



Optimal allocation of urban new energy vehicles and traditional energy vehicles considering pollution and cost

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Abstract

With a large number of new energy vehicles being put into use, it is the general trend for traditional fuel vehicles to withdraw from the market in an orderly manner. Determining the optimal ratio between them in this process is of great significance to the low-carbon sustainable development of cities. Therefore, considering the constraints of urban automobile development planning and air pollution prevention and control policies, a multi-objective model to minimize pollutants and costs is constructed in this paper. Through model calculation and sensitivity analysis of dynamic impact relationship of different types of vehicles, it is determined that when new energy vehicles account for around 36% in Beijing, 57% in Shanghai and 46% in Guangzhou, the pollutant emissions can be minimized without causing a significant increase in social costs. Additionally, compared with 2030, Beijing, Shanghai and Guangzhou can achieve emission reductions of 320,000 tons, 200,000 tons and 250,000 tons, respectively, in 2050 if they implement the policy of banning the sale and delisting of fuel vehicles, which could provide suggestions for the guidance of the low-carbon development plan of the automobile industry.

Keywords Automobile exhaust emission · New energy vehicles · Traditional energy vehicles · Multi-objective optimization

1 Introduction

With the increasing number of motor vehicles, the air pollution in many cities has changed from soot pollution dominated by SO₂ to compound pollution including soot pollution and other motor vehicle exhaust pollution dominated by CO, NO_x (Guo, 2018). In the process of combating air pollution and reducing carbon emissions all over the world, low-pollution and zero-carbon

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transportation is often one of the main concerns in policy formulation. As an emerging industry with low pollution and high energy conservation, new energy vehicles have received strong support from the national government and the industry has been able to grow significantly.

New energy vehicles mainly include pure electric vehicles, plug-in hybrid electric vehicles and fuel cell vehicles (N. Wang et al., 2017). The question of whether new energy vehicles need to be used to replace traditional energy vehicles has been widely discussed around the world. Among them, as early as 2015, the Netherlands put forward a proposal to ban the sale of fuel cars in 2025. Then European countries also put forward their own ban time points. Norway, France, Spain and other countries proposed 2025 as the ban time. Britain announced that it would prohibit the sale of fuel vehicles by 2030. To reduce traffic pollution and achieve the goal of zero-carbon transportation, China also proposed an exploratory policy to ban the sale of fuel cars. The Ministry of Industry and Information Technology issued a response to the "Proposal to Study and Develop a Timetable for Banning the Sale of Fuel Cars to Accelerate the Construction of a Strong Automotive Country", stating that China will coordinate the study and development of a timetable for the withdrawal of fuel cars with the development of the New Energy Vehicle Industry Development Plan (2021–2035). It also conducted a pilot project in Hainan Province and introduced the Clean Energy Vehicle Development Plan, which stipulates that the sale of fuel cars will be banned from 2030.

Before the full withdrawal of fuel vehicles, China proposed the "Parallel Management Measures for Average Fuel Consumption of Passenger Vehicle Enterprises and New Energy Vehicle Credits" and revised it for implementation in 2020 to better develop new energy vehicles and promote the development and promotion of new energy vehicles by enterprises. With the implementation of the double credit policy and the new energy vehicle subsidy policy, the composition of private vehicles in China has been adjusted accordingly, and the proportion of new energy vehicles has increased, but the proportion of fuel vehicles is still very high.

At the same time, compared with the shortcomings of pure electric vehicles in terms of range, plug-in hybrid electric vehicles have great advantages in terms of energy saving in actual use (Zhou et al., 2018). However, at present, the quantity allocation pattern formed by the proportion of new energy vehicles in total private cars is still unreasonable, and even in individual cities, there are phenomena such as idle charging piles, for example, in the central city of Beijing area, the utilization rate of charging piles is high, but in the surrounding urban areas, there are phenomena such as idle charging piles and fuel cars occupying space.

Therefore, before the full retirement or ban of fuel cars, it is urgent to manage the existing fuel cars and solve the problems of people's livelihood and enterprise development brought by the policy. In this process, a proper ratio of traditional energy vehicles to new energy vehicles will provide an extremely strong support role for the government to formulate policies. This ratio can manage the development of enterprises and protect people's livelihood, but also can play the role of new energy vehicles to combat air pollution and zero carbon, which could be improved continuously with social development and economic growth.

However, most of the existing literature about new energy vehicles focus on the areas of technical cost (Franzò et al., 2022), market analysis (Liu et al., 2022; Wang et al., 2022), automatic driving (Acheampong et al., 2021; Xu et al., 2021; Yi & Smart, 2020) and infrastructure of new energy vehicles. For example, in terms of technology costs, power consumption can be used as an indicator to obtain the optimal coolant temperature by simulating the battery and motor cooling circuit of electric vehicles by AMESim (Yang et al., 2020). The cost-benefit

model can be used as a research method to study and analyze the development of new energy vehicle industry. In terms of market analysis, the literature (He and He, 2015) integrated technology acceptance theory (TAM) and innovation diffusion theory (IDT) to analyze the factors influencing consumers' purchase of new energy vehicles in 2 dimensions: individual consumers and product interface factors.

