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Modeling of vehicle CO_2 emissions and signal timing analysis at a signalized intersection considering fuel vehicles and electric vehicles

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Abstract

Background: An intersection is an area with more energy consumption and emissions by motor vehicles, and the energy consumption and emissionsof vehicles at intersections should be reduced in road planning and traffic control to improve the urban traffic environment.

Objectives: In order to analyze the influence of signal timing on CO_2 emission of traffic flow under the mixed traffic environment of fuel vehicles and electric vehicles.

Methods: A set of CO_2 incremental emission models is established to estimate the CO_2 emissions of fuel vehicles and electric vehicles at signalized intersections. Then, a signal timing model with minimum CO_2 emissions is established, and the influence of signal timing with minimum CO_2 emissions on vehicle control delay and stop rates under different traffic conditions is analyzed.

Conclusions: The case study shows that optimizing of the timing parameters of intersections from the perspective of vehicle CO_2 emissions is different from the perspective of control delay or stop rate; the model's timing optimization will effectively balance the CO_2 emissions generated by vehicles during the acceleration, deceleration and idling stages, essentially achieving a comprehensive consideration of vehicle control delay and stop rates. When the road section speed and the mixed proportion of electric vehicles are low, the timing results tend to reduce the vehicle delay at intersections, but when the road section speed and the mixed proportion of electric vehicles are high, the timing results tend to reduce the vehicle stop rate.

Keywords: Urban traffic, Signalized intersection, Fuel vehicle, Electric vehicle, CO_2 emissions, Signal timing

1 Introduction

To date, series of studies on vehicle energy consumption and emissions at signalized intersections have been performed by several research groups; authors such as Liao and Machemehl [1], Liao [2], Huang et al. [3], Zhang et al. [4] and Li et al. [5] have put forward different mathematical estimation models. However, although these results have analyzed and estimated the CO_2 emissions of vehicles at signalized intersections, they were all obtained under specific assumptions, such as the acceleration and deceleration of vehicles in the processes of acceleration and deceleration at intersections remaining unchanged, respectively, or the fuel consumption and emissions characteristics of vehicles in the process of driving being characterized by equivalent fuel consumption and emission rates; these overideal assumptions limit the applicability. To solve this problem, Lv and Zhang [6], Gao and Hu [7], Liu et al. [8] and Zhang [9] et al. used the combination of traffic models and vehicle fuel consumption and emission models to analyze vehicle fuel consumption and emissions at signalized intersections.

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Although these works combined VISSIM traffic simulation software with different fuel consumption and emissions models to study vehicle fuel consumption and emissions at signalized intersections, their research overcame the limitations in the hypotheses of the works of Liao and Machemehl [1], Liao [2], Huang et al. [3], Zhang et al. [4] and Li et al. [5] that were too ideal. However, the combination of VISSIM simulation software and fuel consumption and emissions models is complex and requires a large amount of data processing, resulting in some limitations of research on the fuel consumption and emissions of traffic flow at signalized intersections based on the combination of VISS IM and vehicle fuel consumption and emission models. Tang et al. [10] combined a car-following model and VT-Micro model [11] to analyze the influence of the green signal ratio on vehicle fuel consumption and emissions at signalized intersections, and they obtained meaningful conclusions. In addition, in the work of Zhao et al. [12], the combination of a car-following model and vehicle-specific power emissions model was used to estimate vehicle emissions, including the CO_2, CO, HC, and NO_X emissions at unsaturated signalized intersections. However, Tang et al. [10] and Zhao et al. [12] analyzed vehicle fuel consumption and emissions at signalized intersections based on vehicle trajectory simulations but did not provide a general estimation model of vehicle fuel consumption and emissions at signalized intersections.

Electric vehicles are considered to be an effective means to alleviate traffic energy security and environmental pollution problems because they can achieve "zero emissions" at the operation stage. To study and analyze the energy consumption characteristics of electric vehicles in the course of driving and to quantitatively analyze their specific effects on energy savings and emissions reduction, some scholars have proposed energy consumption estimation models of electric vehicles from different perspectives, including the energy consumption models of unit mileage proposed by Shankar and Marco [13], Qi et al. [14], Yuan et al. [15], and Yuan [16] and some instantaneous energy consumption estimation models proposed by Yao et al. [17], Zhang and Yao [18], Genikomsakis and Mitrentsis [19], Wu et al. [20], Cedric et al. [21], and Abousleiman and Rawashdeh [22]. Based on the research results of an instantaneous energy consumption estimation model of electric vehicles, Yang et al. [23] and Asamer et al. [24] analyzed the impact of different factors on the energy consumption of electric vehicles. At the same time, Ning et al. [25] and Wang et al. [26] analyzed the use economy of electric vehicles from the perspectives of energy consumption and emissions. With in-depth understanding of the problem of electric vehicle energy consumption, some scholars have performed research and explorations from the perspectives of electric vehicle transportation path optimization and charging station planning (e.g., [27–33]). In the existing research literature, research on the energy consumption of electric vehicles has attracted extensive attention from researchers. However, few scholars have taken electric vehicles as their research object to analyze their energy consumption and emissions characteristics at signalized intersections and their impacts on mixed traffic flow emissions. In addition, due to the differences in energy consumption and emission characteristics between electric vehicles and fuel vehicles, the problem of signal timing at intersections under a mixed environment of electric vehicles and fuel vehicles deserves further study.

In summary, although some research results have provided in-depth analyses of vehicle energy consumption and emissions at road sections and intersections, there remain many shortcomings, especially against the background of the increasing popularity of electric vehicles, so the characteristics of energy consumption and emissions of mixed traffic flow require further study. Considering that electric vehicles and fuel vehicles consume electricity and fuel, respectively, in the course of driving, the energy consumption of these vehicles cannot be directly compared horizontally. Because the emissions from fuel vehicles and electric power production include CO_2 [12, 34–36], in this paper, under a mixed traffic environment of fuel vehicles and electric vehicles, the traffic flow CO_2 emissions are considered as the evaluation criterion, signal timing is performed at intersections, and the differences in timing results under different road section speeds and mixed proportions of electric vehicles are analyzed. We propose a statistical regression model for fuel vehicles and electric vehicles to estimate vehicle CO_2 incremental emissions at intersection approaches based on the stop rate and control delay. Due to the influence of many factors on vehicle CO_2 emissions at signalized intersections, some models have been obtained based on a series of assumptions and specific methods in the existing literature, but these models are very complex, and their estimation accuracy must be further improved. The model proposed in this paper can solve this problem well. The stop rate and delay of vehicles are regarded as the direct variables of the model, which can well describe the influence of road conditions, such as vehicle arrival rate and signal timing, on vehicle CO_2 emissions and render the model sufficiently simple under the premise of ensuring the accuracy of estimation. Furthermore, the paper analyzes the signal timing of intersections from the perspective of vehicle CO_2 emissions. The analysis results show that the signal timing of intersections from the perspective of vehicle CO_2 emissions is essentially a balanced consideration of vehicle stop rate and control delay. This conclusion gives scientific meaning to the comprehensive evaluation of stop rate and delay when conducting multiobjective timing optimization at signalized intersections. It should be noted that electric vehicles can be generally divided into pure electric vehicles, hybrid electric vehicles and fuel cell vehicles. The electric vehicles in the scope of this study are pure electric vehicles. Moreover, the

CO_2 emissions of electric vehicles referred to in this paper are the CO_2 emissions generated by the electric vehicle consumption of power produced by power plants.

