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Article

An Optimization Method Based on Multivariate Linear Programming for Urban Green Transportation Carbon Emission Control

Dazhang Liu *

China Eco-city Academy Ltd. Co., Beijing 100048, China; liu11081108@126.com

Abstract: In order to implement the concept of environmental protection and achieve the goal of urban green transportation, this study controls and optimizes the urban transportation carbon emission through the method of multivariate linear programming. This paper proposes a multivariate universe-interval linear programming algorithm, which is applied to the control of transportation carbon emissions. At the same time, the urban traffic carbon emission is measured, and the BP neural network is used to predict the traffic carbon emission, and the urban traffic carbon emission optimization model based on multivariate linear programming is constructed. The practical utility is tested by experiments. Taking the carbon emissions of residents' commuting in Q city as an example, the carbon emissions of Q city after the optimization of the model in this paper were reduced by 860 tons. The per capita carbon emissions of buses, subways, motorcycles and cars all show a decreasing trend. The average values of CO, CO_2 and fuel emissions of this paper's model at traffic flow of 400 pcu/h and 900 pcu/h are much lower than other control methods. The model in this paper has a greater advantage in reducing carbon emissions from transportation.

Keywords: multivariate linear programming; BP neural network; carbon emission control; green transportation

1. Introduction

Climate change caused by carbon emissions poses an unprecedented threat to the international community. However, global emissions continue to rise as energy consumption increases [1-2]. According to data from the International Energy Agency (IEA), global carbon dioxide emissions from energy combustion and industrial processes reached 36.3 billion tons in 2021, an increase of 6% compared to 2020, reaching the highest emission level in history. Due to China's high-energy consumption, heavy industry-driven economic growth model and coal-based energy consumption structure, carbon emissions have surged over the past 20 years. In 2006, China surpassed the United States to become the world's largest carbon dioxide emitter [3-5]. Therefore, addressing climate change has evolved from a scientific understanding to a political consensus. The government has proposed "lacing ecological civilization construction in a prominent position, integrating it into economic, political, cultural, social development, and throughout the entire process, striving to build a beautiful China and achieve sustainable development for the Chinese nation," establishing a green transition pathway for socio-economic development and reducing carbon emissions [6-8]. On September 22, 2020, China announced its "carbon neutrality" plan at the United Nations General Assembly, aiming to peak carbon dioxide emissions by 2030 and achieve carbon neutrality by 2060.

Against the backdrop of urbanization, the transportation industry has flourished. As the third-largest emitting sector, the transportation industry is characterized by diverse and complex emission sources. From 1990 to 2018, its compound annual growth rate reached 8.3%, significantly higher than the global transportation carbon emissions growth rate (2.1%) and China's overall carbon emissions growth rate (5.6%) [9-10]. Among these, vehicle exhaust emissions from road transportation are the most prominent [11]. As the number of vehicles continues to increase, energy consumption and carbon emissions also rise accordingly. In 2024, global carbon dioxide emissions reached 41.6 billion tons, an increase of 2.5% compared to 2023, with transportation accounting for one-quarter of carbon emissions, primarily from fossil fuel combustion [12]. As per capita GDP grows, the demand for transportation will continue to increase, placing significant upward pressure on carbon emissions from transportation systems [13]. The government has explicitly stated that it will accelerate the advancement of green and low-carbon development, aiming for carbon dioxide emissions in the transportation sector to peak as soon as possible. From the perspective of transportation carbon emissions structure, urban transportation accounts for a staggering 84% of the sector's total carbon emissions, making it the absolute main contributor and key focus for emissions reduction [14-15]. Therefore, it is necessary to control transportation carbon emissions.

Controlling carbon emissions in the transportation sector can help mitigate global climate change, reduce the damage caused by greenhouse gases to the ecological environment, promote technological innovation and upgrading in the transportation industry, improve transportation efficiency, reduce operational costs, and enhance the industry's competitiveness [16-18]. Literature [19] analyzed the effectiveness of traffic control policies implemented in Zhengzhou for carbon emission control. While these policies have contributed to reducing carbon emissions to some extent, their effectiveness is weakened under conditions of high traffic volume, such as during peak hours or when buses and heavy trucks are in operation. Literature [20] utilized deep reinforcement learning to develop a signal timing optimization strategy for controlling intersection signals, aiming to reduce carbon emissions from vehicles at intersections and thereby achieve carbon emission control. Similarly, Literature [21] employs multi-agent reinforcement learning to achieve adaptive control of traffic signals, considering the state and actions of intersections to control vehicle carbon emissions. Literature [22] proposes a multi-objective (vehicle delay, total number of stops, average fuel consumption, and emissions) intelligent traffic control protocol designed using a non-dominated sorting genetic algorithm II. Reference [23] addresses the impact of traffic conditions (traffic state and congestion) on carbon emissions in road traffic, providing control strategies for various fuel vehicle combinations and mainline speed limit control strategies. Although carbon emissions from traffic decrease under various control strategies, the reduction trend is not significant, so continuous optimization of traffic carbon emission control is necessary.