As the ownership of new energy vehicles surges year by year, the ensuing infrastructure construction problems associated with new energy vehicles have attracted widespread attention from scholars and society (Tian and Zhang, 2013). For example, the charging station siting and capacity determination method with the total cost minimization as the planning objective can consider the interests of charging station investors, electric vehicle users and distribution network operators (Hong et al., 2020). Hierarchical analysis method (AHP) can also be used to optimize the location demand degree of charging network in two dimensions of time and space using Fuzhou city as a research case (Chen et al., 2019).

When the number of new energy vehicles proliferates, another problem arises, which is the impact on the grid load. For the study of this problem, a multi-objective planning model with the lowest economic cost, the highest utilization of charging stations, and the highest reliability level is proposed (Xiang et al., 2016), and the model solution results show that the model can capture the interactive impact between charging infrastructure planning and distribution network planning in terms of economics, utilization, and reliability. The dynamic price offer framework for different charging durations can be aimed at maximizing the charging station operational efficiency and reducing the electrical load peaks (Limmer & Rodemann, 2019).

According to the above literature review, it can be found that most of the research on new energy vehicles focuses on the analysis of technology and market, but less on how to reasonably plan the proportion of new energy and traditional energy vehicles in different stages, so as to gradually replace traditional fuel vehicles with new energy. Therefore, based on the previous research, this paper constructs a multi-objective optimization model for the quantity allocation of new energy vehicles and traditional fuel vehicles in the development of urban private automobile industry. The contributions of this paper are mainly in the following three aspects:

- (1) The multi-objective model constructed in this paper can balance the economic and environmental objectives well under the consideration of comprehensive urban policies, development planning and other influencing factors, which could provide a reference model for the number allocation of different types of motor vehicles in cities.
- (2) The optimal planned proportion of traditional fuel vehicles and new energy vehicles in Beijing, Shanghai and Guangzhou in different periods was clarified, and suggestions were provided for the route planning of replacing traditional fuel vehicles with new energy vehicles.
- (3) The dynamic influence relationship of different types of vehicles is reflected, and the optimal proportion setting under different initial number of vehicles is further clarified through sensitivity analysis.

2 Problem formulation

With the continuous growth of the number of motor vehicles in China, the energy consumption and pollutant emissions of the transportation industry have increased significantly. In order to support low-carbon development, China has started to use new energy vehicles to replace traditional fuel vehicles since 2009. Therefore, it is very important

and complex to determine the ratio of new energy vehicles and traditional fuel vehicles in different urban development periods. This section proposes a mathematical model for addressing the above problems.

2.1 Problem statement

To solve the problem of gradually replacing traditional fuel vehicles with new energy vehicles and rationally allocating the proportion of traditional fuel vehicles and new energy vehicles in different periods, both economic and environmental objectives should be considered. At the same time, it is necessary to carry out research based on multiple constraints such as vehicle emissions, the number of new energy vehicles, and the development planning of vehicles. Therefore, it must rely on a multi-objective optimization model to solve this problem, which could satisfy a series of equal or unequal constraints (Ma et al., 2022). This section proposes a multi-objective optimization model to control air pollutants and minimize costs, and optimize the development of urban private automobile industry as shown in Fig. 1.

In the multi-objective model proposed in this paper, the main research subjects are fuel vehicles (N_1), pure electric vehicles (N_2), and plug-in hybrid vehicles (N_3). Additionally, the air pollutants are selected as PM_{10} , SO_2 , NO_x , and CO_2 . This paper mainly studies the proportion of different types of vehicles, so make reasonable assumptions about the relevant basic situation of the vehicles industry:

Assumption 1 The charging of new energy vehicles will be supplied at full load, and there will be no power outage. Only the cost of electricity will be considered during the use of new energy vehicles, and not the cost of lack of electricity.

Assumption 2 The amount of new energy compared to the amount in the policy introduced by the government can be exceeded, but there should be no shortage phenomenon as much as possible.

Assumption 3 Under the energy internet, the supply ratio of thermal power, wind power, hydropower, photovoltaic, biomass power generation and other power generation types will remain unchanged, and all electricity for urban cars will be produced locally.

Assumption 4 The purchase cost and end-of-life cost of the car are fixed values, and the usage cost is fuzzy value, which is calculated in the model by using its mean value.

Assumption 5 The costs related to charging piles are all fixed values, and only the number of expansions of charging piles is considered.

3 Notations

To establish a mathematical model for the considered problem, decision variables used in the proposed model are provided in Table 1.

