Evaluating the Impact of Signal Control
on Emissions at Intersections

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Abstract. Transport emission has become an increasingly serious problem, and it is an urgent issue in sustainable transport. In this study, by constructing traffic emission models for different vehicle types and operating conditions, the changes in CO, HC, and NOx emissions of light-duty and heavy-duty vehicles before and after signal control optimization were quantified based on VISSIM simulation. The OBEAS-3000 vehicle emission testing device was used to collect data on the micro-operational characteristics of different vehicles under different operating conditions as well as traffic emission data. Based on the data collected, the VSP (Vehicle Specific Power) model combined with the VISSIM traffic simulation platform was used to calculate the emissions of light and heavy vehicles in the mixed traffic flow before and after intersection signal optimization. It is known from the study that signal control optimization has a greater impact on heavy vehicles than on light vehicles. Emissions of CO, HC, and NOx from heavy vehicles and light vehicles are all reduced, but NOx emissions from light vehicles remain largely unchanged. The research results reveal the emission patterns of light and heavy vehicles in different micro-operating conditions and establish a traffic emission model. It provides a theoretical basis for accurate traffic emission analysis and traffic flow optimization, as well as a scientific basis for the formulation of traffic management measures and emission reduction in large city transport systems.

Keywords: Mixed traffic flow · Instantaneous emissions · Traffic simulation

1 Introduction

In recent years, vehicle ownership in Chinese major cities has increased year by year, it brings convenience to transportation but also causes numerous urban problems, especially urban air pollution caused by traffic emissions [1, 2], and pollutants from traffic emissions have become one of the main sources of urban pollutants [3]. Global environmental problems are becoming increasingly serious, and with the increase of motor vehicles, traffic emissions are one of the "main culprits" [4]. According to the proportion of pollutants emitted by air pollution sources published by the Chinese Environmental

Protection Administration, motor vehicle emissions account for 20%–30% of air pollution, and in some cities even reach 30%–50%, urban air pollution is gradually transforming from "soot type" to "tailpipe type" [5, 6]. Excessive emissions of pollutants from transport have already had a serious negative impact on air quality, public health and climate [7]. Vehicles account for 87.7% of traffic emissions of CO, 84.1% of HC and 92.5% of NOx [8]. Vehicle fuel consumption in peak hours increases by an average of 10%, CO, HC, and NOx emissions in-crease by 20% compared to off-peak hours [9].

In mixed urban traffic flows, especially where heavy vehicles account for a certain proportion, the high density of vehicles and the many interweaving points result in high traffic emissions, which not only endanger the urban living environment but also cause incalculable economic losses [10–13]. Traffic emissions have become one of the most important problems facing cities [14]. Urban managers need management measures and instruments that can effectively reduce traffic emissions. This requires accurate analysis and modeling of motor vehicle emission patterns [15]. This study aims to analyze the emission patterns of light and heavy vehicles, a traffic emission model for different vehicle types and operating conditions is construct-ed. On this basis, the emission ratios of different vehicle types in mixed traffic flows are quantified by building traffic simulations.

2 Literature Review

Traffic signals have come a long way since traffic signal control was first introduced to prevent traffic accidents. Kerosene-lit traffic lights were first used as traffic signals in London's Westmeath district in 1868 [16]. The hand-controlled three-colored traffic signal (red, green, and yellow) was first used in 1925 in Piccadilly Street, London, England [17], the yellow light was placed before the appearance of the red light as a preparatory signal for drivers to stop. The advent of intersection signals has improved the transport efficiency of traffic systems, and typically traffic signals operate in three modes: fixed signal timing, prior and adaptive control [18, 19].

In the early stages of traffic signal development, researchers developed methods to determine fixed signal timings assuming that the traffic flow from each intersection remained constant [20], which did not take into account the uncertainty of traffic flow and has lost its relevance in the contemporary traffic climate [21]. From the recognition of the uncertainty of traffic, a great deal of research work has been de-voted to improving the analysis of delay models and the development of computer software [22].

In previous studies, scholars have focused more on optimizing signal timing in terms of vehicle queue lengths, stopping times, and vehicle delays at intersections [23]. But there is no focus on the transport environment. As traffic pollution has become more serious, researchers have not only limited research to solving the problems of time and delays, but more and more studies are linking signal control and traffic emissions. Scientific signal control can be effective in reducing traffic emissions. As early as 1981, Gipps et al. [24] assumed the speed and acceleration of following vehicles based on the desired braking that each driver sets for himself under intersection signal control, the traffic prevalence was assessed to have an impact on traffic emissions. Zhang et al. [25] investigated the relationship between vehicle emissions and simulated operating conditions,

traffic emissions were measured by superimposing vehicle emissions under different simulated operating conditions (queuing and waiting at intersections, the proportion of accelerating vehicles, the proportion of decelerating vehicles, etc.) for vehicles at signalized intersections. Meszaros [26] gave traffic flow parameters, such as the concentration of traffic flow and the overall speed of traffic flow, based on real traffic data from the investigated intersections. Not only intersections but also the whole road network were calculated the emissions of CO2, CO, CH, NOx.