Multivariate linear programming obtains the optimal solution among multiple objective functions through a certain linear constraint condition. It is widely used in production planning, resource allocation, traffic network design, and other fields, and is an effective method for optimizing carbon emission control strategies in complex traffic environments [24].

Based on stochastic linear programming, this paper introduces the multiverse algorithm and constructs the multiverse-interval linear programming algorithm to solve the carbon emission control problem of urban transportation. The author adopts the “bottom-up” calculation method in the carbon emission accounting method of IPCC inventory to measure the carbon emission of urban transportation. At the same time, the BP neural network model is used to predict the carbon emissions of urban transportation. Based on the control of urban transportation carbon emissions, the whole life cycle carbon emission optimization method is proposed. In order to test the effectiveness of this paper's multivariate linear programming-based carbon emission control optimization model for urban transportation, it is used to optimize the carbon emissions of residents' commuting in Q city, and compared with other control methods in terms of carbon emissions and fuel emissions.

2. Transportation Carbon Emission Optimization Model Based on Multivariate Linear Programming

2.1. Stochastic Programming

Consider a linear programming model:

$$\begin{cases} \min c^T x \\ Ax = b \\ x \geq 0 \end{cases} \tag{1}$$

The coefficients A, B and C are defined constants, often representing parameters such as price, cost, demand, number of resources, technical conditions and economic indicators. In production practice, due to a variety of uncertainties, these parameters often fluctuate, rather than a fixed known number. There are three possibilities: they are either random variables with a known (joint) probability distribution, or random variables with an unknown probability distribution, or they are not random variables, but belong to other types of variables. These uncertainties can, on many occasions, be described by certain probability distributions. Therefore, the introduction of random variables in mathematical planning can make the model more realistic, thus making the decisions made more rational. In the above linear programming, if random variables are introduced in some or all of the elements of A, B and C, it becomes a stochastic linear programming problem [25].

Due to the introduction of random variables in the coefficients, the analysis and solution of stochastic planning problems are much more complex than ordinary mathematical planning problems. The initial idea was to replace the random variables in the model with their expected values, thus obtaining a mathematical planning model with definite coefficients, and then solving it with various algorithms of ordinary mathematical planning. In practice, however, this approach is not feasible in many cases. Therefore, it is very necessary to develop the theory of stochastic planning. After the efforts of many people, the stochastic planning problem has been solved to some extent.

Stochastic planning is an effective tool for solving optimization problems containing random variables. There are three kinds of stochastic planning usually discussed: one is the expected value model, i.e., to optimize the objective function under the expectation constraints. The second is chance constrained planning (CCP for short). The chance-constrained planning model allows the decision maker to make a decision that does not satisfy the constraints to some extent, but the decision should make the probability of the constraints holding true no less than a certain confidence level. The third is correlated chance planning, proposed by Baoxuan Liu, which is an optimization theory that makes the chance function of an event optimal in an uncertain environment.

2.2. Multivariate Universe-Interval Linear Programming

In this paper, a newly proposed multivariate universe algorithm is used to solve the carbon emission control problem [26]. The algorithm has a simple structure, relatively few parameters, and better results in low-dimensional optimization, which is more suitable for the case of carbon emission optimization. The uncertainty problem is first transformed into two deterministic subproblems using interval linear programming, and then the Gurobi solver in the Yalmip language environment is invoked to solve them separately.

Multiverse (MVO) algorithm is a new meta-heuristic intelligent algorithm proposed by Seyedali Mirjalili et al. in 2015, which mainly simulates the natural phenomenon of the matter in the universe transferring from white hole to black hole through wormholes.The main parameters of the MVO algorithm are the probability of the existence of wormholes (WEP) and the travel distance rate (TDR), and it is proved through experiments that it performs better in low dimensional optimization has shown more excellent performance.

It can be summarized as the following three points:

1) Objects in high expansion rate universes always tend to converge to those in low expansion rate universes.

2) Objects are transferred between neighboring universes through the white hole/black hole mechanism and the updating of the universe position is carried out with the following updating formula:

$$x_i^j = \begin{cases} x_k^j & r_i < NI(U_i) \\ x_i^j & r_i \geq NI(U_i) \end{cases} \tag{2}$$

where x_i^j is the j th variable of the i th universe; r_i is a random number between 0 and 1; $NI(U_i)$ is the standard expansion rate of the i th universe; and x_k^j is the j th variable of the k th universe selected according to the roulette wheel selection mechanism.