2 CO_2 emissions model based on the vehicle-specific power of fuel vehicles

Scholars have used the VT-Micro model [11] to conduct a series of studies of vehicle fuel consumption and emissions from different perspectives (e.g., [10, 37–40]), and meaningful conclusions have been drawn. However, the VT-Micro model does not consider the principles of engine operation and emissions, and it is not suitable for vehicle fuel consumption and emissions analysis in traffic scenarios with considerable deceleration, such as signalized intersections. Gao and Hu [7] found that the specific power method can be used to determine the exhaust emissions of motor vehicles at the microlevel because it considers factors such as the instantaneous speed and acceleration/deceleration of a vehicle. Lv and Zhang [6], Gao and Hu [7], Zhang et al. [9], Abou-Senna et al. [41], Lv et al. [42], Li et al. [43] and Coelho et al. [44] used the specific power method to evaluate vehicle exhaust emissions on the road and at intersections. Therefore, this paper also uses the specific power method to analyze the CO_2 emissions of fuel vehicles at signalized intersections. The equation for calculating the specific power of a light vehicle under the condition of a road slope is 0 can expressed as follows [45]:

$$VSP = v(1.1a + 0.132) + 0.000302v^3 \tag{1}$$

In Eq. (1), VSP is the vehicle-specific power; v is the vehicle speed; and a is the vehicle acceleration/deceleration.

In this study, we use Eq. (1) to calculate the specific power of a fuel vehicle at a signalized intersection.

Frey et al. [46] divided a light vehicle's specific power into multiple bins, each of which was called a specific power bin. By considering major vehicle parameters, such as the engine capacity and mileage, they reported the average emissions rates of CO_2 for different specific power bins of different types of vehicles. In the following analysis of fuel vehicle CO_2 emissions, it is assumed that the engine capacity of the vehicle is less than 3.5 L and that the mileage is greater than 50,000 miles; this assumption is more in line with the actual traffic phenomenon, and it represents the typical features of urban road traffic flow, which is mainly composed of vehicles with mileage of more than 50,000 miles and an engine capacity of less than 3.5 L. The average emissions rates of CO_2 for different specific power bins of such vehicles are shown in the Table 3 in Appendix.

3 Energy consumption model of electric vehicles

To study and analyze the energy consumption characteristics of electric vehicles, Genikomsakis and Mitrentsis [19], Wu et al. [20], Cedric et al. [21] and Abousleiman and Rawashdeh [22] proposed different instantaneous energy consumption estimation models of the same type of electric vehicle from the point of view of vehicle energy conversion. Based on the instantaneous energy consumption models from the work of Genikomsakis and Mitrentsis [19], Wu et al. [20], Cedric et al. [21] and Abousleiman and Rawashdeh [22], we determine the CO_2 incremental emissions of electric vehicles according to the CO_2 emissions factor of the power grid. It should be noted that the electric vehicle energy consumption model used in this paper is a mature model in this research field, although there are other types of models in this field (e.g., [17, 18]). However, through the comprehensive analysis and experimental comparison of various models, the results show that the model selected in this paper is relatively reasonable, and its physical meaning is clearer. Therefore, this model is chosen as the basic model to analyze the CO_2 emissions of pure electric vehicles at signalized intersections.

According to the principle of force balance, the force acting on a vehicle during driving can be analyzed as follows:

$$F_t = C_R m g_a \cos\alpha + m g_a \sin\alpha + 0.5 C_D A \rho_a v^2 + (1+\varepsilon_i) m a \tag{2}$$

In Eq. (2), F_t is the traction force on the vehicle; m is the vehicle mass; C_R is the coefficient of rolling resistance; g_a is the acceleration of gravity; α is the road gradient; C_D is the aerodynamic drag coefficient; A is the frontal area of the vehicle; ρ_a is the air density; ε_i is the mass factor; and v is the vehicle speed.

When the vehicle travels at speed v, the battery output power of the vehicle is estimated as follows:

$$P_{out} = \frac{F_t v}{\eta_{pow}} + P_0 \tag{3}$$

In Eq. (3), η_{pow} is the energy efficiency of the vehicle power system, and P_0 is the power of vehicle auxiliary components.

Unlike fuel vehicles, electric vehicles can convert the kinetic energy of the vehicle into electrical energy during the braking stage to realize battery charging. The battery charging power in the braking stage is estimated as follows:

$$P_{in} = k \eta_{pow} F_t v + P_0 \tag{4}$$

In Eq. (4), k is the energy recovery efficiency of the vehicle, which can be determined as follows [23]:

$$k = \begin{cases} 0.5 \times \dfrac{v}{5} & v < 5m/s \\ 0.5 + 0.3 \times \dfrac{v-5}{20} & v \geq 5m/s \end{cases} \tag{5}$$

Then, according to Eqs. (3) and (4), the battery power of the electric vehicle is determined as follows:

$$P = \begin{cases} P_{out} & F_t \geq 0 \\ P_{in} & F_t < 0 \end{cases} \tag{6}$$

Therefore, the energy consumed by electric vehicles from batteries during their journeys can be determined as follows:

$$W_b = \int_0^T P dt \tag{7}$$

In Eq. (7), T is the travel time of the vehicle.

According to the standard GB-T 18386-2005, ISO 8714-2002 and the analysis of Yuan [15], the energy consumption of electric vehicles should be defined as the energy required to charge the batteries from the grid. Therefore, the energy consumption of electric vehicles can be determined as follows:

$$W_t = \frac{W_b}{\eta_{gb}} \tag{8}$$

In Eq. (8), η_{gb} is the charging efficiency of the electric vehicle. Thus, according to the work of Yuan et al. [15], the U.S. EPA [35], Jiménez-Palacios [45], Yang et al. [23], Asamer et al. [24] and Ning et al. [25], the relevant parameters for the electric vehicle model are determined as shown in Table 4 in Appendix.

4 CO_2 incremental emissions model for vehicles arriving at an intersection approach

4.1 CO_2 incremental emissions analysis of arrived vehicles

In actual traffic, vehicles passing through signalized intersections can be divided into three modes: complete stop, incomplete stop and normal driving. A complete stop means that, due to the influence of signal lights and queuing vehicles, the vehicle must slow and stop to wait and then follow the acceleration to a certain speed when the vehicle in front begins to accelerate. An incomplete stop means that the front vehicle has not completely accelerated when the vehicle arrives and must decelerate to a certain speed and then follow the front vehicle to accelerate again. Normal driving means that the arriving vehicle is not affected by the signal lights and queuing vehicles and will pass through the intersection at the road section speed. Since the root cause of the increase in the CO_2 emissions of vehicles at intersections is the change in vehicle driving trajectory, only the CO_2 emissions of acceleration, deceleration and idling stage of complete stop and incomplete stop vehicles must be considered in the analysis process. Then, in the analysis process, we assume that the incomplete stop behavior is a complete stop behavior without an idling process, and the sum of CO_2 emissions generated by a vehicle at deceleration and acceleration stage is *ER*. Because it is difficult to determine the deceleration amplitude of the vehicle with incomplete stops in the signal cycle, we consider the incomplete stop a complete stop behavior without an idling process. In addition, we assume that the average sum emissions of each vehicle during deceleration and acceleration stage is *ER*. However, this parameter will be affected by many traffic conditions; there are great differences in the value of this parameter under different traffic conditions, making it difficult to calibrate accurately. Therefore, there are some differences between the assumptions here and the actual traffic scenarios. However, we make such assumptions only to facilitate the theoretical analysis of vehicle CO_2 emissions and qualitatively understand the relationship between vehicle CO_2 emissions and the delay and stop rate. The model established in section 4.2 of this paper has no relationship with this assumption. Thus, regardless of fuel vehicles or electric vehicles, the average incremental CO_2 emissions per vehicle in a signal cycle can be approximately estimated as Eq. (9). It is worth noting that although the electric vehicle can achieve energy recovery in the deceleration stage, and it is affected by the energy recovery efficiency, the energy recovery in the braking stage is less than the consumption of the vehicle accelerating to the road section speed again.

