

STUDY ON THE ENVIRONMENTAL BENEFITS OF TRUCK PARKING SPACE FOR TRUCKS WAITING TO ENTER FREIGHT TERMINAL - A CASE STUDY OF GANGCHEN LOGISTICS PARK

Zhongning FU¹, Yunzhu YAN², Jintian YUE³

^{1,2,3} School of Traffic and Transportation, Lanzhou Jiaotong University, Lanzhou, China

Abstract:

The gathering effect of trucks at freight terminals and the high emission characteristics of trucks themselves lead to long-term truck queues and serious environmental pollution problems at freight terminals. Repeated stopping and following trucks aggravate the environmental pollution in the terminal. This paper proposes a scheme to plan truck parking spaces during waiting for trucks to enter the freight terminal in order to reduce the repeated stopping of trucks and to quantify the environmental benefits of truck parking spaces in the process. The truck admission process was simulated using the Visual Simulator (VISSIM). The simulation output provided vehicle operating data that was converted into operating mode distribution data using the Python calculation module. Then, the model parameters, including the operating mode distribution, were entered into the Motor Vehicle Emission Simulator (MOVES) to calculate the simulation scenario. Gangchen Logistics Park, for example, statistics of the park's 10 months of freight data, the design of freight volume gradually increased by 11 groups of admission simulation experiments, the simulation learned that the park queuing significant, more than 90% probability of queuing, queuing up to a maximum of 203 vehicles, the average queue of 61 vehicles. Then according to the actual road conditions in the park, add a parking lot in the VISSIM simulation. Signal sensing is realized by calling the COM interface of VISSIM through Python to guide the vehicles to park in order and enter the park. Eleven sets of simulation control experiments after designing and planning parking spaces are designed to calculate the pollutant emissions for each simulation scenario separately. The analysis of the emission measurement results shows that the emissions of CO, HC, NO_x, and PM10 can be reduced by 1.90%, 7.90%, 9.42%, and 10.55% at the average level of the park's cargo volume. At the park's maximum cargo volume, it is possible to reduce HC, NO_x, and PM10 emissions by about one-third. Truck parking space in the truck waiting to drive into the freight terminal process has obvious environmental benefits, queuing significant freight terminals should be reasonably planned truck parking spaces to reduce the freight terminal exhaust emissions pollution.

Keywords: freight terminal, truck parking space, exhaust emissions, VISSIM and MOVES

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Contact:

1) fuzhongning@163.com [<https://orcid.org/0009-0006-4479-5986>], 2) yx196yyz@163.com [<https://orcid.org/0009-0009-4823-3624>] – corresponding author, 3) 478743104@qq.com [<https://orcid.org/0009-0004-4511-2687>]

1. Introduction

China is facing a serious problem with road mobile source emissions, which are causing pollution from fine particulate matter and photochemical smog. This has become a major source of air pollution in large and medium-sized cities, making it essential to prevent and control road mobile source emissions urgently.

The State has been giving great importance to the prevention and control of motor vehicle pollution. It has been promoting the control of pollution from various types of motor vehicles by integrating "oil, road, vehicle, and enterprise." The aim is to improve the pollution prevention and control level of newly-produced motor vehicles and the quality of automotive oil, standardize the emission inspection mechanism of in-use motor vehicles, and establish a perfect system of pollution control of mobile sources. Trucks are an important component of motor vehicles and are responsible for production and transportation roles. However, the environmental pollution caused by their transportation operations should not be underestimated. According to the Ministry of Ecology and Environment of the People's Republic of China's statistics in 2021, the total emissions of CO, HC, NO_x, and PM₁₀ from trucks nationwide were 2,062,000 tons, 516,000 tons, 4,807,000 tons, and 58,000 tons, respectively. These accounted for 29.7%, 28.4%, 84.6%, and 91.1% of the total emissions from vehicles.

Truck exhaust emissions can be divided into normal road traveling emissions and key node emissions from the driving status of vehicles. The key nodes are mainly intersections and freight terminals. Currently, research focuses on the emission of normal road traveling and intersection, and less on the emission of freight terminals. The gathering effect of the freight terminal on the goods leads to the queuing of transport vehicles in the freight terminal, which leads to traffic congestion on the entrance road. Road traffic congestion is the main cause of environmental pollution (Bebkiewicz K., et al. 2021). The solution to the problem of pollution from trucks queuing at freight terminals will be an important breakthrough point in the prevention and control of pollution from road mobile sources.

When trucks queue in the process of entering the freight terminal, the engine fuel is not sufficient, and the release of exhaust also increases (Xu T., et al. 2023). The setup of truck parking spaces can change

the queuing and following state of trucks, effectively reducing the number of vehicle starts and stops, or reducing the exhaust emissions of trucks in freight terminal. This paper aims to find a way to accurately measure the total amount of emissions from trucks entering freight terminals and quantify the environmental performance of truck parking spaces. This will test the necessity of truck parking spaces, and if it can effectively reduce the total amount of emissions, then truck parking spaces should be planned in freight terminals.

2. Literature review

The main measurement methods for motor vehicle exhaust are the real measurement method and the emission modeling measurement method. The actual measurement method includes whole vehicle road test, chassis dynamometer test and bench test, which is a simple, reliable, convenient and intuitive testing method (Xia J., et al. 2023). Li T., et al. (2021) installed sensors or monitoring equipment on the whole vehicle and used the emission test system to launch emission measurement experiments on buses, and analyzed the effects of the load and air conditioning of buses on emissions. Madziel M., et al. (2022) measured the emissions of different fuel vehicles at an intersection in Rzeszow (Poland) by installing a Portable Emission Measurement System (PEMS) in the test vehicle. Yang C., et al. (2021) conducted an experimental comparison of actual and simulated conditions on a green sprinkler and a chassis dynamometer to test the accuracy of using a chassis dynamometer to test emission characteristics. Wang Q., et al. (2022) conducted experiments on heavy-duty vehicles and light-duty vehicles with different emission standards using bench measuring instruments to explore the effects of different working conditions, road conditions and vehicle weight on CO₂ emissions.

A large number of trucks are assembled in the freight terminal, and it is difficult and not easy to measure the total amount of emissions from the process of trucks entering the freight terminal by using the actual measurement method, and it is more feasible to measure the tailpipe emissions of the process by using the emission model.