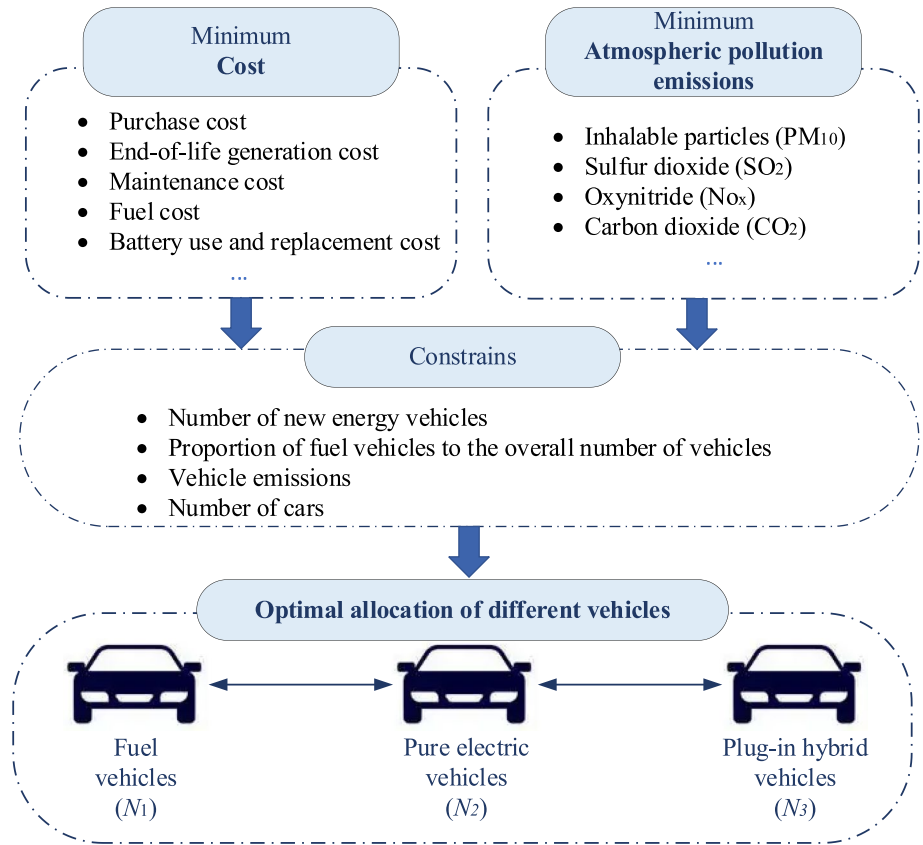


Fig. 1 The framework of the multi-objective-analysis model

3.1 Mathematical model

Based on the above analysis, the multi-objective optimization model is constructed as follows:

(1) Minimal atmospheric pollution emissions

$$\min f_1(N_i) = \sum_{j=1}^n \sum_{i=1}^m a_{ij} N_i + \sum_{j=1}^n \sum_{i=1}^m e_{ij} (N_i p_i \times 365 \times q) \times 10^{-6} \tag{1}$$

(2) Minimal cost

$$\min f_2(N_i) = \sum_{i=1}^m (b_i + \tilde{a}_i) * N_i + c \times \left(\sum_{i=2}^m N_i - num \right) \tag{2}$$

Among them, emission factors are used as indicators that best reflect the emission levels of motor vehicle pollutants. In 2000, a new round of motor vehicle emission

Table 1 Model variable description

| Variables | Meaning | Unit | Range of values |
|---------------|--|------------------|-----------------|
| $f_i(N_i)$ | Total air pollution emissions | Ton | > 0 |
| a_{ij} | The unit emissions of each type of exhaust gas for each model, i indicates the type of vehicle, j indicates the type of major pollutant | Ton | ≥ 0 |
| A_{ij} | Total emissions of each type of exhaust gas for each model, i indicates the type of vehicle, j indicates the type of major pollutant | Ton | ≥ 0 |
| N_i | Number of various types of cars | - | N^+ |
| N_{iy} | Number of various types of cars in year y | - | N^+ |
| e_{ij} | Pollutant emissions per unit of thermal power generation, i denotes the model, j denotes the main pollutant category | $g/(kW \cdot h)$ | ≥ 0 |
| P_i | Electricity required for Class i vehicles | $kW \cdot h$ | ≥ 0 |
| q | Share of thermal power generation capacity | % | $0 \sim 1$ |
| E_{hy} | Thermal power generation in year y | $kW \cdot h$ | ≥ 0 |
| E_y | Total power generation in year y | $kW \cdot h$ | ≥ 0 |
| $f_2(N_i)$ | All costs in the model | Millions of CNY | > 0 |
| b_i | Unit cost determined for each model (cost of vehicle purchase and cost of end-of-life generation costs) | Millions of CNY | ≥ 0 |
| \tilde{a}_i | Uncertain and ambiguous unit costs for each model (maintenance costs, fuel costs, electricity costs for charging formation, and costs for battery use and replacement) | Millions of CNY | ≥ 0 |
| c | The cost of expanding a charging post | Millions of CNY | > 0 |
| num | Number of existing charging posts | - | > 0 |
| G | The number of cities planning for new energy vehicles | - | N^+ |
| G_0 | The number of cities planning for non-private new energy vehicles | - | N^+ |
| G_1 | The number of private new energy vehicles planned by cities | - | N^+ |
| x | The proportion of conventional energy vehicles in the total number of vehicles in the city in the future | % | $0 \sim 1$ |
| G_2 | City's target plan for vehicle emissions | - | N^+ |
| G_3 | Number of private motor vehicles in 2020 | - | N^+ |
| L_y | Number of motor vehicles in the city in year y | - | N^+ |