3) The current optimal universe and the optimal universe transfer objects between them via wormhole tunneling and update the position of the universe with the following update formula:

$$x_i^j = \begin{cases} X_j + TDR \times ((ub_j - lb_j) \times r_4 + lb_j) & r_3 < 0.5, r_2 < WEP \\ X_j - TDR \times ((ub_j - lb_j) \times r_4 + lb_j) & r_3 \geq 0.5, r_2 < WEP \\ x_i^j & r_2 \geq WEP \end{cases} \tag{3}$$

where X_j is the j th variable of the current optimal universe; ub_j and lb_j are the maximum and minimum values of the j th variable, respectively; r_2, r_3, and r_4 are random numbers between 0 and 1; and WEP and TDR are the probability of the existence of a wormhole and the travel distance rate, respectively.

2.3. Methodology for Measuring CARBON emissions

2.3.1. Measurement of Carbon Emissions

The IPCC inventory carbon accounting method is a carbon emission accounting method that maintains the compatibility, comparability and consistency between carbon measurement methods of various countries, and is divided into two forms: "top-down" and "bottom-up". Compared with the "top-down" method, the "bottom-up" method has stronger pertinence and accuracy than the "top-down" method, which is helpful to compare and analyze the impact of different transportation modes on the carbon emission scale of urban transportation system.

The formula for calculating carbon emissions from intercity transport is as follows:

$$C = \sum_{ij} F_{ij} \times T_{ij} \times E \tag{4}$$

where, C represents the carbon emissions generated by intercity transportation; F_{ij} represents the unit turnover energy consumption of the i th type of transportation passenger or freight; T_{ij} represents the passenger turnover or freight turnover of the i th type of transportation mode; E is the carbon emission coefficient of tons of standard coal, and takes the value recommended by the National Development and Reform Commission, $2.4567\left(t - CO_2 / tce\right)$; i denotes different transportation modes ($i = 1,2,3,4$; 1 is road, 2 is waterway, 3 is railroad, 4 is aviation); j denotes different transportation categories ($j = 1,2$; 1 is freight transport, 2 is passenger transport).

The carbon emissions from intra-city transportation are calculated as:

$$R = \sum_{k} M_k \times E \tag{5}$$

where R is the carbon emissions generated by intra-city transportation; M_k denotes the fuel consumed on behalf of the k th intra-city transportation mode; E is the carbon emission coefficient of tons of standard coal, which takes the value recommended by China's National Development and Reform Commission, $2.4567\left(t - CO_2 / tce\right)$.

2.3.2. Decomposition of Factors Affecting Carbon Emissions

The LMDI method is a model proposed by Ang and other scholars based on Kaya's constant equation, and the LMDI method has the characteristics of eliminating residual terms and intuitive decomposition results, which is widely used in the field of energy research [27]. In order to comprehensively consider the influencing factors of urban carbon emissions, based on previous scholarly research and industry characteristics, the article selects carbon emission intensity, transportation energy intensity, transportation energy consumption structure, economy and population as the factors influencing urban transportation carbon emissions. Based on the above analysis, the following Kaya constant equation is constructed to analyze the factors influencing urban carbon emissions:

$$Q = \sum_i M_i = \sum_i \frac{M_i}{F_i} \times \frac{F_i}{F} \times \frac{F}{T_{GDP}} \times \frac{T_{GDP}}{P} \times P \tag{6}$$

where Q is the carbon emission of urban transportation; M_i is the carbon emission of the i th transportation mode; F_i is the comprehensive energy consumption of different transportation types; F is the total comprehensive energy consumption of urban transportation; T_{GDP} denotes the gross domestic product of urban transportation, warehousing, and postal service industry, referred to as the GDP of transportation; P is the population of the city; and i denotes different transportation modes ($i = 1,2,3,4,5,6$; where 1 is highway, 2 is waterway, 3 is railroad, 4 is aviation, 5 is intra-city transportation, and 6 is port). Equation (6) can be simplified as:

$$Q=\sum_i Q_i=\sum_i E_i\times S_i\times N\times J\times P \tag{7}$$

where E_i is the carbon emission intensity, i.e., $\frac{C_i}{F_i}$; S_i is the structure of transportation energy consumption, i.e., $\frac{F_i}{F}$; N is the energy intensity of transportation, i.e., $\frac{F}{T_{GDP}}$; J is the per capita transportation GDP, i.e., $\frac{T_{GDP}}{P}$; P is the city population.

The author uses an additive formula to decompose the extended Kayak's constant equation, which can be decomposed into the following five factors:

$$\Delta Q=Q^T-Q^0=\Delta C_E+\Delta C_S+\Delta C_N+\Delta C_J+\Delta C_P \tag{8}$$

The five factors can be calculated from the following equation:

$$\Delta C_E=\sum_i W_i\times\ln\frac{E_i^T}{E_i^0} \tag{9}$$

$$\Delta C_S=\sum_i W_i\times\ln\frac{S_i^T}{S_i^0} \tag{10}$$

$$\Delta C_N=\sum_i W_i\times\ln\frac{N^T}{N^0} \tag{11}$$

$$\Delta C_J=\sum_i W_i\times\ln\frac{J^T}{J^0} \tag{12}$$

$$\Delta C_P=\sum_i W_i\times\ln\frac{P^T}{P^0} \tag{13}$$

$$W_i=\frac{M_i^T-M_i^0}{\ln M_i^T-\ln M_i^0} \tag{14}$$

where 0 is the base period and T is the current period; ΔQ is the change in carbon emissions; Q is the carbon emissions, Q^T is the carbon emissions in the current period, and Q^0 is the carbon emissions in the base period; ΔC_E is the carbon emissions intensity effect, ΔC_S is the energy consumption structure effect of transportation, and ΔC_N is the energy intensity effect. ΔC_J is the economic effect, ΔC_P is the population effect; W_i is the weighting coefficient.