$$\begin{aligned} Afe &= \frac{St \times qC \times ER + It \times qC \times FR - St \times qC \times SR}{qC} \\ &= St \times (ER - SR) + It \times FR \end{aligned} \tag{9}$$

In Eq. (9), *FR* represents the vehicle CO_2 emissions rate in the idling stage; *SR* represents the average CO_2 emissions of the vehicle passing through the distance of deceleration and acceleration processes at road section speed; C is the signal cycle of the intersection; q is the vehicle arrival rate of the intersection approach; St is the stop rate of the intersection approach; and It is the average vehicle idle time at the intersection approach. According to the analysis of Shao [47], the control delay of vehicles at intersections is equal to the sum of the lost time in the process of acceleration and deceleration and idle time (stopped delay), and the U.S. Road Capacity Manual proposes that the average stopped delay is approximately 0.76 times the average control delay through repeated observations and measurements of actual traffic phenomena. Thus, St and It can be calculated as follows [48]:

$$St = f\left(\frac{1-\eta}{1-q/s} + \frac{N_o}{qC}\right) \tag{10}$$

$$It = 0.76 \times d \tag{11}$$

$$d = \frac{C(1-\eta)^2}{2(1-\eta x)} + \frac{xN_o}{q} \tag{12}$$

$$N_o = \begin{cases} \frac{QT}{4}\left((x\text{-}1) + \sqrt{(x\text{-}1)^2 + \frac{12(x-x_0)}{QT}}\right), x > x_0 \\ 0, x \leq x_0 \end{cases} \tag{13}$$

$$x_0 = 0.67 + \frac{sg}{600} \tag{14}$$

In Eqs. (10) to (14), g is the effective green light time of the intersection approach; η is the green time ratio of the intersection approach; s is the vehicle saturation flow rate of the intersection approach; $x = {qC}/{sg}$ is the saturation level of the intersection approach; N_o is the average number of vehicles held up at the intersection approach in one signal cycle; Q is the traffic capacity of the intersection approach; T is the time duration for which the vehicle arrival rate is equal to q; f is the correction factor for a complete stop; and d is the control delay of the intersection approach.

Through the analysis of Eq. (9), it can be seen that, on the premise that parameters ER, FR and SR have been determined, the average incremental CO_2 emission per vehicle of a signal cycle can be determined by the stop rate and idle time. At the same time, according to analysis of the work of Zhao et al. [12] and actual traffic phenomena, we can draw the general conclusion that the changes in vehicle CO_2 emissions at an intersection approach are caused by the different stop behaviors and idle times of vehicles. The incremental emissions of a vehicle will change with changes in the stop rate and idle time. When the idle time is similar, the incremental emissions will increase with an increase in the stop rate. In the case of a similar stop rate, the incremental emissions will increase with an increase in the idle time. However, the average incremental CO_2 emissions of vehicles at signalized intersections will be affected by many factors, such as the random arrival of vehicles, speed fluctuations, incomplete stop behaviors, etc., and the accuracy of incremental CO_2 emission of vehicles cannot be guaranteed through the method of equivalent averages of parameters ER, FR and SR. Therefore, it can be explained to some extent that there is a specific mapping relationship between the changes in incremental emissions and the stop rate and delay, but the estimation accuracy of the model must be further improved if establishing a simple linear relationship, as in Eq. (9).

4.2 Modeling

According to the polynomial combination of vehicle speed and acceleration/deceleration, Ahn et al. [11] used a statistical regression method to determine the instantaneous fuel consumption and emissions model of fuel vehicles. Yao et al. [17] and Zhang and Yao [18] also used the same method to study a statistical model of the instantaneous energy consumption of electric vehicles. Inspired by this idea, we analyze the different polynomial combinations of stop rate and control delay based on the data of vehicle average CO_2 incremental emissions under different traffic conditions and establish a statistical model of vehicle CO_2 incremental emissions. It should be noted that the delay in vehicles at intersections mainly includes three stages—deceleration, idling, and acceleration—for comprehensively evaluating the operating efficiencies of signalized intersections in actual traffic, and researchers have conducted a series of studies based on the control delay rather than the stopped delay [49], and the control delay and stopped delay approximately follow a linear relationship. Therefore, we use the stop rate and control delay models shown in Eqs. (10) and (12), respectively, to establish incremental emissions models from the perspective of regression statistics.

The establishment of a vehicle emissions model eventually turns to practical applications. Although it is possible to build a more realistic model relying only on the relevant data obtained from a large number of observations and in-depth analysis of actual traffic phenomena, the CO_2 emissions of vehicles at signalized intersections are affected by many factors, such as signal timing and vehicle arrival rate, resulting in vehicle energy consumption and emissions that will also differ under different traffic conditions. Therefore, it is difficult to collect the actual emissions data of different vehicles at signalized intersections, and the vehicle emissions under different traffic conditions are difficult to cover comprehensively. In addition, it is easy to cause certain deviations in many data processing processes. To overcome the difficulty of data collection, Zhao et al. [12] used the full velocity difference (FVD) car-following model to simulate vehicle trajectories at signalized intersections and combined the model with vehicle-specific power emissions model to analyze the influences of signal timing, arrival rate and road section speed on fuel vehicle emissions. This approach provides a simple and convenient way to analyze vehicle energy consumption and emissions at signalized intersections. Therefore, we use the FVD car-following model combined with the instantaneous emissions model of fuel vehicles in section 2 and the instantaneous energy consumption model of electric vehicles in section 3 to simulate the CO_2 emissions of fuel vehicles and electric vehicles under different traffic conditions, respectively. The simulation conditions in the process of data acquisition are shown in Table 5 in Appendix.