In mixed traffic flows, particularly with a proportion of heavy vehicles, it is unclear whether optimizing traffic signal control will achieve emission reductions. Most of the existing studies have been conducted for single traffic flow situations, while less research has been conducted on mixed traffic flows, and the changes in vehicle emissions under different operating conditions have not been considered. This study summarises research and makes a quantitative study of emissions from mixed traffic flows in intersections, and compared the effects of signal control optimization on light and heavy vehicles, and analyzed the changes in CO, HC, and NOx emissions before and after signal optimization.

3 Methods

3.1 VSP Model

In order to obtain more accurate vehicle emission factors and build a detection system for traffic emissions, this study made use of the vehicle driving data obtained by the testing equipment in the urban road. The distribution pattern of motor vehicle emissions was different under different operating conditions of the vehicle. To unify the calibrated traffic emission model and improve the accuracy of traffic emission calculation, this study uniformly adopted VSP distribute intervals to study the emission factors of vehicles. VSP is the instantaneous power per unit mass of the vehicle in kW/t, and the transient emissions of the vehicle are closely related to the VSP value [27]. The formula VSP of is:

$$VSP = v \times (a + g \times grade(\%) + g \cdot C_R) + \frac{1}{2} \cdot \rho_\alpha \cdot \frac{C_D}{m} \cdot A \cdot v^3 \qquad (1)$$

where v is the instantaneous speed, m/s; a is the instantaneous acceleration, m/s^2; g is the acceleration of gravity, m/s^2; $grade$ is the road gradient, %; C_R is the rolling resistance coefficient; ρa is the air ambient density; C_D is the air resistance coefficient, m^2; m is the total vehicle mass, kg.

Wyatt [28] provided detailed values on VSP modeling based on the data taken for each relevant parameter of the light vehicle. The VSP values are related to speed and acceleration and it can be expressed in Eq. (2).

$$VSP = v \times (1.1a + g \times grade + 0.132) + 0.000302v^3 \qquad (2)$$

The VSP formula is not uniform because of the large variability in the values taken for each parameter of heavy vehicle [29]. This study simplified the VSP calculation formula

for heavy vehicles using vehicle weight, front-end cross-section, and other parameters to obtain.

$$VSP = v \times (a + g \times grade + 0.09199) + 0.000169v^3 \tag{3}$$

In the formula, the vehicle speed and acceleration are real-time data of the vehicle, the road gradient is 0 and the gravitational acceleration is 9.81 m/s^2.

By making full use of real-time vehicle operating data to accurately quantify the instantaneous emission rate based on VSP, we divided the VSP value by a step of 1 kW/t to generate the BIN partition.

$$\forall VSP \in VSP_{\text{BIN}_i} = \begin{cases} (-\infty, -30] \\ [n-1, n), n = (-29, 29], n \in Z \\ [30, +\infty) \end{cases} \tag{4}$$

3.2 Mixed Traffic Flow VSP

Based on the real-time speed and acceleration recorded by the instrument, the corresponding instantaneous motor vehicle emissions detected by the OBEAS-3000 system are simultaneous. The system can relate instantaneous emission rates to VSP values by averaging multiple instantaneous emission values for the same VSP interval. The mean value of the instantaneous emissions in each interval of the VSP is obtained. These results construct a relationship between light and heavy vehicle VSP intervals and vehicle proportions.

Table 1. Proportion of light and heavy vehicles in different VSP intervals

VSP intervals (kW/t)	Proportion of light vehicles	Proportion of heavy vehicles
[−5, 5]	60.31%	50.26%
[−10, 10]	67.93%	65.37%
[−15, 15]	75.20%	80.11%
[−20, 20]	88.46%	90.62%
[−25, 25]	94.28%	95.81%
[−30, 30]	97.33%	98.45%