2.4. Transportation Carbon Emission Forecasting Model

2.4.1. Modeling Principles

BP neural network is a multi-layer feed-forward neural network trained based on the error back-propagation algorithm [28], which consists of an input layer, an output layer and one or more hidden layers.

The basic idea of BP neural network is that the learning process consists of two parts: signal forward propagation and error back propagation. In the forward propagation process, the characteristics of the sample are input through the input layer and signal processing through each hidden layer, and finally derived from the output layer; if the actual output of the output layer and the desired output is inconsistent, the error is back-propagated through the output layer to the input layer, and all units of each layer are assigned the error to obtain the error signal of each unit of each layer, which is the basis for the correction of the weights of each unit, and then the error learning signal is corrected according to the This error signal is also the basis for correcting the weights of each unit, and then the neuron weights of each layer are corrected according to the error learning signal. The continuous adjustment process of the weights using the gradient descent algorithm is the process of network learning and training. The process is performed until the network output error is reduced below a preset threshold or greater than a preset upper training limit. The chain derivation method in calculus is the core element of the mathematical solution idea of the BP model, if z is a function of y and is derivable, and y is a function of x and is derivable, then there exists a relationship as in equation (15):

$$\frac{\partial z}{\partial x}=\frac{\partial z}{\partial y}\cdot\frac{\partial y}{\partial x} \tag{15}$$

2.4.2. Modeling BP Neural Network Predictions

In this paper, according to section 2.3, the five main influencing factors of carbon emission intensity effect, transportation energy consumption structure effect, energy intensity effect, economic effect, and population effect are taken as the input variables of the urban transportation carbon emission prediction model, and the 2005-2014 data are used as the training set to establish the prediction model, and the 2015-2024 data are used as the test set to carry out the prediction performance of the model. Test. The prediction model is mainly composed of two parts: the training set and the test set. The model construction process is as follows:

(1) In order to eliminate the quantitative differences between the data, the relevant data are normalized to between (0,1), and at the same time, it is convenient to shorten the model training time.

(2) Construct the BP neural network model. In the process of constructing the BP neural network, the number of nodes in the input layer and the output layer should be determined firstly, and then the number of layers in the hidden layer should be determined according to the characteristics of the data, and then the number of nodes in the hidden layer should be determined after trial and error. Since this paper chooses six input variables and the output variable is transportation carbon emissions, the nodes of the input layer are 6 and the nodes of the output layer are 1. In determining the number of hidden units, based on the existing research results, when the number of hidden layers of BP neural network is 1, it can be approximated with any accuracy for any complex function. As a result, the neural network structure with 1 hidden layer is chosen in this paper. However, at present, for the determination of the number of neurons in the hidden layer, empirical formulas are generally used to estimate the approximate range of the number, and then the optimal parameters are determined by modifying a variable. The available empirical formulas for determining the hidden layer neurons are shown in Eqs. (16)-(18):

$$k=2m+1 \tag{16}$$

$$k=\log_2 m \tag{17}$$

$$k=\sqrt{m+n}+\alpha \tag{18}$$

where m and n are the number of neurons in the input and output layers, respectively, and k is the number of neurons in the hidden layer; α is a constant from 1-10.

Through empirical formulas and single-variable experimental trial-and-error method, the optimal number of hidden layer neuron nodes set up in the paper is 4, and the optimal neural network structure constructed in the end is 6-4-1.

(3) After completing the training process of the prediction model, the model prediction performance is examined and the predicted value of the test data is returned to the prediction model, and finally the model predicted value is obtained by inverse normalization.

2.5. Whole Life Cycle Carbon Emission Optimization Approach

Combined with the results of carbon emission of the whole life cycle of urban transportation system and the current status of carbon emission reduction research, this section summarizes the methods that can reduce carbon emission of the whole life cycle.

During the planning and design process in the construction stage: 1. Building design should be combined with factors such as vehicle operating efficiency, energy consumption and pedestrian flow to reasonably plan building scale, equipment layout, etc. 2. Rail transit, on the premise of considering the line's own conditions, sets station locations, station spacing, station gradient, curve radius, etc., and sets energy-saving slopes to realize energy-saving train operation. 3. During the design stage of public rail transit trains, it is Consider reducing the weight of the vehicle by choosing lightweight materials such as lead alloy and stainless steel as well as integrating various components of the train on the premise that it meets the operating conditions, which can reduce carbon emissions in urban transportation.