We set the road section speed at 10 m/s, in line with the actual speed of most urban roads. For fuel vehicles and electric vehicles, the simulations are conducted separately. It is worth noting that under these conditions, the vehicle arrival rate has 51 situations, the signal cycle has 35 situations, and the green signal ratio situations for each traffic condition composed of vehicle arrival rate and signal cycle are different and can be determined by the upper and lower bounds and the step size. Finally, the number of traffic situations, composed of different vehicle arrival rate, signal cycle and green signal ratio, is 17,010. In addition, in Zhao et al. [12], to simplify the analysis process, under the condition that the vehicle arrival rate is determined, it is assumed that the time intervals of all vehicles arriving at the intersection are the same, but this assumption condition is too strong, making it insufficient for describing actual traffic phenomena. To overcome this shortcoming, this paper assumes that the time headway of a vehicle arriving at an intersection approach obeys a shifted negative exponential distribution when simulating the vehicle trajectory under different traffic conditions, considering the randomness of vehicle arrival at the intersection approach to render the model more applicable to actual traffic analysis. At the same time, the signal cycle average vehicle emissions within 1 h of each traffic situation are considered the simulation value of the corresponding traffic situation. Then, based on a large number of simulation data in different traffic situations, which almost achieve comprehensive cover of different traffic situations, we uses SPSS statistical software to analyze the different polynomials of the stop rate and control delay and determine the structure of the statistical model of average CO_2 incremental emissions of fuel vehicles and electric vehicles as follows:

$$Afe = \sum_{i=0}^{3}\sum_{j=0}^{3} l_{i,j} St^i d^j \tag{15}$$

Table 6 in Appendix shows the regression coefficients of the statistical model. To simplify the model and avoid the influence of multicollinearity between explanatory variables in the model as much as possible, when determining the corresponding model, a polynomial combination that cannot explain the changes in the model significantly is not considered. Through SPSS analysis, the adjusted R^2 values of the CO_2 incremental emissions statistical models of fuel vehicles and electric vehicles are both 0.932, and the regression equation and explanatory variables pass the significance test at the 95% confidence level. To evaluate the accuracy of the model more intuitively, based on the simulation results of incremental emissions under different traffic situations, the model-calculated values of Eq. (15) are compared with the simulation values. The statistics of the comparison results show that the mean absolute percentage errors of the statistical models of CO_2 incremental emissions of fuel vehicles and electric vehicles are 10.62% and 8.56%, respectively, and the standard deviations of the absolute percentage errors are 0.10 and 0.07, respectively. It can be concluded that the statistical models of CO_2 incremental emissions are reasonable through the linear regression of different polynomials of the stop rate and control delay, and the estimation accuracy of the statistical model can be guaranteed.

However, in this paper, the model is established on the premise that the road section speed is 10 m/s. According to the simulation analysis in the work of Zhao et al. [12], when the vehicle has different road section speeds, the driving trajectory of the vehicle under the intersection approach will change, rendering the CO_2 emissions generated in the processes of vehicle deceleration and acceleration different. Therefore, there are some deficiencies in calculating the incremental emissions using the above model under different road section speeds. In actual traffic, the speed of different urban road intersections will be different, and the speed limit range is mostly between 30 km/h and 50 km/h. Thus, to render the statistical model proposed in this paper more general, it is assumed that the range of vehicle road section speeds is from 8 m/s to 14 m/s. The incremental emissions results of fuel vehicles and electric vehicles under different traffic situations, comprising different road section speeds, signal cycles, green signal ratios and vehicle arrival rates, are obtained by the above simulation method and conditions. Based on Eq. (15), under the premise of considering the road section speed, SPSS statistical software is used to test different polynomial combinations of the stop rate, control delay and road section speed. The statistical model structure of the average CO_2 incremental emissions in one signal cycle is reestablished, as shown in Eq. (16), and the regression coefficient is shown in Table 7 in Appendix.

$$Afe = \sum_{i=0}^{1}\sum_{j=0}^{3}\sum_{k=0}^{3} l_{i,j,k} vol^i St^j d^k \tag{16}$$

Through SPSS analysis, the adjusted R^2 values of the CO_2 incremental emissions statistical models considering the road section speed of fuel vehicles and electric vehicles are 0.916 and 0.899, respectively, and the regression equation and explanatory variables pass the significance test at the 95% confidence level. Through analysis of the vehicle incremental emissions results, it is found that, when the vehicle road section speed increases, although it can reduce the travel time of the vehicle on the road, the duration times of deceleration and acceleration at the intersection will increase, resulting in an increase in incremental emissions at the intersection. To describe the influence of the road section speed on the CO_2 incremental emissions of vehicles at the intersection approach, the statistical model shown in Eq. (16) considers the road section speed. It can be seen from a comparison with Eq. (15) that although the complexity of the model structure shown in Eq. (16) is increased under the premise of considering the road section speed, the adjusted R^2 values of the models of fuel vehicles and electric vehicles are reduced correspondingly but still close to 1. This outcome shows that the statistical model considering road section speed is relatively reasonable, making it more general and broadening the application scope of the model. It is worth noting that the model in this paper aims to study the average vehicle CO_2 incremental emissions under the whole intersection approach rather than a single vehicle. Therefore, for an intersection approach, the road section speed of vehicles can be determined by the average speed of all of the vehicles before the change in vehicle speed. When the vehicle speed of different intersection approaches is different, leading to changes in vehicle CO_2 emissions, the *vol* of the model is a description of this situation.

5 Signal timing analysis of intersections considering vehicle CO_2 emissions

Based on the stop rate and vehicle delay, an estimation model of vehicle CO_2 incremental emissions at a signalized intersection approach is established. Considering that signal control can significantly affect the vehicle stop rate and delay of signalized intersections, Liao and Machemehl [1], Liao [2], Zhang et al. [4] and Li et al. [5] found that optimizing of signal timing at intersections will have positive significance for reducing energy consumption and emissions generated by vehicles passing through intersections. However, as in the previous analysis, the research conclusions of the work of Liao and Machemehl [1], Liao [2], Zhang et al. [4] and Li et al. [5] were all obtained under specific assumptions that were too ideal, resulting in certain deficiencies. In addition, in the previous research process, the analysis of the emissions characteristics of electric vehicles at signalized intersections and their impact on signal timing was ignored. Therefore, in this section, considering the mixed driving environment of fuel vehicles and electric vehicles, we analyze the signal timing of signalized intersections from the perspective of reducing vehicle CO_2 incremental emissions while emphasizing the influence of the road section speed and mixed proportion of electric vehicles.

Because different types of intersections have different approach components, the method in this paper needs only to consider the different approaches separately, and then the comprehensive calculation can realize the estimation of vehicle CO_2 emissions for the whole intersection, with no special requirements for the type of intersection. Therefore, this paper chooses a more common intersection as the following research case, and the intersection geometry is shown in Fig. 1. It should be noted that the car-following model is used to simulate the vehicle driving trajectories at the intersection in this paper. To simplify the analysis process, the simulation method of the car-following model for the driving trajectories of conflicting traffic flow at the intersection is not involved. Therefore, the model proposed in this paper is not applicable for estimating the CO_2 emissions of traffic flow in each direction under a conflicting environment.

As shown in Fig. 1, lanes 1, 4, 6 and 9 are the south, east, north and west straight vehicle inbound approaches, respectively; lanes 2, 5, 7 and 10 are the south, east, north and west right-turning vehicle inbound approaches, respectively; and lanes 3 and 8 are the east and west left-turning vehicle inbound approaches, respectively. In actual traffic, to improve the traffic efficiency of signalized intersections, the right-turn approach is not controlled by a signal in most cases. Therefore, in the subsequent analysis process of this paper, the CO_2 emissions of vehicles turning right at the intersection are not considered; only the CO_2 emissions of vehicles arriving in intersection lanes 1, 3, 4, 6, 8 and 9 are analyzed, and then the signal timing of the intersection is realized by integrating the CO_2 emissions of vehicles in different lanes.