4 Case Study and Results

4.1 VISSIM Simulation

In this study, the intersection of Caoan Highway North Jiasong Road in Shanghai was selected as the research object. The traffic volume in VISSIM was input according to

the traffic volume of the intersection in the field survey, and the road network was built according to the actual construction of the intersection in the original scenario of the simulation. The VISSIM simulation platform was built based on field research. The road network structure was divided into two parts: road sections and connectors. In the process of constructing road sections, the length of the road section coverage in the simulation was 500m in order to facilitate subsequent lanes and to ensure smooth vehicle operation before entering the intersection in VISSIM, it could reduce vehicle operation errors. The running screen is shown in Fig. 1.
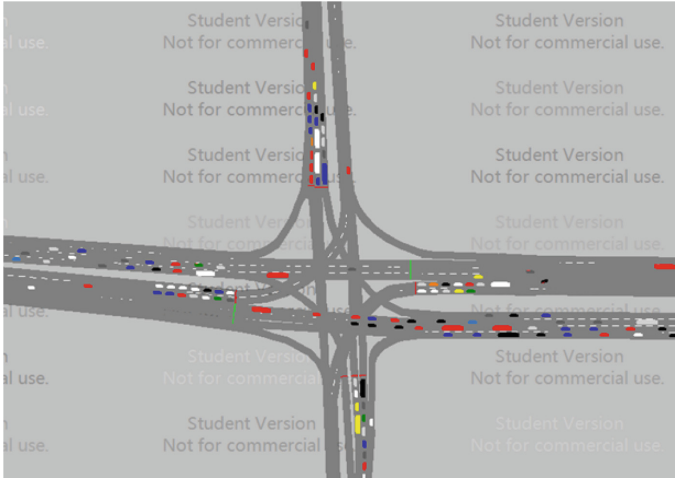

Fig. 1. Simulation screen

4.2 Signal Timing Optimization

The signal timing cycle at the intersection of Caoan Highway North Jiasong Road is 230 s. The timing of each phase's signal cycle is shown in Table 2, where the yellow light flashes for 3 s and the all-red time is 2 s. In Table 2, 1 is east-west straight ahead, 2 is east-west left turn, 3 is north-south straight ahead, 4 is north-south left turn.

The optimum signal period is 205 s according to the headway of heavy ve-hicles and light vehicles. The left-turn signal timing for the east-west import is 29 s, the straight-ahead signal timing is 41 s, the left-turn signal timing for the north-south import is 45 s, and the straight-ahead signal timing is 69 s.

Table 2. Signal timing diagram before and after optimization by conventional method

	1(S)	2(S)	3(S)	4(S)
Red light before signal optimization	177	187	157	177
Yellow light before signal optimization	3	3	3	3
Green light before signal optimization	50	40	70	50
Red light after signal optimization	173	161	157	133
Yellow light after signal optimization	3	3	3	3
Green light after signal optimization	29	41	45	69

4.3 Emission Calculation

For intersection emissions, the peak hourly emissions of CO, HC and NOx for heavy and light vehicles before and after intersection signal control optimization are shown in Table 3.

Table 3. Emissions of light vehicle and heavy vehicle before and after signal control optimization

	Light vehicles before signal optimization (g/h)	Light vehicles after signal optimization (g/h)	Heavy vehicles before signal optimization (g/h)	Heavy vehicles after signal optimization (g/h)
CO	1208.69	1169.92	3129.98	2713.72
HC	196.62	188.33	425.32	361.03
NOₓ	32.65	32.53	542.88	473.78

By vehicle type, the CO emissions of the light vehicle in the peak hour were 1208.69 g before signal control optimization and 1169.92 g after signal control optimization, a reduction of 3.21%.

HC emissions were 196.62 g in the peak hour for light vehicles and 188.33 g in the peak hour for light vehicles after signal control optimization, a reduction of 4.22%. The NOx emissions from light vehicles in the peak hour were 32.65 g. After signal control optimization, the NOx emissions from light vehicles in the peak hour were 32.53 g, and the NOx emissions remained unchanged.

CO emissions were 3129.98 g for heavy vehicles in the peak hour before signal control optimization, and 2713.72 g for heavy vehicles in the peak hour after signal control optimization, a reduction of 13.30%. HC emissions were 425.32 g in the peak hour for heavy vehicles, and 361.03 g in the peak hour for heavy vehicles after signal control optimization, a reduction of 15.12%. The NOx emissions of heavy vehicles in the peak hour were 542.88 g. After signal control optimization, the NOx emissions of heavy vehicles in the peak hour were 473.78 g, a reduction of 12.73%.

5 Summary

This study analyses the impact of intersection signals on traffic emissions, and signal control optimization of intersections is carried out based on vehicle conversion factors. VISSIM simulation is used for data collection of vehicle operating conditions to analyse traffic emissions at intersections. The results of their research are as follows.

(1) After signal control optimization, emissions from both heavy and light vehicles in the intersection are reduced, and the effect on emissions from heavy vehicles is more significant than those from light vehicles.
(2) After signal control optimization, the emissions of CO, HC, and NOx of heavy vehicles are reduced, as well as CO and HC of light vehicles, but NOx emissions of light vehicles remained unchanged.

This study quantifies the changes in CO, HC, and NOx emissions from light and heavy vehicles before and after signal control optimization. It can quantify the emission patterns of vehicles under traffic control, providing a theoretical basis for the development of measures to reduce traffic emissions.

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