1. Reasonable selection of new energy sources, processes, materials and equipment. (1) New energy, such as wind turbines, biological boilers, solar photovoltaic panels and other new energy technologies to generate electricity. (2) The new process, such as the use of screen doors at the station, prevents the train from bringing cold air into the station when it enters the station, so as to load the ventilation and air conditioning system of the station. (3) New materials, such as finding low-carbon materials to replace concrete. (4) New equipment, such as new low-carbon equipment, such as inverter air conditioning, etc.

2. Conserve resources by reducing the loss of construction materials, reducing the transportation process, and using local construction materials wherever possible.

3. Carbon Emission Control Optimization Analysis

3.1. Analysis of Overall Urban Carbon Emissions

This paper takes city Q as the study site to control and optimize the urban transport carbon emissions in the city. Better than commuting is the most important reason for urban residents to travel, so the control and optimization of transport carbon emissions when residents commute is mainly carried out. The carbon emission coefficients generated by different residents using different means of transportation in Q city before and after control were calculated, and the total carbon emissions generated by residents' commuting in Q city in August 2024 were about 7652.5 tons.The characteristics of carbon emissions from residents' commuting in Q city are shown in Table 1.

As shown in Table 1, cars produce the most carbon emissions within the study area, accounting for 90% of the total emissions, totaling 6888.48 tons of CO_2, buses emit 545.85 tons of CO_2, accounting for 7% of the total emissions, subways emit 132.74 tons of CO_2, accounting for 2% of the total emissions, and motorcycles emit 85.43 tons of CO_2, accounting for about 1% of the total emissions.

The per capita carbon emissions of different commuting modes correspond to the carbon emission factor, in which the carbon emissions of commuters who drive cars reach 9012.80 g/person, followed by motorcycle commuters with 1179.97 g/person, and the carbon emissions of commuters who take buses and subways are relatively low, with 898.08 g/person and 561.27 g/person, respectively.

Table 1. Urban commuter carbon emission characteristics of Q city.

Commute mode	Walking	Bike	Bus	Subway	Motorbike	Car
Carbon emission/ton	0	0	545.85	132.74	85.43	6888.48
Commuter/10^4	20.57	22.63	60.78	23.65	7.24	76.43
Per capita carbon emission/g	0	0	898.08	561.27	1179.97	9012.80
Proportion of carbon emission	0%	0%	7%	2%	1%	90%
Proportion of per capita carbon emission	0%	0%	8%	5%	10%	77%

After using this paper's transportation carbon emission optimization model based on multivariate linear programming to control and optimize the carbon emission of urban transportation in Q city during the commuting time, the carbon emission of residents' commuting in Q city is shown in Table 2.

As can be seen from Table 2, after the optimization of the model in this paper, the total carbon emissions from residents' commuting in Q city is 6792.5 tons, which reduces 860 tons of CO2 emissions compared with the uncontrolled time, among which cars are still the largest carbon emission source. The carbon emissions from buses, subways, motorcycles, and cars were 550.15, 130.65, 70.42, and 6041.28 tons, accounting for 8%, 2%, 1%, and 89% of the total emissions, respectively. In addition, the per capita carbon emissions of buses, subways, motorcycles and automobiles have decreased to different degrees, which are 869.94, 486.41, 1165.89, and 8782.21 g/person, respectively.

It can be seen that the carbon emission optimization model of urban transportation based on multivariate linear programming in this paper is of great help to improve the urban transportation environment and promote the development of urban green transportation.

Table 2. Urban commuter carbon emission condition of Q city.

Commute mode	Walking	Bike	Bus	Subway	Motorbike	Car

Carbon emission/ton	0	0	550.15	130.65	70.42	6041.28
Commuter/10^4	22.52	23.85	63.24	26.86	6.04	68.79
Per capita carbon emission/g	0	0	869.94	486.41	1165.89	8782.21
Proportion of carbon emission	0%	0%	8%	2%	1%	89%
Proportion of per capita carbon emission	0%	0%	8%	4%	10%	78%

3.2. Comparison of Carbon Emission Control Effects

Due to the high degree of dependence on fossil fuels in the transportation sector, for the main exhaust gas CO_2, CO, etc. emission base is large, it is very easy to fall into a difficult situation to reduce emissions, and the impact on the environment is more and more obvious. The reduction of fuel consumption can be reflected in the side of the improvement of carbon emissions by control methods. In order to avoid the influence of traffic flow, so take the north-south flow 400-900 pcu/h as the reference range, this section only shows the control effect comparison under 400 pcu/h and 900 pcu/h. In this paper, fixed timing control, coordinated control and induction control are selected to compare with the carbon emission control model based on multivariate linear programming in this paper, and the comparison results are shown in Fig. 1~Fig. 6.