5.1 Objective function of the signal timing model

The mathematical model of the objective function should be determined first during signal timing. Although the incremental emission models of fuel vehicles and electric vehicles determined in section 4 have the same model structure, the explanatory variables and their coefficients in the different models are not the same. Therefore, in an environment of mixed traffic of fuel vehicles and electric vehicles, when calculating the CO_2 emissions generated by the traffic flow passing through the intersection, it is necessary to calculate the average CO_2 emissions of fuel vehicles and electric vehicles according to the CO_2 incremental emissions models of fuel vehicles and electric vehicles in section 4, respectively. Then, based on the mixed proportion of fuel vehicles and electric vehicles, the sum of the CO_2 incremental emissions generated by the traffic flow in the lanes is determined, and the average vehicle CO_2 incremental emissions of the whole intersection are calculated by combining the traffic flow in different lanes. Under the condition that the mixed proportion of electric vehicles in the lanes is α, the average CO_2 incremental emissions of the intersection in a signal cycle are calculated as follows:

$$Z = \frac{\sum_{i=1}^{n} q_i((1-\alpha)IAfe_i + \alpha EAfe_i)}{\sum_{i=1}^{n} q_i} \tag{17}$$

In Eq. (17), i denotes the intersection approaches, n is the number of controlled approaches at the intersection, q_i is the vehicle arrival rate of the i th approach, and $IAfe_i$ and $EAfe_i$ represent the average CO_2 incremental emissions of fuel vehicles and electric vehicles in the i th approach, respectively, which can be determined by Eq. (16).

5.2 Constraint conditions of the signal timing model

(1) Constraint of the saturation level

In the previous analytic process, the research object was the unsaturated intersection. To ensure the validity of the model analysis, the saturation of the intersection approach should be considered when optimizing signal timing. In this model, the saturation of each approach should meet the requirement of $x_i < 0.9$.

(2) Constraint of the signal cycle

In traffic control, the signal cycle should be flexibly controlled in accordance with traffic flow. Generally,

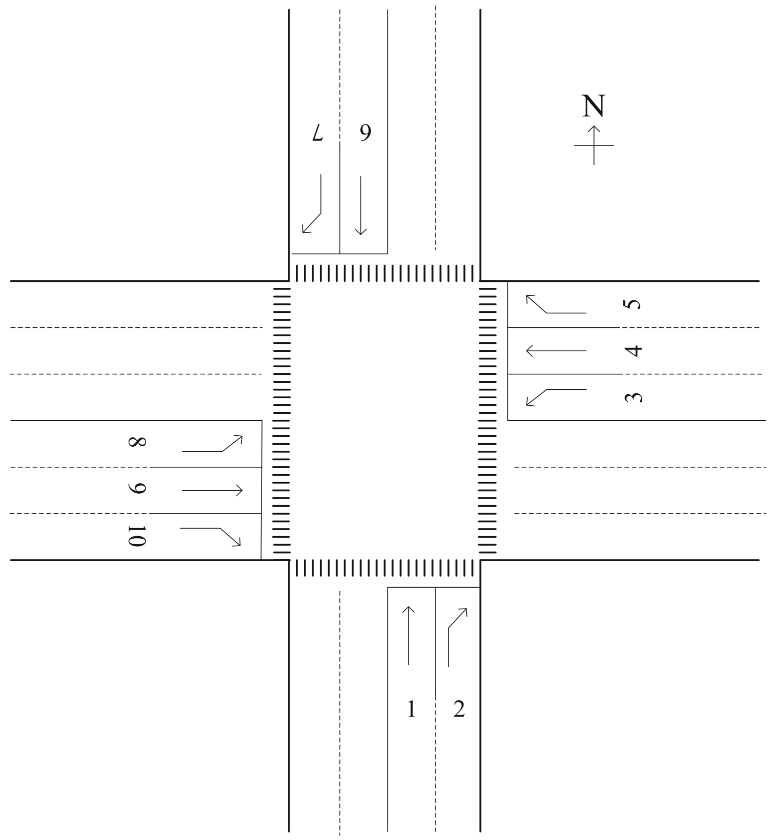

Fig. 1 Geometric configuration of the intersection

when the traffic flow is low, the signal cycle is set short. However, if the signal cycle is too short, vehicles and pedestrians cannot cross the intersection safely. When the traffic flow is high, to improve the traffic capacity of the intersection, the signal cycle is set relatively long. However, if the signal cycle is too long, it will lead drivers and pedestrians to attempt to run the red light. Therefore, to implement traffic control scientifically, research has shown that the signal cycle should meet $15k \le C \le 200$, where k is the number of signal phases [34, 36].

5.3 Establishment and solution of the signal timing model

Based on the above analysis, the signal timing model is established under specific constraints as follows:

$$\min\ Z = \frac{\sum_{i=1}^{n} q_i((1-\alpha)IAfe_i + \alpha EAfe_i)}{\sum_{i=1}^{n} q_i} \tag{18}$$

$$x_i < 0 \tag{19}$$

$$15k \le C \le 200 \tag{20}$$

$$L + \sum_{j=1}^{k} g_j = C \tag{21}$$

where $L = 3k$ is the lost time of the signal cycle. Equation (18) minimizes the objective functions of the signal timing model, Eq. (19) is the constraint of the saturation level per intersection approach, Eq. (20) is the constraint of the signal cycle, and Eq. (21) constrains the sum of the signal lost time, with the green time of each phase equal to the signal cycle.

Considering that the optimization model includes a total of k decision variables, including the signal cycle and green light time of different signal phases, and the range of different variables is also limited, the enumeration method used to solve the model for the quality and efficiency of solution can thus be guaranteed.

5.4 Case study

When the road section speed varies, the CO_2 incremental emissions generated by vehicles passing through the intersection will be different. To explain the influence of the road section speed on the optimal signal timing considering vehicle CO_2 incremental emissions, the road section speed of vehicles is considered in the case study process. In addition, from the analysis of the CO_2 incremental emission models of fuel vehicles and electric vehicles, it can be seen that the different mixed proportions of electric vehicles will lead to differences in the average CO_2 emissions of vehicles at intersections. Therefore, this paper considers the intersection shown in Fig. 1 as a case study, in which the vehicle arrival rate and saturation flow rate of each approach are shown in Table 1. It is assumed that the road section speeds of the intersection approach are 10, 12 and 14 m/s and the mixed proportions of electric vehicles are 0, 0.5 and 1. Different traffic situations comprise different road section speeds and different mixed proportions of electric vehicles. The enumeration step size of the signal cycle and green light time of each signal phase are 1 s when solving the model, and a smaller enumeration step size can guarantee the final solution quality. The results of the model solution under different traffic situations are shown in Table 2.

Table 2 shows that the optimal objective function values under different traffic situations are not the same due to the influence of the road section speed and the mixed proportion of electric vehicles. According to different traffic situations, to minimize the CO_2 incremental emissions of vehicles at intersections, there are certain differences in the signal cycle and green light time of each phase from the model solution. The comparison of timing results under different traffic situations is shown in Fig. 2.

From Fig. 2, we can see that when the road section speed is low, the signal cycle and green light time of each phase from the model solution are relatively short, and when the road section speed is high, the signal cycle and green light time of each phase will increase. It can be seen from the analysis of the causes that for both fuel vehicles and electric vehicles, when the road section speed of the vehicle is high, the CO_2 incremental emissions generated by the vehicle experiencing a track change will increase accordingly. To reduce the total CO_2 emissions of the intersection, the signal cycle and the green light time of each phase calculated by the model will increase, although the vehicle delay will increase, and the vehicle stop rate will be relatively reduced, so the CO_2 incremental emissions generated in the processes of acceleration, deceleration and idling can be effectively balanced. Additionally, because the proportion of CO_2 emissions generated during the idling period of electric vehicles among the total emissions is less than that of fuel vehicles through the analysis of energy consumption and the emissions characteristics of fuel vehicles and electric vehicles, the signal cycle and green light time of each phase calculated by the model will increase with an increase in the mixed proportion of electric vehicles. Although the CO_2 emissions generated during the idling period of vehicles increase, this increase can effectively reduce the increase in CO_2 emissions caused by acceleration and deceleration.