Motor vehicle emission models can be divided into those based on average speed and those based on driving conditions (Liu Y. 2022). Average speed-based emission models characterize pollutant

parameters in terms of the average speed of the fleet, and mostly take into account the effects of the motor vehicle's mileage, driving speed, and fuel on emissions (Zhang L., et al. 2017). For example, LEJRI D., et al. (2018) and Andrych-Zalewska M., et al. (2023) used the COPERT model to calculate NO_x emissions at the city scale and analyzed the sensitivity of average speed to emissions. Emission models based on driving conditions are used to estimate pollutant emissions by analyzing different operating mode during the complete driving process of a motor vehicle, including emission models based on specific power, emission models based on physical significance, and emission models based on speed-acceleration (Li Z. 2020). For example, Kim M., et al. (2020) used the MOVES model based on the distribution of specific metric power to study the environmental benefits of traffic signal red light countdown. Noriega M., et al. (2023) similarly used the MOVES model to analyze and compare the differences in motor vehicle tailpipe emissions for each pollutant across fuel types. Abdelmegeed M., et al. (2017) used the velocity-acceleration based CMEM model to measure the emissions of heavy-duty diesel vehicles.

Emission models based on specific power distribution, which can reflect diverse actual traffic flow states and patterns, have been widely used in recent years for the measurement of truck emissions (Shan X., et al. 2021). Motor vehicle specific power distribution refers to the proportion of operating time of motor vehicles in each specific power interval, which represents the power required by vehicles in a specific operating mode (Zhang S., et al. 2017). The methods of obtaining about the specific power distribution are as follows.

Huang Y., et al. (2023) constructed the actual specific power distribution based on the trajectory data of trucks with different vehicle weights in Beijing. Song G., et al. (2021) constructed the specific power distribution of motor vehicles based on each average speed. Jia X., et al. (2022) simplified the specific power distribution based on the speed prediction model. Yue Y., et al. (2013) used the approach of substituting the instantaneous speed of vehicle traveling by GPS real measurement into the specific power calculation formula. In addition, more scholars use the simulation output of the vehicle instantaneous speed instead of the actual vehicle speed and substitute it into the motor vehicle specific power

calculation formula to get the specific power distribution. For example, Hu M., et al. (2021) build a set of comprehensive simulation system based on the driving behavior of self-driving vehicles, and calculate the vehicle emissions based on the specific power distribution through the simulation results. Li J. (2022) used the traffic simulation software VISSIM to simulate vehicles at a single-point timed signal-controlled intersection, and microscopic simulation analysis was carried out through vehicle simulation and emission simulation software.

The cost of directly collecting truck trajectory data is too high, and the application of VISSIM to simulate the driving conditions of vehicles has been very extensive (Sun L., et al. 2021 & Zhang H., et al. 2024). And the MOVES model is localized with high computational accuracy, and many scholars have verified that its computational results have good consistency with the actual measurement results (Shan X., et al. 2021). Therefore, this paper adopts the approach of combining a traffic simulation model (VISSIM) with an emissions model (MOVES) to measure the emissions of entering trucks under different levels of freight transportation at freight terminals. The key to model integration is to design a data conversion method to realize the conversion of vehicle operating data to speed parameters (operating condition distribution) of the MOVES model. The approach to measuring emissions from trucks is shown in Fig. 1.

3. Vehicle Specific Power and Operating Mode

3.1.1. Vehicle Specific Power

Vehicle specific power (VSP) is an important parameter with rich physical meaning and good statistical correlation with motor vehicle emissions and motor vehicle fuel consumption calculations, which is widely used in the research of modeling emission factors and other aspects of modeling (Zhong, H., et al. 2023). VSP is defined as the instantaneous output power per unit mass of a motor vehicle, which refers to the power output of the engine per ton of mass moved (including self-weight) in kW/t. It represents the power output required by the engine to overcome the rotational resistance of the wheels, the work done by the aerodynamic resistance, as well as the kinetic and potential energies of the motor vehicle, and the power of the mechanical loss of the drivetrain due to the resistance of internal friction (Wang W., et al. 2023).

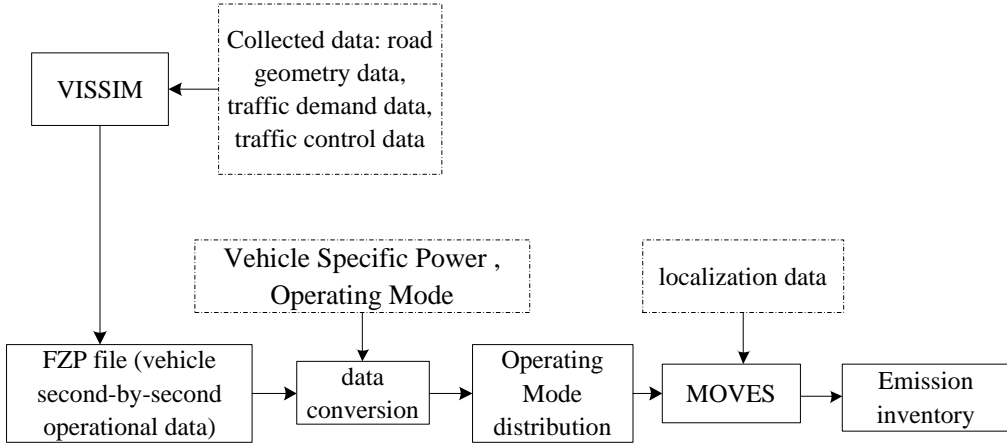


Fig.1. Measurement of truck emissions

3.1.2. Truck specific power

The calculation of specific power for trucks refers to the simplified formula for specific power for heavy-duty vehicles (vehicle weight $\geq 3.5t$) given by the U.S. EPA in the MOVES model as follows (Chen J. 2022):

$$VSP = \frac{1}{f_{scale}} [Mv(a + g * \sin \theta) + Av + Bv^2 + Cv^3] \quad (1)$$

Where: f_{scale} is fixed quality factor; M is motor vehicle mass (tons); v is instantaneous speed (m/s); a is Instantaneous vehicle acceleration (m/s²); g is gravitational acceleration (m/s²); $\sin \theta$ is road gradient; A is rolling resistance coefficient; B is coefficient of resistance to rotation; C is aerodynamic drag coefficient.