Table 1 (continued)

| Variables | Meaning | Unit | Range of values |
|------------|--|------|-----------------|
| G_4 | Number of private motor vehicles in 2018 | - | N^+ |
| L_{2018} | Number of motor vehicles in 2018 | - | N^+ |
| L_{2020} | Number of motor vehicles in 2020 | - | N^+ |
| t | Year | Year | N^+ |
| k | Number of years selected by the model | Year | N^+ |
| m | Number of vehicle categories | - | 3 |
| n | Number of categories of pollutants | - | 4 |

standards was introduced in China (equivalent to Euro I), which basically adopted the European system (Cai & Xie, 2010). For the study of this system, the most widely used is the COPERT model to measure the motor vehicle emission factors, so this paper is also based on the data of this model to determine the emission factors of various motor vehicles. The average speed is used as a parameter in the model to measure the total pollutant emissions with the following equations (Xie et al., 2006).

$$a_{ij} = A_{ij} \div N_i \quad (3)$$

$$A_{ij} = \sum N_i \times M_i \times E_{ij} \times 10^{-6} \quad (4)$$

$$q = \frac{1}{k} \left(\sum_{y=t}^k \frac{E_{hy}}{E_y} \times 100\% \right) \quad (5)$$

The relevant constraints of the model are as follows:

- (1) The number of new energy vehicles constraint

$$\sum_{i=2}^m N_i \geq G_1 \quad (6)$$

- (2) The proportion of fuel vehicles to the overall number of vehicles constraint

$$N_1 \leq \sum_{i=1}^m N_i \times x \quad (7)$$

- (3) Vehicle emission constraints

$$\sum_{j=1}^n \sum_{i=1}^m a_{ij} N_i \leq G_2 \quad (8)$$

- (4) Number of cars constraint

$$\sum_{i=1}^m N_i \leq G_3 \quad (9)$$

$$\sum_{i=1}^m N_i \geq G_4 \quad (10)$$

where

$$G_1 = G - G_0 \quad (11)$$

$$G_3 = \frac{1}{k} \times \left(\sum_{y=t}^k \frac{\sum_{i=1}^m N_{iy}}{L_y} \right) \times L_{2020} \quad (12)$$

$$G_4 = \frac{1}{k} \times \left(\sum_{y=t}^k \frac{\sum_{i=1}^m N_{iy}}{L_y} \right) \times L_{2018} \quad (13)$$

$$x = \frac{(G_3 - G_1)}{G_3} \times 100\% \quad (14)$$

4 Data collation

This paper focuses on Beijing for analysis, and selects cities with large scale of new energy vehicles development, including Shanghai and Guangdong, to verify the universality of the model proposed and summarize the effective path of smooth replacement of fuel vehicles by new energy vehicles in China. The data selection process takes Beijing as an example.

4.1 Calculation of unit exhaust gas emissions

There are three main types of private cars available in Beijing: conventional energy vehicles (N_1), pure electric vehicles (N_2), and plug-in hybrid vehicles (N_3). Private cars travel about 20,000 km a year, and one liter of fuel travels about 10 to 15 km in the city, taking the average value of 12.5 km, a private car needs to refuel about 1,600 L a year.

Assuming that $P_1 = 1$, private cars drive about 20,000 km a year, $M_i = 20000$, and E_{ij} are calculated based on National V standards, and the specific emission factors (Cai & Xie, 2010; Xie et al., 2006) are as follows (Table 2).

And according to the goal in the "Beijing Three-Year Action Plan to Win the Blue-Sky Defense", by 2020, the pollution emissions from the transportation sector in Beijing should be reduced by 30% compared to 2017, that is, the motor vehicle emissions should be reduced by 30%. 2017 Beijing all implement the National V standard, 4.672 million private cars in 2017, including nearly 160,000 new energy cars, then the traditional energy cars A total of about 4.512 million vehicles, then the total emission is about 26,422,001 t calculated using the formula for calculating vehicle emissions and pollutant indicators in this study.

4.2 Percentage of thermal power generation

The main power generation types in Beijing are thermal power generation, hydroelectric power generation and photovoltaic power generation, among which thermal power generation accounts for a much higher proportion than other power generation methods, and the specific power generation capacity of each power generation method is shown in Table 3.

The current battery capacity of pure electric vehicles is 15–60 kWh, and the middle value of 37.5 kWh is taken as the analysis value in this study. Pure electric vehicles are generally recharged when the power reaches about 20% during working life, which means

Table 2 Calculation of unit emissions

| Pollutants | PM10 | SO ₂ | NOx | CO ₂ |
|------------|--------|-----------------|--------|-----------------|
| E_{1j} | 0.02 | 0.01 | 0.1 | 322.3 |
| a_{1j} | 0.0004 | 0.0002 | 0.002 | 6.446 |
| E_{3j} | 0.02 | 0 | 0.002 | 103.3 |
| a_{3j} | 0.0004 | 0 | 0.0004 | 2.006 |

that during the use of new energy, about 30 kWh of power needs to be charged each time, assuming that it is charged once a day, then $p_2 = 30$. Plug-in hybrid battery capacity is about 10 kWh, each time the battery capacity is zero when charging, then $p_3 = 10$.

At present, when thermal power generation is adopted, the emission of soot, SO₂ and NO_x are 0.08, 0.39 and 0.36 g, respectively, for each 1 kWh of power generated. The carbon emissions of per unit power generation for coal-fired and gas-fired generation units are 0.76–0.92 g/kWh and 0.32–0.61 g/kWh, respectively (Jianguo et al., 2018). Nowadays, coal-fired power generation has been eliminated in Beijing and replaced by gas-fired power generation, and the model in this study takes the middle value of 0.465 g/kWh.