It can be seen from the above analysis that, according to different situations, the signal timing model comprehensively considers different traffic conditions, which will effectively balance the CO_2 emissions generated by vehicles during the acceleration, deceleration and idling stages to effectively reduce the average CO_2 emissions of vehicles at the intersection. It shows that the signal timing based on the vehicle CO_2 emissions is different from the signal timing based on control delay or stop rate. Then, we compared the changes in vehicle delay and stop rate under different traffic conditions when the CO_2 emissions of vehicles are at a minimum. The comparison results are shown in Figs. 3 and 4, respectively.

Based on existing achievements, when the vehicle average control delay and stop rate are considered the objective functions to optimize the signal timing, the timing results cannot be affected by the road section speed and the mixed proportion of electric vehicles, indicating that the optimal delay and stop rate of all traffic situations in this paper are consistent. It can be seen from Figs. 3 and 4 that the vehicle delay and stop rate under different traffic conditions is changed under different traffic conditions when the CO_2 emissions of vehicles are at a minimum, indicating that, for the same traffic situation, it is difficult to guarantee the simultaneous optimization of vehicle CO_2 emissions, delays and stop rates during signal timing, and it is necessary to have signal timing for intersections from the perspective of vehicle CO_2 emissions. In addition, we can see from the comparison of delay and stop rates under different traffic conditions in Figs. 3 and 4 that when the mixed proportion of electric vehicles remains unchanged, with the increase in

Table 1 Vehicle arrival rate and saturation flow rate of each approach

Signal phase	1		2		3	
Approach	1	6	3	8	4	9
Vehicle arrival rate (pcu/h)	280	280	350	350	480	480
Saturation flow rate (pcu/h)	1670	1670	1600	1600	1780	1780

Table 2 Timing results of the intersection in different traffic situations

Traffic situations	*vol*	*α*	*C* (s)	g_1 (s)	g_2 (s)	g_3 (s)	Emissions (g)
1	10	0	66	15	19	23	46.2238
2		0.5	70	16	20	25	27.9984
3		1	87	20	26	32	9.5688
4	12	0	73	17	21	26	51.3620
5		0.5	78	18	23	28	31.3029
6		1	107	25	32	41	10.8897
7	14	0	78	18	23	28	56.0918
8		0.5	85	20	25	31	34.3648
9		1	118	28	36	45	12.0676

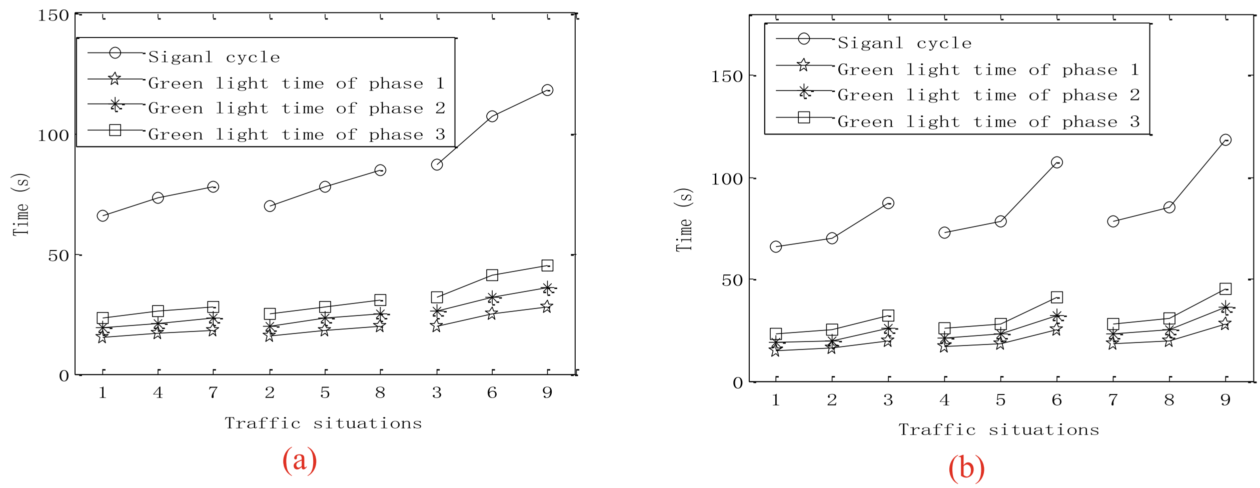

Fig. 2 Comparison of the timing results under different traffic situations. **a** Comparison of the timing results of different road section speeds with the same mixed proportion of electric vehicles. **b** Comparison of the timing results of different mixed proportions of electric vehicles with the same road section speed

vehicle speed (Fig. 3), the vehicle delay corresponding to the optimal timing result of vehicle CO_2 emissions as optimization function will increase, and the stop rate will decrease. When the road section speed remains unchanged, with an increase in the mixed proportion of electric vehicles (Fig. 4), the vehicle delay corresponding to the optimal timing results of vehicle CO_2 emissions will increase, while the stop rate will decrease. Thus, the conclusion can be drawn from the above analysis that the timing parameters of intersections should be optimized from the perspective of minimizing vehicle CO_2 emissions, which essentially achieves a comprehensive consideration of vehicle control delay and stop rate, and with an increase in road section speed and the mixed proportion of electric vehicles, the equilibrium effect of vehicle control delay and stop rate will be more obvious, providing a scientific reference for the comprehensive evaluation of stop rate and delay when conducting multiobjective timing optimization at signalized intersections.

6 Conclusion and discussion

Due to changes in the speed trajectory (complete stop and incomplete stop), the CO_2 emissions generated by vehicles passing through an intersection are increased. In this paper, the CO_2 incremental emissions models of fuel vehicles and electric vehicles are established from the perspective of regression statistics according to the stop rate and control delay of the approach. The statistical model of CO_2 incremental emissions of fuel vehicles and electric vehicles is determined using SPSS statistical software to test different

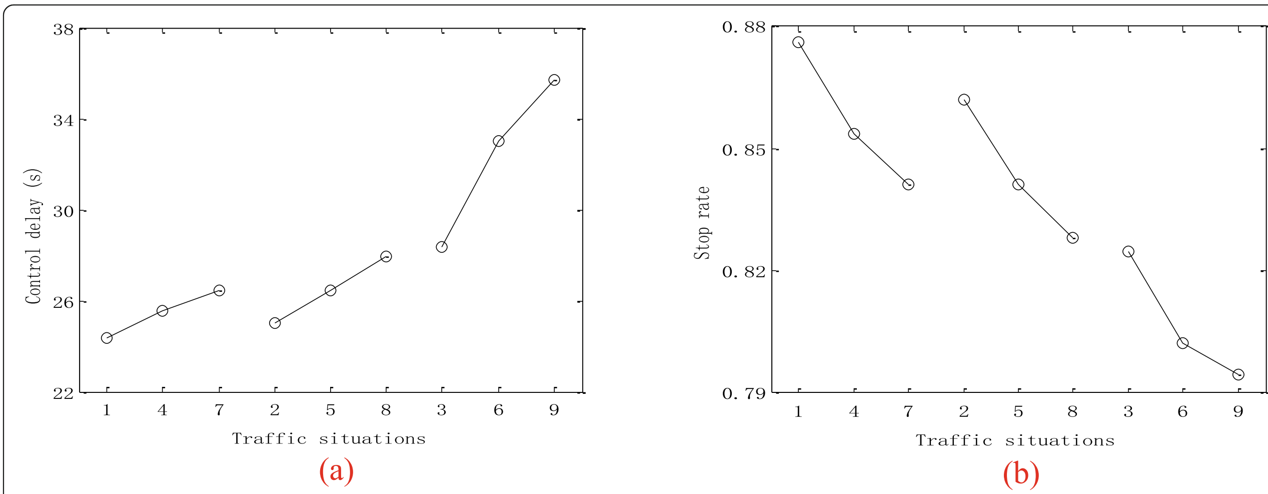

Fig. 3 Comparison of vehicle delays and stop rates at different road section speeds with the same mixed proportion of electric vehicles. **a** Comparison of vehicle delay. **b** Comparison of vehicle stop rate