For all heavy-duty vehicles, equation (1) B takes the value of 0, and the value of 17.1, A and C take the value according to the weight interval of the vehicle, and the specific assignments are shown in Table 1 (Yu J., et al. 2020).

3.1.3. Classification of Operating Mode

Vehicle operating mode, i.e. vehicle driving mode, refer to the working conditions during transportation driving, mainly acceleration, deceleration, idling, cruising and other operating modes. As an important speed parameter of MOVES, the distribution of operating modes describes the proportion of each

operating mode interval in the whole emission detection process, and the MOVES model reasonably divides the vehicle operating modes into 23 intervals according to the specific power of the motor vehicle and the instantaneous speed. The operating modes are divided as shown in Table 2.

4. Truck Emissions Measurement and Analysis

4.1.1. Queuing Entry Vehicle Simulation Design

4.1.2. Model parameters

Model parameters are configuration variables inside the model, which are the main components of the model, generally with default parameter values, the user can be set according to the needs of the parameters in the VISSIM simulation software mainly include road conditions, traffic conditions and driving behavior of three types.

(1) Road conditions

Road conditions include the length of the road section, the direction of the road section, the number of lanes, the relationship between the lanes, the type of lanes and so on.

(2) Traffic conditions

Traffic conditions include the number of input vehicles, the composition of vehicles, static decision paths, parking paths, the expected speed distribution of different vehicle categories, the maximum acceleration distribution and so on. Where the number of input vehicles is the average traffic flow in units of vehicles/hour, the simulation will generate vehicles with a Poisson distribution parameterized as the average flow.

(3) Driving behavior

Driving behavior includes following model and lateral lane changing behavior.

Following model. The Wiedemann74 and Wiedemann99 following model is a built-in VISSIM model based on the physiology and psychology of the driver. When the driver feels that the distance between him and the vehicle in front of him is less than his psychologically safe distance, he starts to decelerate; when the distance between him and the vehicle in front of him is greater than his psychologically safe distance, the driver behind him will accelerate slightly again. This leads to a reciprocal process of deceleration and acceleration.

Lateral lane changing behavior. VISSIM mainly simulates two types of lane changing behaviors: mandatory lane changing and free lane changing. Mandatory lane change is due to the vehicle currently traveling in front of the lane accidents, obstacles, lane use restrictions, or due to the vehicle into and out of the intertwined section (on-ramp, intersection) and must change lanes. Free lane change is to change lanes when the vehicle encounters the same lane ahead of the slower vehicles in order to pursue faster speeds, more free space for driving and lane change behavior occurs.

Table 1. Assignment of coefficients

Vehicle Weight Range (tone)	A	C
[3.5 , 8)	0.4938	0.001475
[8 , 13)	0.7522	0.001950
[13 , 18)	1.0242	0.002450
[18 , 24)	1.3234	0.003000
[24 , +∞]	1.4866	0.003300

Table 2. Classification of operating mode

Operating Mode ID	Operating Mode Name	VSP (kW/t)		Speed (km/h)	
		Lower	Upper	Lower	Upper
0	Braking			0	0
1	Idling			0	1.6
11	Low Speed Coasting		0	1.6	40.2
12	Cruise/Acceleration	0	3	1.6	40.2
13	Cruise/Acceleration	3	6	1.6	40.2
14	Cruise/Acceleration	6	9	1.6	40.2
15	Cruise/Acceleration	9	12	1.6	40.2
16	Cruise/Acceleration	12		1.6	40.2
21	Moderate Speed Coasting		0	40.2	80.5
22	Cruise/Acceleration	0	3	40.2	80.5
23	Cruise/Acceleration	3	6	40.2	80.5
24	Cruise/Acceleration	6	9	40.2	80.5
25	Cruise/Acceleration	9	12	40.2	80.5
27	Cruise/Acceleration	12	18	40.2	80.5
28	Cruise/Acceleration	18	24	40.2	80.5
29	Cruise/Acceleration	24	30	40.2	80.5
30	Cruise/Acceleration	30		40.2	80.5
33	High Speed Coasting		6	80.5	
35	Cruise/Acceleration	6	12	80.5	
37	Cruise/Acceleration	12	18	80.5	
38	Cruise/Acceleration	18	24	80.5	
39	Cruise/Acceleration	24	30	80.5	
40	Cruise/Acceleration	30		80.5	

4.1.3. Traffic flow control

At different application levels, VISSIM uses the concept of hierarchy to define and provide vehicle information. Vehicle type is a collection of vehicles with similar technical characteristics and driving behavior. Typical vehicle types include car, HGV (Heavy Goods Vehicle), bus, tram (rail transit), bike (bicycle), pedestrian, etc. One or more vehicle types make up a vehicle class. Vehicle speeds, ratings, path selection behavior, and certain other road network elements are specific to the vehicle class. Fixed and pre-set vehicle category that have similar transportation interactions. For example, "rail vehicles" are not allowed to change lanes on a multi-lane roadway and do not oscillate around the desired speed. Each vehicle type is assigned to a vehicle category.

4.1.4. Model calibration

To ensure that the vehicles entering the freight terminal will queue up to enter the yard for loading and unloading operations according to the actual situation, the simulation should avoid vehicle queue-jumping, and at the same time, ensure that the current loading/unloading operation vehicle dwell time is in line with the actual situation. Set the roadway attributes, in the prohibition of lane changing selected restrictions (lanes and vehicle categories), to avoid trucks queuing to enter the process of queuing. Add a stop sign on the road section to stop the current operating truck and set the stopping time

according to the vehicle category to realize the stay of different operating vehicles.

In the calibration of the VISSIM simulation model, the average of multiple simulations is generally used to eliminate random effects, and in this paper, the traffic volume of each type of vehicle is selected as a calibration parameter to calibrate the simulation results, and the model calibration process is shown in Fig. 2.

The calibration adopts the GEH (Geoffrey E. Havers) statistical value method, and the $GEH < 3$ of each type of vehicle is taken to pass the calibration test, and the formula of GEH is as follows (Ma L., et al. 2023):

$$GEH = \sqrt{\frac{(E-V)^2}{(E+V)/2}} \quad (2)$$

Where: E is simulated traffic volume; V is measured traffic volume.

4.2. Operating Mode Distribution Statistics

In the second-by-second vehicle operation data (FZP file) output at the end of the VISSIM simulation, information such as simulation time, vehicle number, vehicle type, speed, acceleration, vehicle weight, etc. can be recorded. Vehicle operation data cannot be used directly for emission modeling of MOVES, and need to be converted into the distribution data of vehicle operation modes on the roadway.

