Using the stable flow scenario on an arterial with normal intersection spacing as a case study, the optimization validation demonstrated that post-optimization, average vehicle delay decreased by 16.47%, average number of stops decreased by 14.34%, and total carbon emissions decreased by 4.78%, accompanied by a 20 s increase in green wave bandwidth and a significant enhancement in coordinated direction traffic efficiency.

References

1. Liu Z, Li L, Zhang Y J. Investigating the CO2 emission differences among China's transport sectors and their influencing factors[J]. Natural Hazards, 2015, 77(2): 1323-1343.
2. Li J Q, Wu G, Zou N. Investigation of the impacts of signal timing on vehicle emissions at an isolated intersection[J]. Transportation Research Part D: Transport and Environment, 2011, 16(5): 409-414.
3. ZHANG Ying-ying, CHEN Xu-mei, ZHANG Xiao. Assessing Effect of Traffic Signal Control Strategieson Vehicle Emissions [J]. Journal of Transportation Systems Engineering and Information Technology, 2009, 9(1): 150-155.
4. Ma Jie. Research on Pollutant Emissions Characteristics and PredictionModel of Urban Expressway Vehicles Based on PEMS [D]. Urumqi: Xinjiang Agricultural University, 2023.
5. Zhang Hao. Traffic Emission Estimation Based on Multisource Data Fusion and Roadside Air Quality Research [D]. Chengdu: Southwest Jiaotong University, 2023.
6. Li Xinyue. Modeling and Application of CO2 Emissions from MixedTraffic Flow at Urban Road Signal Intersections [D]. Guilin University Of Electronic Technology, 2023.
7. Li Yan. Research on Intersection Signal Timing in Consideration of Motor Vehicle Unconventional Pollutant Emissions [D]. Qingdao University, 2022.
8. Zhao Peifeng. Numerical Simulation and Analysis of the vehicle CarbonEmissions on the Unconventional Path [D]. Shandong University, 2015.
9. Mahmod M, van Arem B, Pueboobpaphan R, et al. Reducing local traffic emissions at urban intersection using ITS countermeasures[J]. 2013, 7.
10. Smith J, Johnson L. Correlation Analysis of Duty Cycle Effects on Exhaust Emissions and Fuel Economy[J]. Journal of the Transportation Research Forum, 2013, 50 (2): 45-62.