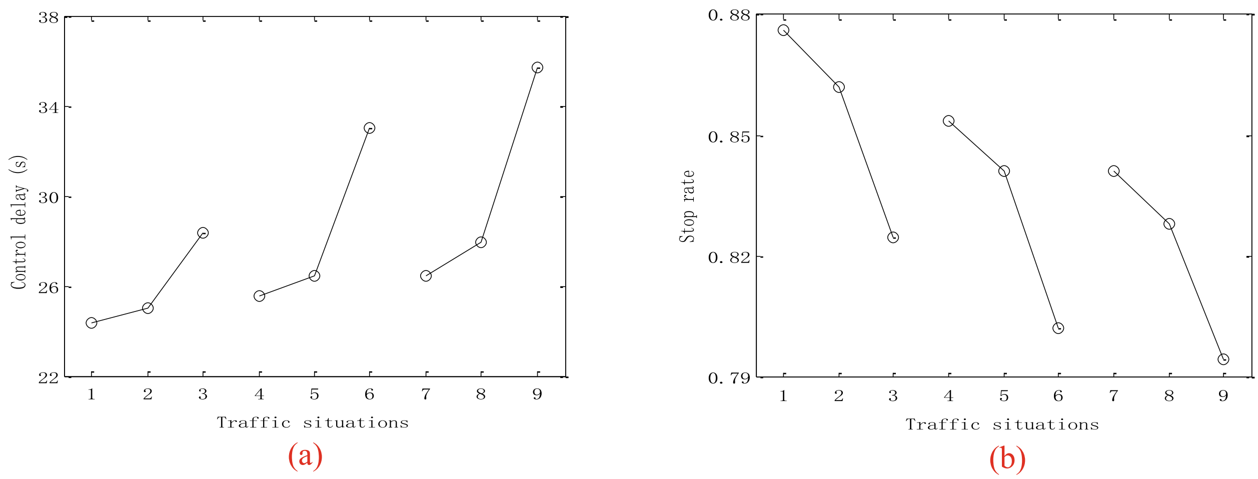

Fig. 4 Comparison of vehicle delays and stop rates of different mixed proportions of electric vehicles with the same road section speed. **a** Comparison of vehicle delay. **b** Comparison of vehicle stop rate

polynomials of the stop rate and control delay, and the adjusted R^2 values of the statistical models of fuel vehicles and electric vehicles are both 0.932. The results show that it is more reasonable to establish the model from the perspective of regression statistics according to the stop rate and control delay. In addition, to render the statistical model established in this paper more generally, the incremental emissions model considering the road section speed is further given. Through SPSS analysis, the adjusted R^2 values of the incremental emission statistical models of fuel vehicles and electric vehicles considering the road section speed are 0.916 and 0.899, respectively. This outcome shows that the estimation accuracy of the statistical model can still be guaranteed under the premise of broadening the application scope of the model.

Based on the CO_2 incremental emissions model proposed in this paper, an intersection signal timing model considering vehicle CO_2 emissions is established. Under the conditions of different road section speeds and a mixed proportion of electric vehicles, the case study shows that the optimization model can solve the optimal timing scheme with the minimum CO_2 incremental emissions according to the different road section speeds and mixed proportions of electric vehicles. It is found that the solution is essentially a comprehensive consideration of vehicle control delay and stop rate, which can effectively balance the CO_2 emissions generated during the acceleration, deceleration and idling stages. The analysis results also show that the vehicle CO_2 incremental emissions, control delay and stop rate cannot be guaranteed to be optimal simultaneously, nor can the time optimization for signal intersections from the perspective of CO_2 incremental emissions, which is essentially comprehensive consideration of vehicle control delay and stop rate under different traffic conditions.

In this paper, the CO_2 incremental emissions model of vehicles at an intersection approach is established from the perspective of regression statistics, and the signal timing analysis of intersections is realized based on this model. The research results of this paper can provide a good idea for the estimation of vehicle emissions at intersections and on urban road networks and can also provide a certain reference for the optimization of urban traffic control. However, this paper establishes the model based on simulation data. Although this method can fully cover vehicle emissions under different traffic conditions, the simulation results cannot fully describe actual traffic phenomena. In future work, we will gradually collect the CO_2 emissions data of vehicles at signalized intersections and perfect the incremental emissions model proposed in this paper. Additionally, we will continue to analyze the timing optimization methods of a single intersection, coordinated control of the main lines of communication and regional collaborative control from the point of view of reducing vehicle CO_2 emissions. In addition, with the development of intelligent transportation systems and autopilot technology, vehicles with different cruise control modes will become increasingly popular. The impact on vehicle CO_2 emissions when a vehicle passes through an intersection in different driving modes deserves further study. In the future, we will also analyze the CO_2 emissions generated by vehicles with different control modes passing through intersections and constantly improve the vehicle CO_2 incremental emissions model based on the analysis results so that the research results of this paper are more reasonable and applicable.

7 Appendix

Table 3 Average emissions rates of CO_2 of fuel vehicles in different specific power bins

Specific power bin ($kW \cdot ton^{-1}$)	Emissions rate ($g \cdot s^{-1}$)	Specific power bin ($kW \cdot ton^{-1}$)	Emissions rate ($g \cdot s^{-1}$)	Specific power bin ($kW \cdot ton^{-1}$)	Emissions rate ($g \cdot s^{-1}$)
$VSP < -2$	1.543686	$7 \le VSP < 10$	3.957732	$23 \le VSP < 28$	7.065985
$-2 \le VSP < 0$	1.604406	$10 \le VSP < 13$	4.752012	$28 \le VSP < 33$	7.617703
$0 \le VSP < 1$	1.130833	$13 \le VSP < 16$	5.374221	$33 \le VSP < 39$	8.322442
$1 \le VSP < 4$	2.386260	$16 \le VSP < 19$	5.940051	$39 \le VSP$	8.475028
$4 \le VSP < 7$	3.210249	$19 \le VSP < 23$	6.427506	–	