4.3 The proportion of traditional energy vehicles

According to the index system in the "13th Five-Year Plan for Transportation Development and Construction in Beijing", the number of motor vehicles in Beijing will be no more than 6.3 million by 2020. In this study, we analyze the average proportion of private cars to the total number of motor vehicles as the proportion of private cars in 2020 based on the data of Beijing Statistical Yearbook 2010–2017 as shown in Table 4, and then confirm the number of private cars in 2020.

4.4 Cost

The deterministic cost of a car can be roughly divided into the cost of purchase and the cost incurred at end-of-life. The production cost of new energy vehicles varies depending on the battery capacity, and most new energy vehicles currently have a battery capacity of 15 kWh to 60 kWh. In this study, a battery capacity of 40 kWh is chosen for pure electric vehicles and 30 kWh for hybrid vehicles. Therefore, the cost of pure electric vehicles and hybrid vehicles is 234,800 CNY and 279,800 CNY. Additionally, the cost of fuel vehicles is set as 250,000 CNY.

The environmental cost generated by scrapping according to the Notice of the Ministry of Finance and Commerce on the Issuance of "Management Measures of Subsidy Funds for Scrapping and Renewing Old Cars": scrapping small passenger cars (excluding sedans) is subsidized by 7000 CNY per vehicle, scrapping micro passenger cars (excluding sedans) is subsidized by 5000 CNY per vehicle, scrapping cars of 1.35 L and above displacement is subsidized by 18,000 CNY per vehicle, and scrapping cars of 1 L (excluding) to 1.35 L

Table 3 Statistics of electricity generation in Beijing by category

| Year | Electricity generation | Hydroelectricity | Thermal power generation | Proportion of thermal power (%) |
|------|------------------------|------------------|--------------------------|---------------------------------|
| 2016 | 434.39 | 12.29 | 417.76 | 96.17 |
| 2015 | 421 | 6.64 | 411.13 | 97.66 |
| 2014 | 363.97 | 6.8 | 354.05 | 97.27 |
| 2013 | 336.01 | 4.72 | 327.88 | 97.58 |
| 2012 | 290.8 | 4.21 | 283.19 | 97.38 |
| 2011 | 262.98 | 4.48 | 255.53 | 97.17 |
| 2010 | 269 | 4.4 | 261.8 | 97.32 |

Table 4 2010–2018 private car statistics

| Year | Total number of motor vehicles | Number of private vehicles | Percentage of private vehicles (%) |
|------|--------------------------------|----------------------------|------------------------------------|
| 2018 | 608.4 | 479 | 78.73 |
| 2017 | 590.9 | 467.2 | 79.07 |
| 2016 | 571.7 | 452.8 | 79.20 |
| 2015 | 561.9 | 440.3 | 78.36 |
| 2014 | 559.1 | 440.3 | 78.75 |
| 2013 | 543.7 | 426.5 | 78.44 |
| 2012 | 520 | 407.5 | 78.37 |
| 2011 | 498.3 | 389.7 | 78.21 |
| 2010 | 480.9 | 374.4 | 77.85 |

(excluding) displacement cars, each is subsidized by 10,000 CNY. Therefore, this paper sets the scrapping cost of vehicles as 10,000 CNY.

The expenses incurred during the use of fuel vehicles, pure electric vehicles and plug-in hybrid vehicles mainly include energy costs and maintenance costs. The specific data are as follows (Table 5).

5 Discussions

5.1 Model results and comparative analysis

In this paper, the constraints (6)–(14) and the objective functions (1) and (2) are integrated and programmed to be solved by MATLAB, and the integer programming theory is considered in the solution process, and the optimal Pareto-optimal solution is finally obtained after tens of thousands of iterations of calculation.

According to the calculation, the appropriate quantity of three different energy vehicles in Beijing, Guangzhou and Shanghai is shown in Fig. 2. The proportion of fuel vehicles in Beijing is higher than that in Shanghai and Guangzhou, while the proportion of plug-in hybrid vehicles is lower than that in Shanghai and Guangzhou. This is due to the existing automobile structure. The transformation pressure of Beijing's automobile industry is greater, and it will take some time to realize the replacement of new energy vehicles.

Table 5 The expenses incurred during the use of vehicles

| Cost | Unit | Fuel vehicles | Pure electric vehicles | Plug-in hybrid vehicles |
|--|----------------|---------------|------------------------|-------------------------|
| Annual mileage | Km | 20,000 | 20,000 | 20,000 |
| Unit energy cost | CNY/l; CNY/kwh | 6.94 | 1.7 | 6.94; 1.7 |
| Total energy consumption | l; kwh | 1600 | 3000 | 800;1500 |
| Annual maintenance and insurance costs | CNY | 15,000 | 15,000 | 15,000 |

In addition, the optimization results of Guangzhou show that the proportion of traditional energy vehicles is less than 50%, which is because in recent years, Guangzhou has more support policies for new energy vehicles and has a better market environment.