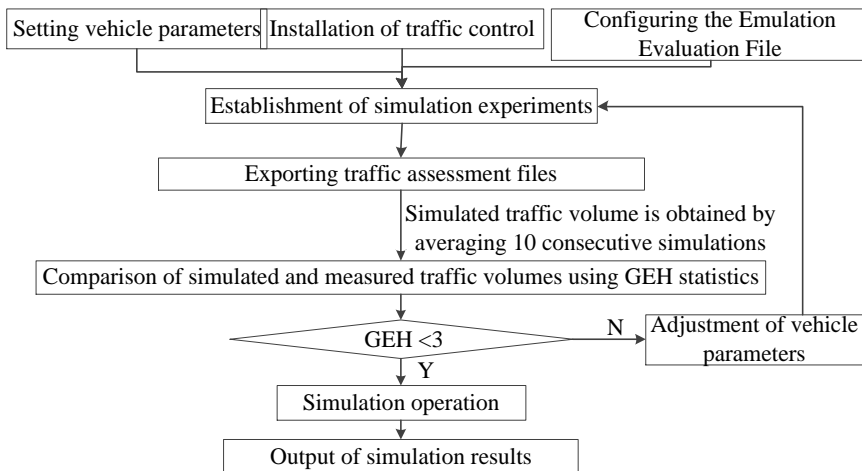


Fig.2. Simulation calibration process

Vehicle operation data in VISSIM is recorded second by second and vehicle by vehicle. If Excel data screening and calculation are used, the data processing workload is huge. Therefore, this paper adopts Python calculation module to realize the calculation of specific power of heavy vehicles, the determination of operating modes and the calculation of the distribution of operating modes. First read the vehicle running track table, according to formula (1) and table 1 to create a function to calculate the specific power. Then the operating mode ID corresponding to each vehicle running data is determined according to the speed and the specific power of the heavy-duty vehicle, and finally the proportion of each operating mode ID can be obtained by initializing a dictionary to store the counts of the operating mode ID values.

4.3. Tailpipe Emission Modeling Application

4.3.1. Modeling Principles

The MOVES model is a method of calculating pollutants from emission sources based on motor vehicle specific power accomplished using the base emission rate as the basic data for emission calculations, and the model calculates emissions using the following equations:

$$TE_{process,source-type} = (\sum ER_{process,bin} \times Ac_{bin}) \times Aj_{process} \quad (2)$$

Where: TE is total emissions; $process$ is emission process; $source-type$ is types of emission sources; bin is emission sources and operating mode; ER is base emission rates; Ac is driving characteristics; Aj is adjustment factors.

The idea of the model to calculate motor vehicle emissions is as follows. Firstly, based on the motor vehicle driving characteristics, all the operating information of the vehicle is assigned to the operating mode. Then the emission characteristics characterized by the base emission rate on the basis of the given emission process and operating mode are combined to calculate the emissions of the specific emission process and operating mode. Finally, the total emissions can be obtained by summing the emissions from all operating modes. The total motor vehicle emissions are also affected by factors such as fuel and temperature, which can be corrected by using an adjustment factor (Cao Y., et al. 2018).

Principle of MOVES calculation is shown in Fig. 3.

4.3.2. Model Construction

The MOVES model is saved as a Run Spec file and constructed by inputting basic model information and importing key parameters. Filling in the navigation panel information is the process of completing the input of the model base information, which determines the scale, time spans, geographic bounds, vehicle/equipment, road type, pollutants and processes, and output under study. The determination of the base information directly affects the parameters required for subsequent data import and is the basis for MOVES data import. After filling in the basic information in the navigation panel, the next step is to provide MOVES with the data to create the input database in the Project Data Manager (PDM). PDM data is inputted in table format, and the accuracy of output results is highly dependent on the quality of data input. MOVES requires data input to represent the location, time, and status of the modeled fleet. The MOVES model needs information about the fleet being analyzed, such as its location, timing, and characteristics, to calculate its total emissions. For the accuracy of the model output results, it is necessary to localize the model and create a localized database by entering local parameter data in the imported data. The main parameters in the imported data include hotelling, I/M programs, operating mode distribution, age distribution, fuel, meteorology data, links, link source types, and off-network.

5. Example Analysis

5.1. Truck Data from Gangchen Logistics Park

This paper takes the Gangchen Logistics Park as a case study. Gangchen Logistics Park located in Ma'anshan City, Anhui Province, is a steel storage and trading as the main business highway freight terminal. The park plays the role of transit transportation between steel production factories and customers. After the steel is produced from the production line, it is transported by car to the logistics park for storage, and customers can have multiple specifications of steel allocated and picked up according to their needs in the park. Come to pick up, delivery vehicles are 13.5 meters, 2.3-2.5 meters wide semi-trailer type, in the park outside the auxiliary road of Tianmen Avenue, a single line of stops waiting for entry loading and unloading operations, as shown in Fig. 4.

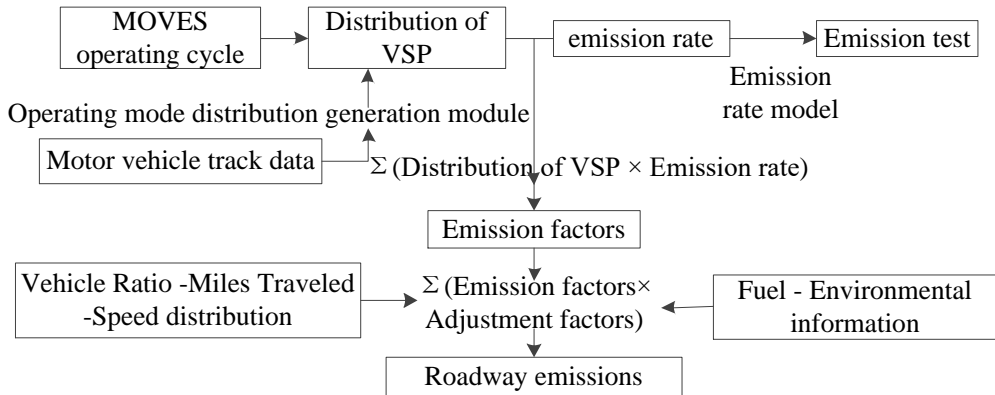


Fig.3. Principles of MOVES model calculation



Fig.4. Gangchen Logistics Park View

In this paper, a total of freight data was obtained from October 2017 to July 2018, with the number of vehicles summarized as shown in Fig. 5, and the distribution of transported weights as shown in Table 3.