For CO emissions, when the traffic flow is 400 pcu/h, the CO emissions under the four control modes are unstable, with large variation ups and downs, but the control model in this paper still embodies the absolute advantage, with an average value of about 25 mg, and comparatively speaking, the worst emission reduction effect is the fixed timing control and the induction signal control.

In the 500-900 pcu/h traffic flow, the advantage of no signal coordination control gradually becomes larger, although the emissions under the control model of this paper by the traffic flow is not significant, but the other three kinds of emissions with the increase in traffic flow changes are very obvious, especially in this paper control model control, in the traffic flow of 600 pcu/h and 700 pcu/h, the emission reduction effect of the control model of this paper is better, but the effect is worse under too high or too low flow rate. For the induction signal control and fixed timing control effects have been in the state of less than ideal emission effects.

For carbon emissions, CO_2 emissions are similar to CO emissions. The emission of CO_2 under coordinated control has been changing greatly, but in the case of the flow rate is getting bigger, the effect is bigger under low flow rate, but after reaching 500 pcu/h, the emission of CO_2 is getting smaller and stabilized as the flow rate is getting bigger. The performance of the control model in this paper is relatively stable as the flow rate increases, while the inductive signal control and fixed timing control continue to be in a high emission state with poor control.

On the other hand, fuel consumption is the main cause of carbon emissions. Attention to fuel consumption can also control or mitigate the increasing carbon emissions at the source. At low traffic volume (400 pcu/h) the difference in fuel consumption among the four control methods is not significant. As the traffic flow continues to increase, the advantages of coordinated control begin to come to the fore, and the fuel consumption increases less, but has a greater impact on the control model in this paper, with consumption located between 2000-2500 ml at low traffic flow, increasing to between 4000-5000 ml at 500-700 pcu/h, and increasing to between 800-900 pcu/h at 800-900 pcu/h. Consumption increases again to between 6000-7000 ml, the stage-like change is obvious, which is influenced by the traffic flow, for the other two control methods, the consumption changes less after the traffic flow reaches more than 600 pcu/h, and continues to keep high consumption.

In conclusion, it can be inferred from the simulation results that in terms of carbon emission and energy saving, the control model control in this paper performs better, while the coordinated control approach is slightly weaker, and the inductive signal control and fixed timing control are not applicable.

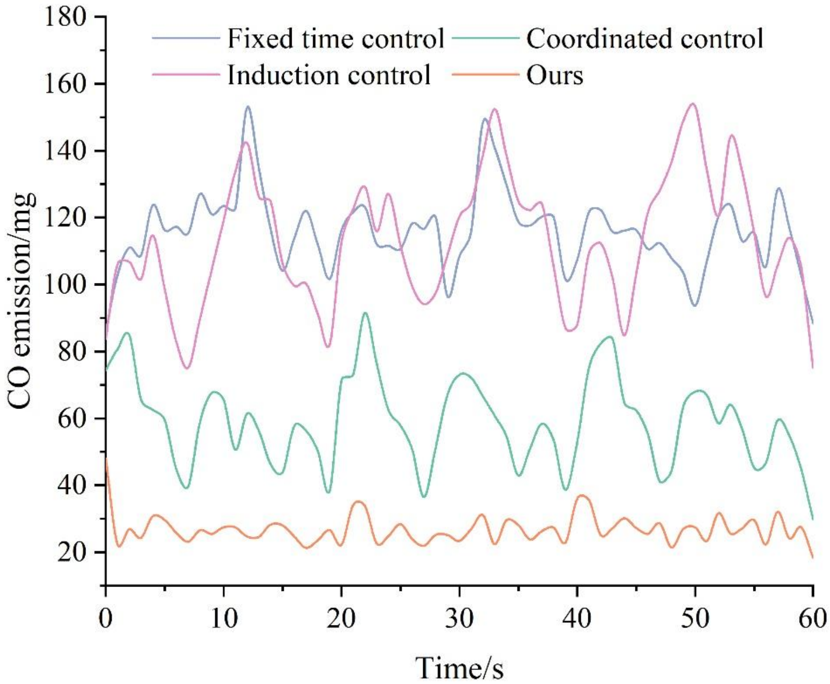

Figure 1. CO emission contrast (400 pch/h).