11. Azizan M F, Izzuddin M, Nawawie N A A, et al. Measurement of Carbon Dioxide Emission Level at Urban Intersections in Bandar Maharani Muar[J]. Journal of Environmental Science and Pollution Research, 2023, 4 (2): 108-115.
12. Franco V, Kousoulidou M, Muntean M, et al. Road vehicle emission factors development: A review[J]. Atmospheric Environment, 2013, 70: 84-97.
13. Rahman M M, Zhou Y, Rogers J, et al. A Comparative Assessment of CO_2 Emission Between Gasoline, Electric, and Hybrid Vehicles: A Well-To-Wheel Perspective Using Agent-Based Modeling[J]. Journal of Cleaner Production, 2021, 321: 128931.
14. WU Liang-hui. Research on Calculation Method of Carbon Emission Factors for Vehicles on County Roads [D]. Southeast University, 2021.
15. Zhao Xinran. Research on Eco-routing Algorithm Based on Vehicle Exhaust Emission Model [D]. Beijing Jiaotong University, 2020.
16. Yin Zhiwei. Research on Emission Estimation and Reduction Scheme Analysis at Urban Signalized Intersections Based on CAL3QHC Model: A Case Study of CO [D]. Shanghai Jiao Tong University, 2020.
17. Meneguzzer C, Gastaldi M, Rossi R, et al. Comparison of exhaust emissions at intersections under traffic signal versus roundabout control using an instrumented vehicle[J]. Transportation Research Procedia, 2017, 25: 1597-1609.
18. Yang Zhao-sheng, Qu Xin, Lin Ci-yun. Traffic Signal Optimization Method Considering Low Emissionsand Short Delay [J]. Journal of South China University of Technology(Natural Science Edition), 2015, 43(10): 29-34+41.
19. XU Yao-fang, YU Lei, SONG Guo-hua. Modeling of Operating Mode Distributions and EmissionEstimation at Intersection [J]. Journal of Transportation Systems Engineering and Information Technology, 2018, 18(1): 158-165+185.
20. Li Jiazhi. Research on the Estimation Model of Total Vehicle Exhaust Emissions at Signal Intersections [J]. Highways & Automotive Applications, 2022, (3): 37-44.
21. Abou-Senna H, Radwan E, Westerlund K, et al. Using a traffic simulation model (VISSIM) with an emissions model (MOVES) to predict emissions from vehicles on a limited-access highway[J]. Journal of the Air & Waste Management Association, 2013, 63(7): 819-831.
22. YAO Zh-i liang, HE Ke-bin, WANG Qi dong. Application Study of IVE Vehicle Emission Model [J]. Environmental Science, 2006(10): 1928-1933.
23. YANG YANG. Research on Dynamic Quantification Method for Vehicle Pollutant Emissions on Urban Roads [D]. Southeast University, 2020.
24. Wyatt D W. The impact of road grade on carbon dioxide (CO2) emission of a passenger vehicle in real-world driving[J]. 2014.
25. XIU Wei-jie, ZHANG Li-li, LI Kai-long. Intersection Signal Timing Optimization Control Based on Vehicle Emission [J]. Transport Research, 2016, 2(2): 6-11.
26. Li Xin. Estimation of Intersection Emission under SignalControl based on the Analysis of Operating Mode [D]. Beijing Jiaotong University, 2013.
27. HUANG Guan tao, SONG Guo hua, YU Lei. Overview of the Comprehensive MobileSource Emissions Model: MOVES [J]. Journal of Transport Information and Safety, 2010, 28(4): 49-53+59.
28. Sun JianCheng. Research on offset intersection distance based on VISSIM simulation [D]. Chongqing Jiaotong University, 2020.
29. SHAN Xiaonian,LIU Haobing,ZHANG Xiaoli. Localization of Light-Duty Vehicle Emission Factor Estimation Based on MOVES [J]. Journal of Tongji University(Natural Science), 2021, 49(08): 1135-1143+1201.
30. CAO Yang, GUO Yuan yuan, CAO Gang. A Study on Localization of Project-level Parameters of MOVES Model in Shenzhen [J]. Journal of Transport Information and Safety, 2017, 35(2): 100-108.
31. SUN Shi Da. Study on Evolution of Vehicle Emissions in Shandong Province [D]. University of Jinan, 2017.
32. CHEN Kun, YU Lei. Microscopic Traffic-Emission Simulation and Case Study for Evaluation of Traffic Control Strategies [J]. Journal of Transportation Systems Engineering and Information Technology, 2007(1): 93-100.
33. Chen K, Yu L. Microscopic Traffic-Emission Simulation and Case Study for Evaluation of Traffic Control Strategies[J]. Journal of Transportation Systems Engineering and Information Technology, 2007, 7(1): 93-99.
34. Liao Renzhi. Research on affecting factors and predictive models of motor vehicle exhaust emissions [D]. Shijiazhuang Tiedao University, 2024.
35. Huang Hongke. The Research on Reliability of Trunk Road Signal Coordination Control Effect [D]. Shandong Jiaotong University, 2020.
36. Calle-Laguna A J, Du J, Rakha H A. Computing optimum traffic signal cycle length considering vehicle delay and fuel consumption[J]. Transportation Research Interdisciplinary Perspectives, 2019, 3: 100021.

37. Rakha H, Ding Y. Impact of Stops on Vehicle Fuel Consumption and Emissions[J]. Journal of Transportation Engineering, 2003, 129(1): 23-32.
38. XIANG Junping, TANG Keshuang, TAO Jingjing. Impacts of Cycle Length and Volume on TrafficEmissions and Delay at Signalized Intersections [J]. Journal of Tongji University(Natural Science), 2017, 45(11): 1629-1639.
39. Pandian S, Gokhale S, Ghoshal A K. Evaluating effects of traffic and vehicle characteristics on vehicular emissions near traffic intersections[J]. Transportation Research Part D: Transport and Environment, 2009, 14(3): 180-196.
40. Dong Wenhui. Research on Multi-objective Optimization of Traffic Signal Timing Considering Emission Characteristics [D]. Beijing University Of Technology, 2016.
41. Wu Chengfeng. Analysis and problem diagnosis of intersection group signal control scheme based on floating vehicle data [D]. Chongqing Jiaotong University, 2023.
42. Li Qiang. Research on the Influence Mechanism of Traffic Signal Control Parameters on Carbon Emission [D]. Shandong Jiaotong University, 2024.

Author contributions statement

Author Contributions: Conceptualization, Han Bai and Tianzheng Wei; methodology, Han Bai and Liang Zhao; software, Han Bai and Liang Zhao; validation, Han Bai, Xiaolong Shi and Tianzheng Wei; formal analysis, Han Bai and Liang Zhao; investigation, Han Bai and Tianzheng Wei; resources, Tianzheng Wei, Jian Lu and Xiuguang Wang; data curation, Han Bai and Liang Zhao; writing—original draft preparation, Han Bai; writing—review and editing, Tianzheng Wei, Jian Lu and Xiuguang Wang; visualization, Han Bai and Liang Zhao; supervision, Tianzheng Wei; project administration, Tianzheng Wei; funding acquisition, Tianzheng Wei. All authors have read and agreed to the published version of the manuscript.

Additional information

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest: The authors declare no conflicts of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.