As shown in Fig. 3, the optimal proportions of the three types of vehicles in 2030 and 2050 are analyzed. Compared with 2020, the automobile industry structure in 2030 has been optimized, and the proportion of new energy vehicles has increased. By 2050, new energy vehicles will completely replace traditional fuel vehicles.

Using Eqs. (1) and (2), the pollution and cost function values are calculated, respectively. A comprehensive comparison of the actual data for 2018, 2020 and the data calculated by the model is shown in the table below.

Take Beijing as an example, as can be clearly seen from the Table 6, the results of the model solution are very effective in reducing air pollutant emissions by approximately 9 million tons compared to the 2020 plan. This is a significant reduction in air pollutants for an additional \$16.4 billion, which is worthwhile for the Beijing government. In the cost function, a large part of the cost also belongs to the construction cost of charging piles, which is an infrastructure that will help improve the well-being of the residents.

Meanwhile, based on the planning data of Shanghai and Guangzhou, all the data are substituted into the model of this paper, and the emission reduction of pollutants after optimization is significantly reduced, which is quite different from the current situation. Assuming that the number of motor vehicles in Beijing, Shanghai and Guangzhou are all 6.3 million, the comparison of pollutant emission and cost for each city is shown in Fig. 4.

As shown in Fig. 4, after the model optimization, the pollutant emissions will be significantly reduced, and all of them reach the emission reduction effect of ten million tons. However, due to the higher cost of new energy vehicles, the total costs associated with the three cities will be increased. With the widespread use of new energy vehicles, the social cost will

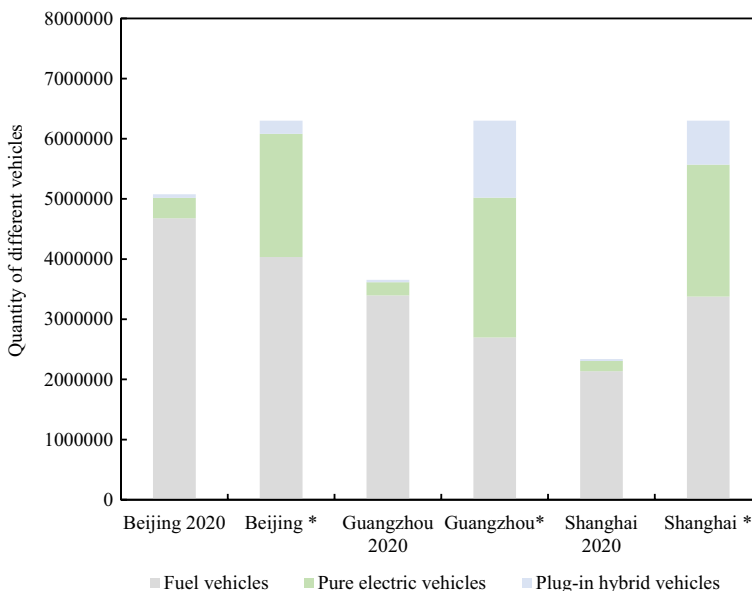


Fig. 2 Current status and optimization for the quantity of different vehicles. *Note* Beijing 2020, Shanghai 2020, and Guangzhou 2020 indicate the calculation results based on the existing ratio, and Beijing*, Shanghai*, and Guangzhou* indicate the calculation results based on the ratio after model optimization

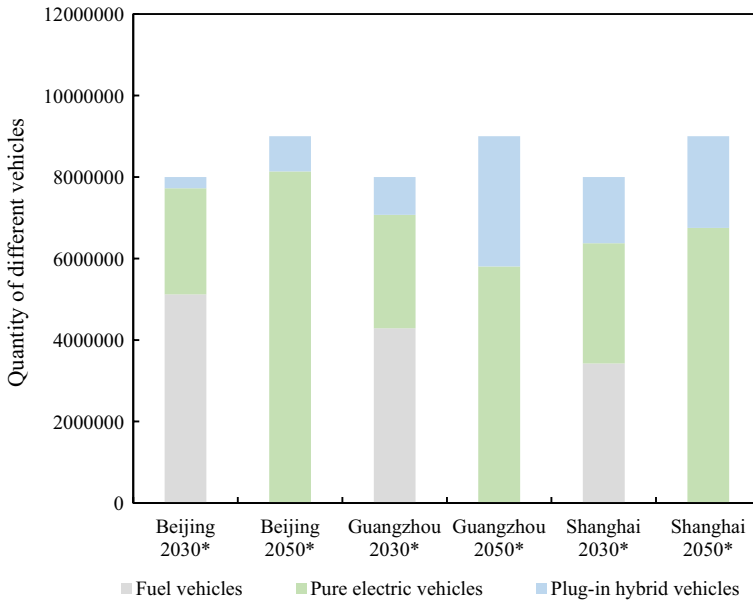


Fig. 3 Optimization for the quantity of different vehicles in 2030 vs. 2050

decrease under the influence of the scale effect, and the construction cost of charging piles will be significantly reduced when the charging demand of new energy vehicles is met. Therefore, in the future, the optimized model results can significantly reduce the pollutant emissions and slow down the increase of the total cost, and such model results are of great reference significance for urban transportation planning.