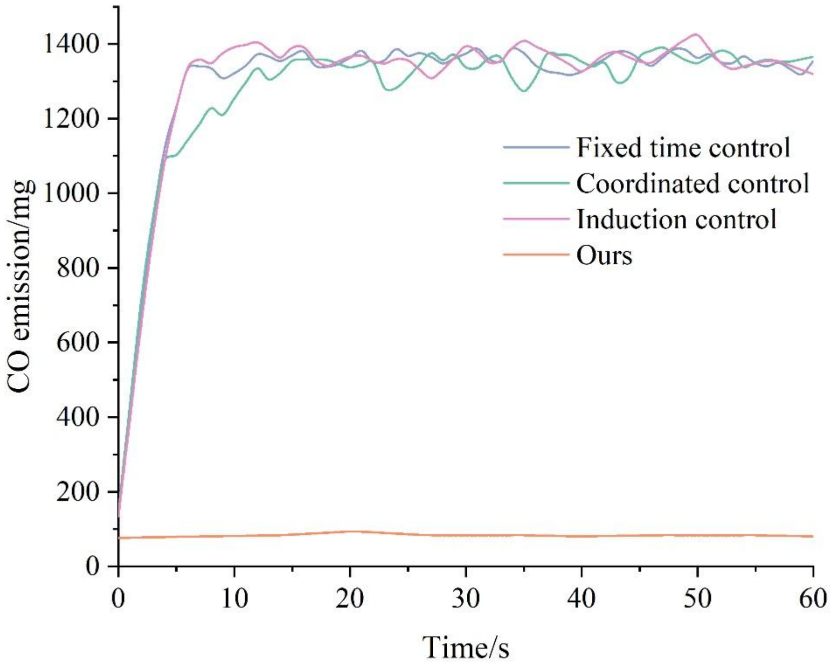

Figure 2. CO emission contrast (900 pch/h).

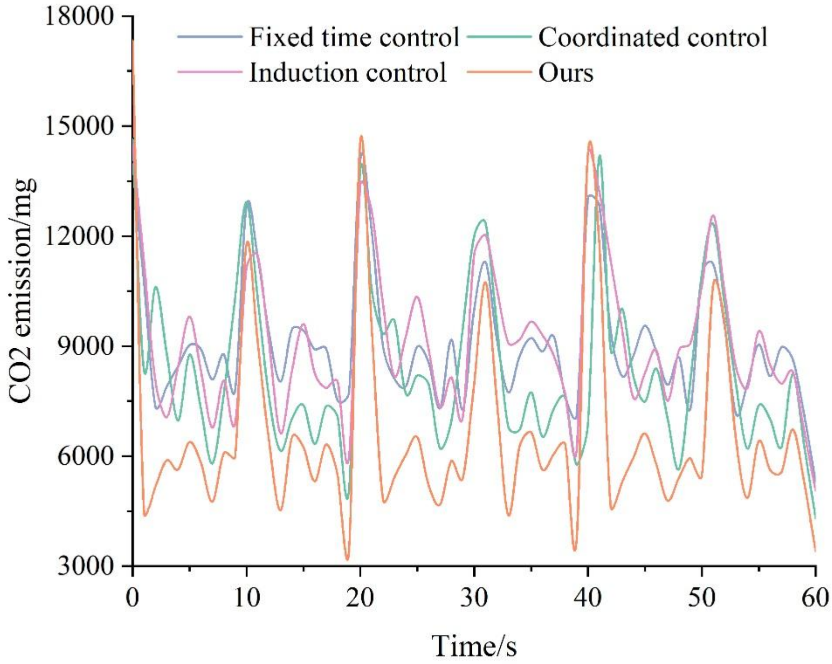

Figure 3. CO_2 emission contrast (400 pch/h).

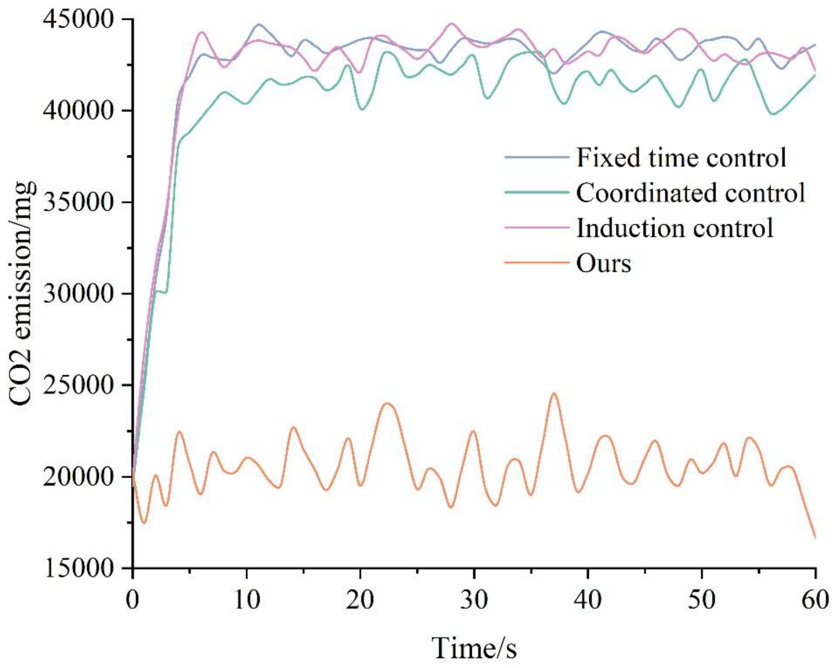

Figure 4. CO_2 emission contrast (900 pch/h).