Table 4 Relevant parameters for the simulation of electric vehicle emissions

Parameters	Symbols	Values	Parameters	Symbols	Values
Vehicle mass	m	1400 kg	Air density	ρ_a	1.207 kg/m^3
Coefficient of rolling resistance	C_R	0.0135	Mass factor	ε_i	0.1
Acceleration of gravity	g	9.81 m/s^2	Energy efficiency of the vehicle power system	η_{pow}	0.78
Road gradient	α	0^0	Power of vehicle auxiliary components	P_0	750 W
Aerodynamic drag coefficient	C_D	0.35	Charging efficiency of electric vehicle	η_{gb}	0.97
Frontal area of the vehicle	A	1.91 m^2	CO_2 emissions factor of power grid	Eer^{CO_2}	452.867 g/kWh

Table 5 Simulation conditions in the process of data acquisition

Relevant indices	Change range and step length	Setting remarks
Vehicle arrival rates	Change range: 250 pcu/h-750 pcu/h; Step length: 10 pcu/h.	(1) Under-saturated intersection is considered the research object. (2) Vehicle arrival rates in the range of 250–750 pcu/h can cover most of the variation range of vehicle arrival rates at urban intersections. (3) Signal cycle in the range of 30–200 s can cover most of the variation range of signal cycles at urban intersections. (4) Small simulation step length can cover almost all traffic situations; a large number of simulation data can ensure the accuracy of the model.
Signal cycle	Change range: 30 s–200 s; Step length: 5 s.	
Green signal ratio	Upper bound: 0.8; Lower bound: determined according to saturation of the intersection approach less than 0.9; Step length: 0.05.	

Table 6 Regression coefficient of the statistical model of CO_2 incremental emissions of fuel vehicles and electric vehicles

Fuel vehicle				Electric vehicle			
Parameters	**Values (*P*-value)**	**Parameters**	**Values (*P*-value)**	**Parameters**	**Values (*P*-value)**	**Parameters**	**Values (*P*-value)**
$l_{0,0}$	1.3893E+ 01 (0.000)	$l_{2,0}$	1.8799E+ 02 (0.000)	$l_{0,0}$	2.3652E+ 00 (0.000)	$l_{2,0}$	2.4473E+ 01 (0.000)
$l_{0,1}$	1.2201E+ 00 (0.000)	$l_{2,1}$	–	$l_{0,1}$	-1.2291E-01 (0.000)	$l_{2,1}$	1.1269E-01 (0.000)
$l_{0,2}$	2.7522E-02 (0.000)	$l_{2,2}$	–	$l_{0,2}$	9.0985E-03 (0.000)	$l_{2,2}$	–
$l_{0,3}$	−4.3807E-04 (0.000)	$l_{2,3}$	5.5512E-04 (0.000)	$l_{0,3}$	−3.0337E-05 (0.000)	$l_{2,3}$	–
$l_{1,0}$	−7.1173E+ 01 (0.000)	$l_{3,0}$	−8.8988E+ 01 (0.000)	$l_{1,0}$	−1.3992E+ 00 (0.000)	$l_{3,0}$	−1.5379E+ 01 (0.034)
$l_{1,1}$	−1.9095E+ 00 (0.000)	$l_{3,1}$	4.2620E-01 (0.000)	$l_{1,1}$	–	$l_{3,1}$	–
$l_{1,2}$	–	$l_{3,2}$	–	$l_{1,2}$	−8.5649E-03 (0.000)	$l_{3,2}$	1.1612E-03 (0.000)
$l_{1,3}$	–	$l_{3,3}$	−2.6285E-04 (0.000)	$l_{1,3}$	–	$l_{3,3}$	2.3111E-05 (0.000)

"-" means that the corresponding polynomial is not involved in the interpretation of the model

Table 7 Regression coefficient of the statistical model considering road section speed

Fuel vehicle				Electric vehicle			
Parameters	**Values (*P*-value)**	**Parameters**	**Values (*P*-value)**	**Parameters**	**Values (*P*-value)**	**Parameters**	**Values (*P*-value)**
$l_{0,0,0}$	5.2868E+ 00 (0.000)	$l_{1,0,0}$	1.2414E+ 00 (0.000)	$l_{0,0,0}$	2.9775E+ 00 (0.000)	$l_{1,0,0}$	–
$l_{0,0,1}$	7.2794E-01 (0.000)	$l_{1,0,1}$	–	$l_{0,0,1}$	5.0576E-01 (0.000)	$l_{1,0,1}$	−7.3529E-02 (0.000)
$l_{0,0,2}$	–	$l_{1,0,2}$	5.3589E-03 (0.000)	$l_{0,0,2}$	–	$l_{1,0,2}$	1.3056E-03 (0.000)
$l_{0,0,3}$	–	$l_{1,0,3}$	−4.4353E-05 (0.000)	$l_{0,0,3}$	−2.4177E-05 (0.000)	$l_{1,0,3}$	–
$l_{0,1,0}$	−4.3139E+ 01 (0.000)	$l_{1,1,0}$	−4.7234E+ 00 (0.000)	$l_{0,1,0}$	−2.8401E+ 01 (0.000)	$l_{1,1,0}$	2.4590E+ 00 (0.000)
$l_{0,1,1}$	3.4846E+ 00 (0.000)	$l_{1,1,1}$	−4.7815E-01 (0.000)	$l_{0,1,1}$	–	$l_{1,1,1}$	1.2375E-02 (0.000)
$l_{0,1,2}$	−6.2582E-02 (0.000)	$l_{1,1,2}$	–	$l_{0,1,2}$	−8.3109E-03 (0.000)	$l_{1,1,2}$	−3.9900E-04 (0.000)
$l_{0,1,3}$	4.0231E-04 (0.000)	$l_{1,1,3}$	–	$l_{0,1,3}$	–	$l_{1,1,3}$	−9.1665E-06 (0.000)
$l_{0,2,0}$	−2.0361E+ 01 (0.000)	$l_{1,2,0}$	2.5328E+ 01 (0.000)	$l_{0,2,0}$	2.8214E+ 01 (0.000)	$l_{1,2,0}$	1.8262E-01 (0.004)
$l_{0,2,1}$	–	$l_{1,2,1}$	–	$l_{0,2,1}$	–	$l_{1,2,1}$	–
$l_{0,2,2}$	–	$l_{1,2,2}$	2.9694E-03 (0.000)	$l_{0,2,2}$	–	$l_{1,2,2}$	–
$l_{0,2,3}$	–	$l_{1,2,3}$	–	$l_{0,2,3}$	7.3183E-05 (0.000)	$l_{1,2,3}$	4.2764E-06 (0.000)
$l_{0,3,0}$	–	$l_{1,3,0}$	−1.2805E+ 01 (0.000)	$l_{0,3,0}$	−1.3939E+ 01 (0.000)	$l_{1,3,0}$	−5.7155E-01 (0.000)
$l_{0,3,1}$	1.7337E-01 (0.002)	$l_{1,3,1}$	8.9991E-02 (0.000)	$l_{0,3,1}$	1.3060E-01 (0.000)	$l_{1,3,1}$	–
$l_{0,3,2}$	–	$l_{1,3,2}$	−1.0256E-03 (0.000)	$l_{0,3,2}$	–	$l_{1,3,2}$	–
$l_{0,3,3}$	–	$l_{1,3,3}$	–	$l_{0,3,3}$	–	$l_{1,3,3}$	–

"-" indicates that the corresponding polynomial is not involved in the interpretation of the model

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Authors' contributions
The author Hongxing Zhao establish different models and optimized the signal timing of intersection and drafted the original manuscript. Ruichun He supervised the manuscript. Na Yin put forward some positive suggestions and polish writing make the paper more perfect. The author(s) read and approved the final manuscript.

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