Here is a sample of 10 months (304 days) of freight data for rebar at Gangchen Logistics Park. In order to the comprehensiveness of the sample selection, can reflect the overall freight data characteristics of the park, to rebar daily freight volume distribution cumulative probability of 0% (minimum freight

volume day), 10%, ..., 100% (maximum freight volume day) of the 11 days of freight data as a sample dataset, the sample extraction results shown in Table 4.

The aim of this study was to examine the pattern of vehicle arrivals in a freight sample set. For this purpose, we focused only on March 31, 2018 and counted the number of empty vehicles arriving between 9:00 and 17:00, with a counting interval of 10 minutes. The frequency counts of vehicle numbers is shown in Fig. 6. The frequency histogram of the

number of vehicles closely matches the Poisson distribution curve, indicating that vehicle arrivals are Poisson-distributed. To confirm this, we conducted a one-sample K-S precision test in SPSS. The asymptotic significance (two-tailed) was found to be greater than 0.05, which means that empty vehicle arrivals do conform to the Poisson distribution. We also tested the sample set of 11 groups of empty and heavy truck arrivals separately. The results showed

that the P-value was greater than 0.05, indicating that the sample set of empty and heavy truck arrivals also conformed to the Poisson distribution. This is in line with the VISSIM simulation of traffic flow inputs, which ensures that the later use of VISSIM simulation trucks to enter the Gangchen Logistics Park is reasonable. The results of the Poisson test for the freight sample set of truck flow data and the number of truck arrivals are shown in Table 5.

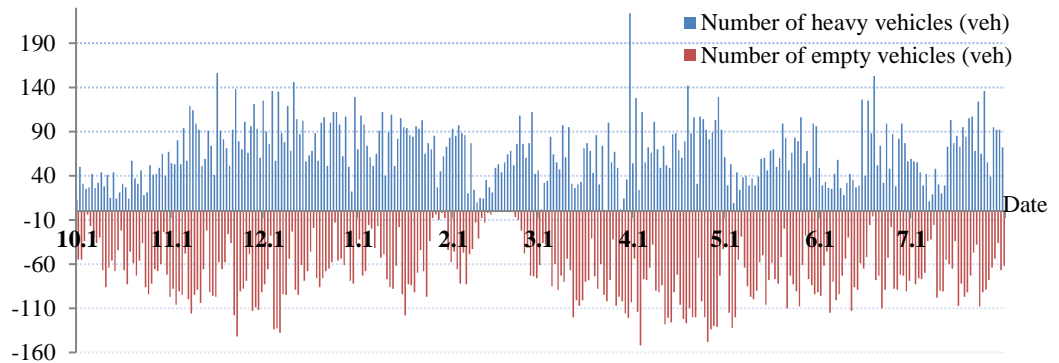


Fig.5. Number of Vehicles Statistics

Table 3. Transportation weight distribution

Transportation weight interval (tons)	Proportion of empty vehicles	Proportion of heavy vehicles
(0 , 10]	0	0.004
(10 , 20]	0.010	0.002
(20 , 30]	0.058	0.057
(30 , 40]	0.301	0.207
(40 , 50]	0.631	0.730

Table 4 Results of Sample Sampling

Groups	Cumulative Probability Decomposition Values	Dates	Total freight volume (tons)
0	0%	Feb 14st, 2018	896.580
1	10%	Jun 24st, 2018	2792.074
2	20%	Jan 6st, 2018	3933.465
3	30%	Oct. 17st, 2017	4477.220
4	40%	Feb 7st, 2018	4960.756
5	50%	Nov 5st, 2017	5627.995
6	60%	Jul 28st, 2018	6222.793
7	70%	Dec. 31st, 2017	6936.827
8	80%	Dec 7st, 2017	7419.223
9	90%	May 21st, 2018	8215.847
10	100%	Mar 31st, 2018	13997.135

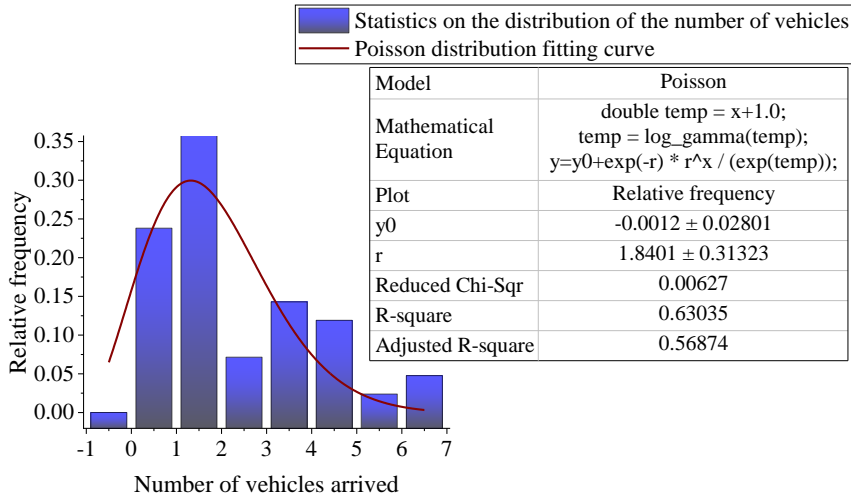


Fig.6. Frequency counts of vehicle numbers

Table 5 Sample set of van arrival data and tests

Groups	Empty vehicles		Heavy vehicles	
	Traffic flow (veh/h)	Significance P-value	Traffic flow (veh/h)	Significance P-value
0	0	N/A	2.25	0.551
1	2	0.725	5.125	0.576
2	4.5	0.331	5.375	0.568
3	8.75	0.513	2.875	0.340
4	4.5	0.729	8.125	0.759
5	5.125	0.454	9.875	0.406
6	5.75	0.496	10	0.651
7	4	0.521	13.5	0.672
8	9.875	0.523	9.25	0.341
9	11.5	0.602	8.75	0.404
10	10.75	0.516	23.5	0.503

5.2. Vehicle Simulation Design and Analysis

5.2.1. Vehicle Simulation Design

The road outside the park where the trucks enter is a one-way single lane. The average weight of the park transport vehicles is 7 tons empty, and the maximum load is 50 tons. VISSIM simulation sets the vehicle type as trucks, and the vehicle model is a tram with a length of 15.7 meters and a width of 2.4 meters. Vehicle type reflects the composition of the simulation traffic, vehicle category determines the vehicle parking time, and each vehicle type should be defined to belong to the vehicle category. Trucks entering the park are stopped at the park entrance by setting up stop signs. Then with the average loading 100 tons/hour and unloading 200 tons/hour

efficiency of rebar, the vehicle parking time is set according to the vehicle category. The vehicle composition and parking time settings are shown in Table 6.