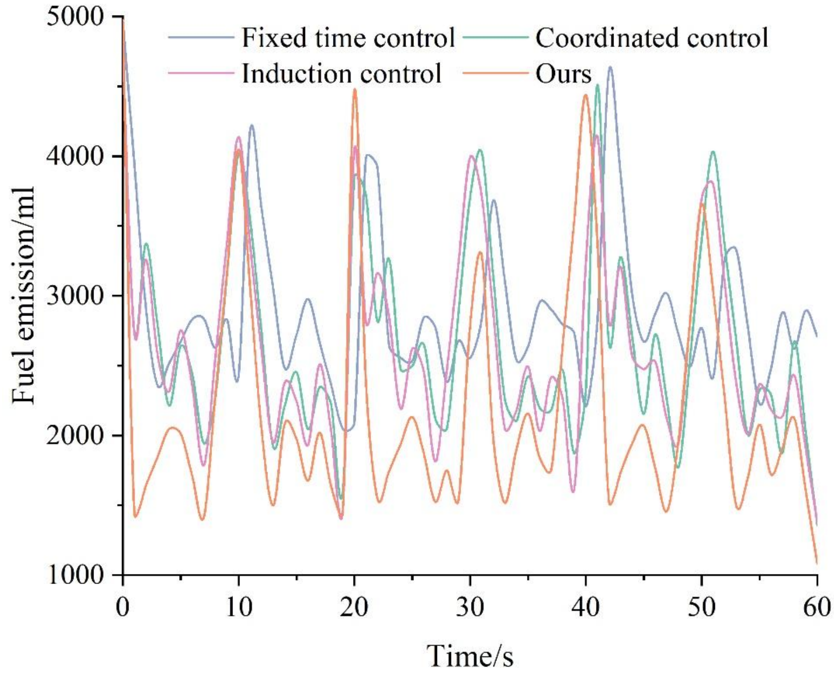

Figure 5. Fuel emission contrast (400 pch/h).

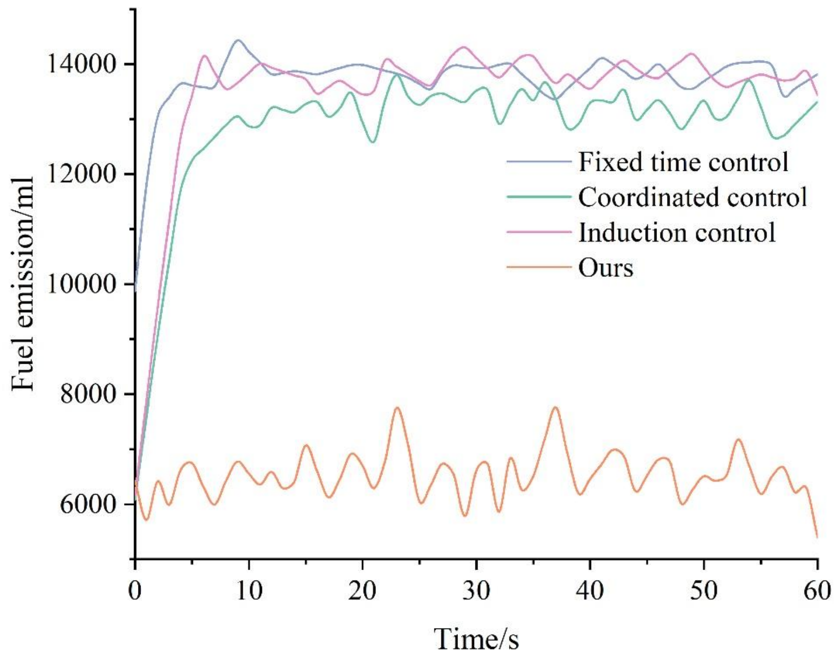

Figure 6. Fuel emission contrast (900 pch/h).

4. Conclusion

The article uses multivariate linear programming to control and optimize urban transportation carbon emissions. The multivariate universe-interval linear programming is used to construct the optimization model of transportation carbon emission. And its effect in carbon emission control is studied.

Taking the carbon emission of residents' commuting in Q city as an example for comparison, the residents' commuting in Q city after the optimization of the model in this paper reduces 860 tons of CO_2 emission. Moreover, the per capita carbon emissions of four commuting modes, namely, bus, subway, motorcycle and automobile, are all decreased, and the most obvious decrease is in automobile commuting. The urban transport carbon emission optimization model based on multivariate linear programming in this paper can effectively reduce urban transport carbon emissions.

Comparing this paper's model with other control methods, the average values of CO, CO_2 and fuel emissions when the traffic flow is 400 pcu/h are 26.81 mg, 6660.24mg, and 2197.67ml, respectively, and when the traffic flow is 900 pcu/h, the average values of CO, CO_2 and fuel emissions when the traffic flow is 900 pcu/h are 83.31 mg, 20557.73 mg, respectively, 6523.25 ml. The control effect of this paper's model on carbon emissions is obviously better than other control methods.

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