Meanwhile, according to the existing policy, Hainan Province will ban the sale of fuel cars in 2030. Therefore, this paper assumes that three cities, Beijing, Shanghai, and Guangzhou, also ban the sale of fuel cars in 2030, at which time the proportion of fuel cars is the model-optimized proportion and the number of motor vehicles is 8 million. The ratio of pure electric vehicles to plug-in hybrid vehicles is the relative ratio after model optimization, and the pollutant emissions and costs of the three cities in 2030 and 2050 are calculated by the model, as shown in Fig. 5.

As can be seen from Fig. 5, the pollutant emissions of the three cities achieve obvious reduction effect, with Beijing reducing about 32 Mt, Shanghai reducing about 20 Mt, and Guangzhou reducing about 25 Mt. In terms of cost, Beijing increases by about 60 billion, Shanghai increases by about 36 billion, and Guangzhou increases by about 47 billion. And in the future development, with the scale effect of new energy vehicle production, its related costs will be reduced. Therefore, in the future planning of the city, it makes sense to exchange a lower expenditure for a great effect of emission reduction.

Table 6 Comparison between model and current situation

| | Model Optimization | 2020 | 2018 |
|------------|--------------------|------------|------------|
| $f_1(N_i)$ | 20,795,571 | 29,618,976 | 29,620,209 |
| $f_2(N_i)$ | 1,608,594 | 1,410,378 | 1,379,941 |

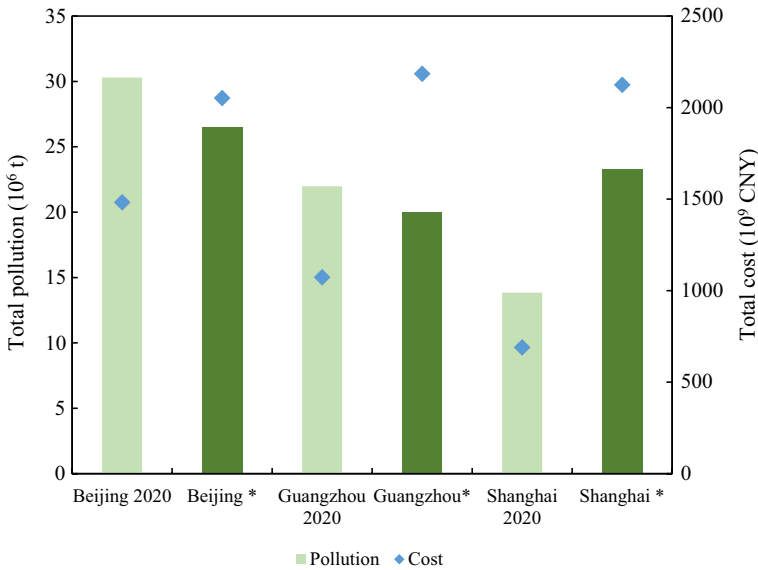


Fig. 4 Current status and optimization of pollutant emissions versus costs. *Note* Beijing 2020, Shanghai 2020, and Guangzhou 2020 indicate the calculation results based on the existing ratio, and Beijing*, Shanghai*, and Guangzhou* indicate the calculation results based on the ratio after model optimization

5.2 Sensitivity analysis

When the proportion of a certain type of car quantity changes, it will inevitably lead to dynamic changes in the proportion of other types of car quantity, so it is necessary to conduct a sensitivity analysis. In the sensitivity analysis section, this paper takes Beijing as an example, and controls the proportion of one type cars among the three energy vehicles to increase or decrease by 0.2% equal to 5%, respectively. Whenever a change in the proportion of the number of cars is controlled, 11 corresponding changes occur, so a total of 33 changes are analyzed in the sensitivity analysis phase. Due to space limitations, some of these changes are selected for analysis in this section.

The six scenarios shown in Fig. 6 are formed by controlling two changes and one constant for each of the three types of vehicles. When the ratio of controlling the number of different types of cars is changed, the optimal points all change slightly, as shown in Table 7.

When the proportion of N_1 quantity increases and the proportion of N_2 and N_3 quantity decreases in different proportions, there is an increasing trend of pollutant emissions and a decreasing trend of costs. When the proportion of N_2 quantity increases the N_1 and N_3 quantities decrease in different proportions. Meanwhile, there is an upward trend of cost and a downward trend of pollutant emissions. When the ratio of N_3 quantity increases and the ratio of N_1 as well as N_2 decreases is 0.4 and 0.6, there is an increasing trend of pollutants and a decreasing trend of costs. After this ratio, there is a downward trend in pollutant emissions and an upward trend in costs. All the best points are in the fluctuation range of 1%. The above phenomenon occurs mainly because the pollutant emissions of N_1 are high. When the starting quantity is high, the overall pollutant emissions are high. Additionally, as the ratio of N_2 and N_3 quantities rises and the ratio of N_1 quantities decreases, the air