5.2.2. Vehicle Queuing Analysis

Due to the specificity of the sample set selection, the overall queuing of the admitted trucks in the Gangchen Logistics Park can be determined based on the queue length of each set of simulation experiments. The maximum number of vehicles in the parking queue is statistically 203, and the admission truck queue becomes more and more significant with the increase in freight volume. The maximum queue length of 35 meters (2 vehicles) for Simulation

Experiment 1 (the 10% threshold for the cumulative probability of freight volume) is at a critical point where a queue is just forming. The arrival and departure levels of trucks are comparable at this point, indicating that the probability that there is no truck queue in the park is approximately 10%.

The park queuing level is represented by the maximum number of vehicles in queue, as shown in Fig. 7. During the peak cargo period, the queuing level of the park ranges from 103 to 203 vehicles, which is significantly different from the queuing level during ordinary times. The queuing level during the off-peak period gradually increases with the cumulative probability of the freight distribution. By fitting the

linear relationship between the two, it is found that for every 10% increase in the cumulative probability of the freight distribution, the number of vehicles in the queue increases by about 12.4 vehicles.

5.3. Parking Space Setting

The Gangchen Logistics Park boasts excellent road modes and a substantial amount of green area in front of its warehouse center. To ease the traffic pressure caused by the trucks outside the park, a plan to allocate parking spaces in the green area in front of the warehouse center is being considered. The parking space planning diagram is shown in Figure 9.

Table 6 Vehicle composition and parking time

Empty vehicles					Heavy vehicles				
Vehicle weight (tons)	Vehicle type	Proportion	Vehicle class	Parking time(s)	Vehicle weight (tons)	Vehicle type	Proportion	Vehicle class	Parking time(s)
(6.9,7.1]	Empty1	0	Empty1	180	(7,17]	Heavy1	0.004	Heavy1	90
(6.9,7.1]	Empty2	0.010	Empty2	540	(17,27]	Heavy2	0.002	Heavy2	270
(6.9,7.1]	Empty3	0.058	Empty3	900	(27,37]	Heavy3	0.057	Heavy3	450
(6.9,7.1]	Empty4	0.301	Empty4	1260	(37,47]	Heavy4	0.207	Heavy4	630
(6.9,7.1]	Empty5	0.631	Empty5	1620	(47,57]	Heavy5	0.730	Heavy5	810

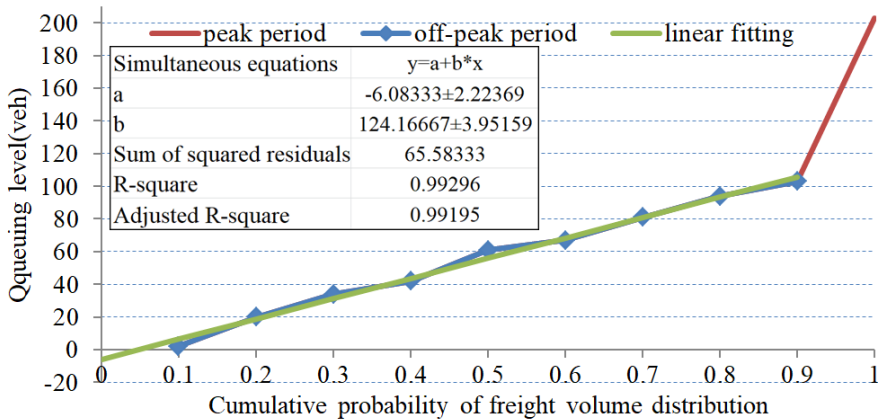


Fig.7. Park queue level

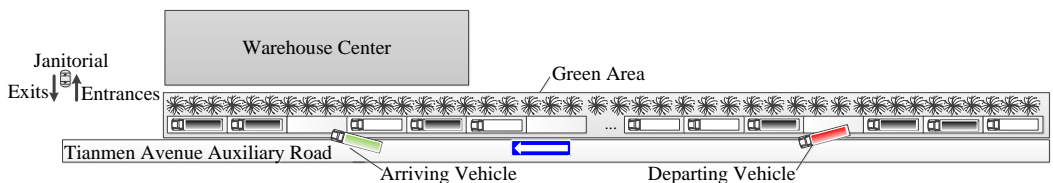


Fig.8. Schematic diagram of parking space planning

Add a parking lot to the VISSIM simulation and set up truck parking spaces and parking paths. To ensure that the trucks are prioritized to enter the parking spaces closest to the station, the simulation needs to set the parking attraction value of the parking space closest to the entrance of the station to be the largest. Sensors are set up in each parking space and the yard operation area to collect truck IDs. Signal lamps are set up at the entrance of each parking space, and Python calls the COM interface of VISSIM to realize signal sensing.

1. Ensure that the trucks enter the vacant parking spaces. The sensor detects whether each parking space is occupied or not, if the parking space is free, the signal light at the entrance of the parking space is green.
2. Ensure that trucks enter the yard in order of arrival. If the sensor detects that there is no vehicle in the operation area of the yard, and if the vehicle ID of the parking space is the smallest value of the vehicle IDs in all the current parking spaces, the signal light at the entrance of the parking space is green.

Except for the above two cases, the parking space entrance signal light is red.

5.4. Environmental Benefit Analysis of Parking Spaces

5.4.1. Localization of the MOVES Model

The MOVES model is a database that combines various factors such as U.S. roadway driving characteristics, traffic geography, and fuel characteristics to estimate tailpipe emissions from motor vehicles in different regions of the United States. Direct

measurements of domestic tailpipe emissions are not directly comparable, and the model needs to be localized according to the characteristics of the location where the emissions are measured. Taking the period of 14:00-15:00 on March 31, 2018 in Ma'an-shan Gangchen Logistics Park as an example, the tailpipe emission model of admission trucks is constructed, and the specific input parameters are shown in Table 7.

5.4.2. Statistics of Operating Modes

Simulate the truck admission process of the freight sample set for 11 days after planning the parking space, and calculate the distribution of operating mode before and after setting up the truck parking space according to 4.2. The truck operating conditions during the whole waiting admission process are mainly operating conditions 0, 1, 11 and 12, in which the time distribution of operating conditions 1, 11 and 12 decreases and the time distribution of operating condition 0 increases, and the specific changes are shown in Fig. 9. Setting up the truck parking space reduces the idling and low-speed driving condition of truck queuing to follow the truck, and the overall parking time ratio is significantly improved.

5.4.3. Emission Analysis

After localizing the MOVES emission model and inputting each parameter, it is possible to calculate tailpipe emissions for each traffic scenario simulated by the VISSIM experiment. The emissions before and after setting up the truck parking spaces are shown in Fig. 10.1. and 10.2.

Table 7 MOVES model localization data

Parameter Name	Explicit Description
Simulated year and month	March 2015
Time spans	Weekend; 14:00~15:00
Geographic bounds	LOUISIANA-Orleans Parish
Vehicle/Equipment	Single Unit Long-Haul Truck(53)/Diesel
Fuel	Diesel fuel - National V diesel fuel
Age distribution	0 to 30 years
Pollutants	CO; HC; NO _x ; PM10
Meteorology data	Temperature: 60.26°F Humidity: 78%
Road type	Urban unrestricted access
I/M (Inspection and Maintenance)	Default
Operating mode	Op Mode

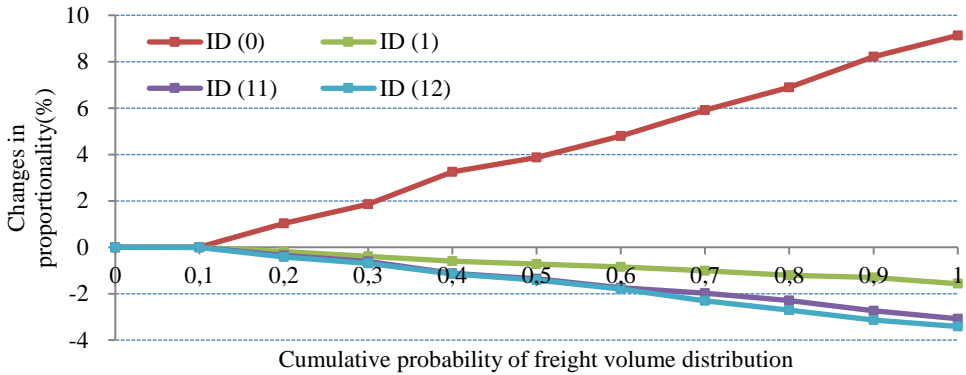
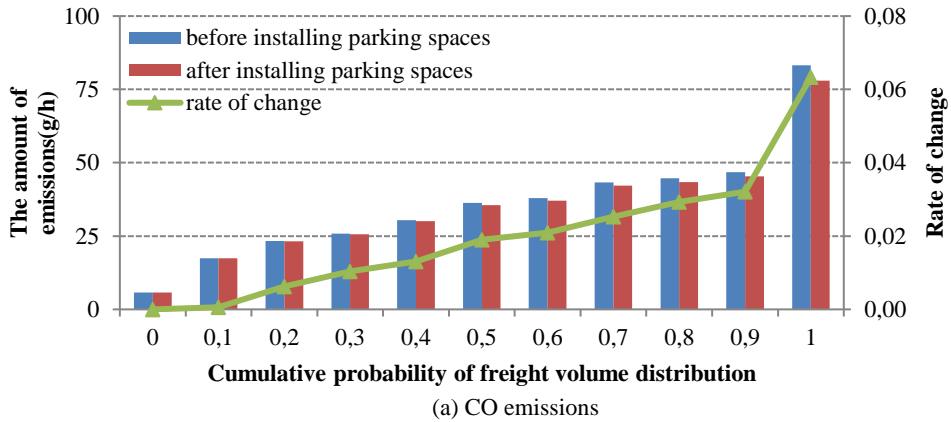
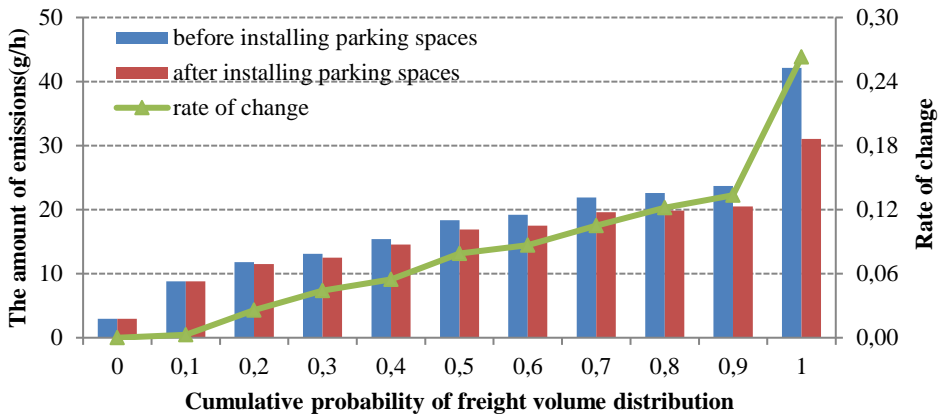


Fig. 9. Changes in the distribution of operating mode after the installation of parking spaces



(a) CO emissions



(b) HC emissions

Fig. 10.1. Emissions before and after planning for parking spaces (a-b)

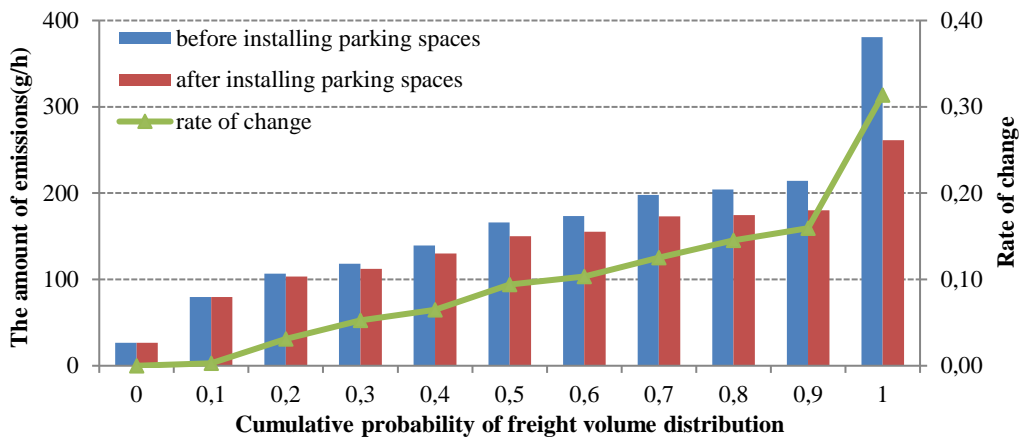
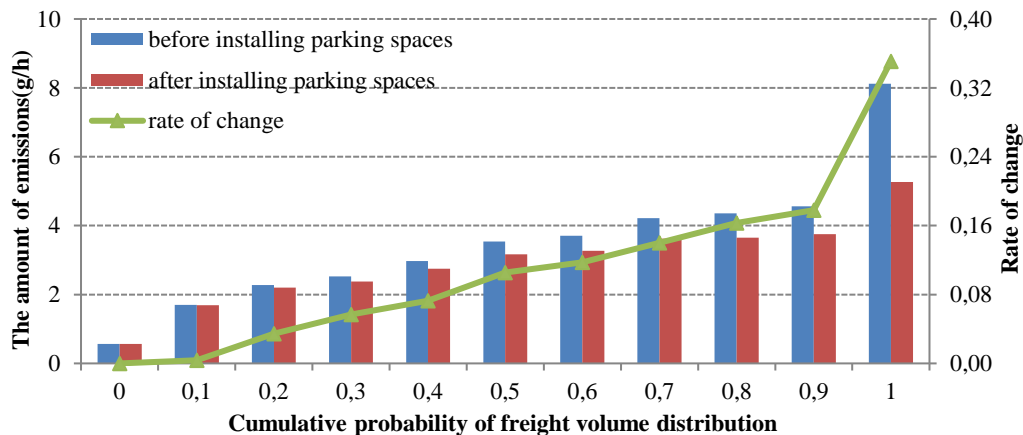
(c) NO_x emissions(d) PM₁₀ emissions

Fig. 10.2. Emissions before and after planning for parking spaces (c-d)

(1) Emission characteristics

The truck exhaust emissions calculated by the MOVES model for the entrance section of the park varied due to the variations in the distribution of operating conditions and traffic volume parameters. The emissions of major pollutants (CO, HC, NO_x, and PM₁₀) from truck exhaust were measured, with NO_x emissions being the largest, CO emissions being larger, HC emissions being smaller, and PM₁₀ emissions being the smallest. Under the off-peak freight period, pollutant emissions increase slowly with freight levels, with emissions significantly

higher during each peak freight period than during the off-peak period.

The emissions of each pollutant increased with the level of freight transportation. On the day of minimum freight transportation, the emissions of CO were 5.78 g/h, HC were 2.93 g/h, NO_x were 26.53 g/h, and PM₁₀ were 0.57 g/h. On the day of maximum freight transportation, the emissions of CO were 83.25 g/h, HC were 43.12 g/h, NO_x were 380.80 g/h, PM₁₀ were 8.12 g/h, and PM₁₀ were 8.12 g/h. At the average freight level, CO emissions were 36.27 g/h, HC

emissions were 18.35 g/h, NO_x emissions were 165.87 g/h, and PM₁₀ emissions were 3.54 g/h.

(2) Emission reduction effect

After setting up the truck parking space, the truck arrives at the road section outside the park, then the truck enters the parking space and waits for the number to be called to enter the park for loading/unloading operations, and calculation of truck exhaust emissions from this process by MOVES modeling. In the 10% days when the volume of freight is the smallest, there is no queuing of trucks in the park nearly, and the truck driving process is not subject to repeated starting and stopping of the front vehicle's driving status, so there is no change in the exhaust emissions before and after the setup of the parking space. As the volume of freight increases, the impact of the truck parking space on emissions gradually increases, and it has obvious environmental benefits in the process of waiting for the entry operation. Under the average volume of freight level, it can reduce 1.90% CO, 7.90% HC, 9.42% NO_x and 10.55% PM₁₀ emissions. On the day of maximum volume of freight, it was possible to reduce emissions of 6.33% CO, 26.29% HC, 31.36% NO_x and 35.10% PM₁₀.

6. Conclusions

This paper takes the Gangchen Logistics Park as a research example, uses VISSIM simulation to simulate the process of trucks entering the park, and combines the MOVES emission model to measure the exhaust emissions of trucks. From the perspective of planning truck parking spaces to reduce the number of starts and stops of entry queuing trucks, and test the environmental benefits of truck parking spaces. The results of the study can provide a certain decision-making basis for freight terminal planners to improve operational efficiency while promoting the development of green freight transportation. The results of the example analysis are as follows:

1. The queuing situation of the trucks entering the Gangchen Logistics Park is remarkable, and the

queuing length is basically linearly related to the freight volume.

2. In the process of truck admission, the main operating condition is condition 0 (parking), and the distribution of operating conditions changes significantly after setting up truck parking spaces.
3. Truck parking spaces play a significant environmental benefit in the process of trucks entering the freight terminal, and the larger the freight volume, the more significant the effect of emission reduction. Therefore, from the perspective of changing the truck flow driving state to reduce exhaust emissions of the idea is feasible, it is recommended that the freight volume, queuing significant freight terminal planning truck parking spaces to contribute to the reduction of air pollution.

However, this paper only considers the weight of goods loaded and unloaded by trucks. It ignores the diversity of the cargo categories carried by trucks. Using the overall loading and unloading efficiency handles vehicle loading and unloading efficiency roughly. The simulation portrayal of truck entry is not precise enough. To address these issues, the subsequent research should focus on the following:

1. Further refining the simulation process to plan the truck entry process according to the type of goods being transported.
2. Considering the internal layout of the freight terminal, refining the truck loading and unloading process, planning the driving path in the yard, and improving the efficiency of vehicle admission.

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