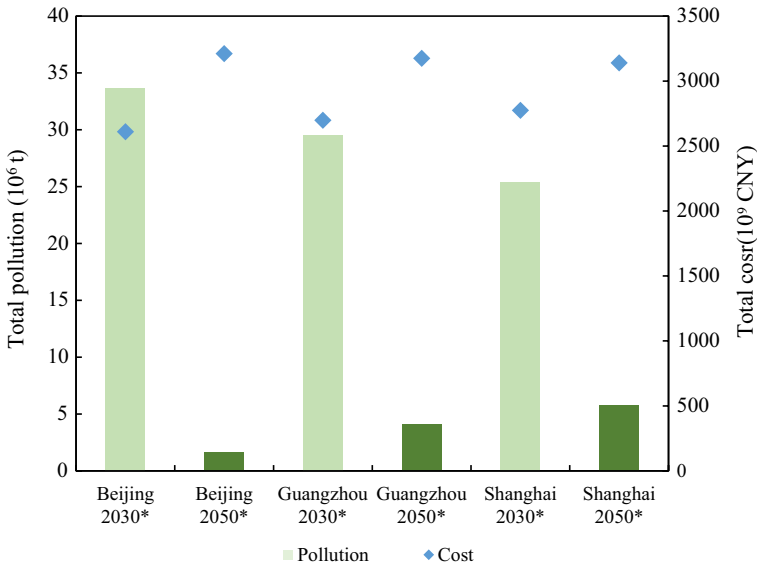


Fig. 5 Optimization for Pollutant emissions and costs in 2030 vs. 2050

pollutant emissions will show a downward trend. When the starting quantity of N_1 is low, the air pollutants show an increasing trend as the ratio of N_2 and N_3 quantities decreases. Analyzed from the cost perspective, N_2 and N_3 are costly, and as the ratio of the number of these two increases, the cost shows an upward trend.

From the Fig. 6 and Table 7, it can be learned that when N_1 is kept constant, the optimal point becomes N_2 proportional increase of 0.3% and N_3 decrease of 0.3%. N_2 itself is pollution-free, and the pollutant emission of electricity production due to charging is much lower than N_3 , and in order to make the target optimal, N_2 should increase and N_3 should decrease. When N_2 is kept constant, the optimal point becomes

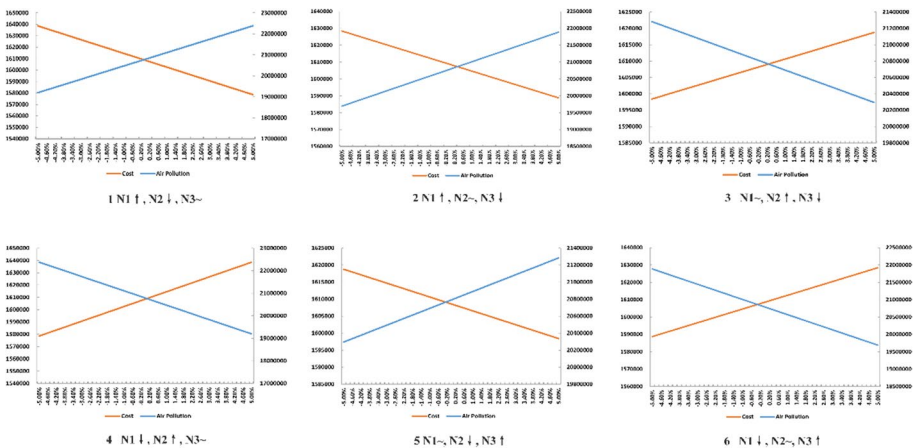


Fig. 6 Line chart of changing the proportion of the number of any two vehicles. Note↑ indicates an increase, ↓ indicates a decrease, and ~ indicates no change

Table 7 Optimal position under the change of the proportion of the two kinds of cars

| | N_1 | N_2 | N_3 |
|---|----------------|----------------|---------------|
| 1 | 64.32% (↑0.3%) | 32.53% (~) | 3.15% (↓0.3%) |
| 2 | 63.92% (↓0.1%) | 32.63% (↑0.1%) | 3.45% (~) |
| 3 | 64.02% (~) | 32.83% (↑0.3%) | 3.15% (↓0.3%) |
| 4 | 63.92% (↓0.1%) | 32.63% (↑0.1%) | 3.45% (~) |
| 5 | 64.02% (~) | 32.83% (↑0.3%) | 3.15% (↓0.3%) |
| 6 | 64.32% (↑0.3%) | 32.53% (~) | 3.15% (↓0.3%) |

() indicates the change in the proportion of this optimal point compared to the model results

↑ indicates an increase

↓ indicates a decrease, ~ indicates no change

N_1 increasing by 0.3% and N_3 decreasing by 0.3%. N_3 is more costly than N_1 , and N_3 's own pollutant emission capacity is slightly lower than that of N_1 , and the phenomenon of N_1 increasing and N_3 decreasing occurs in order to achieve the overall optimum. When N_3 is kept constant, the optimal point becomes N_1 decreases by 0.1% and N_2 increases by 0.1%. This is because N_1 's own pollutant emission capacity is stronger than N_3 , and when N_3 remains unchanged, N_1 must be reduced and N_2 increased in order to achieve the overall optimal goal.

The nine scenarios in Fig. 7 show the change results of the overall carbon emissions and costs obtained by controlling the increase of one type vehicles and the reduction of the other two types of vehicles in different proportions. The change ratio in 1–3 scenarios is set as 0.2:0.8. The change ratio in 4–6 scenarios is set as 0.5:0.5, and the change ratio in 7–9 scenarios is 0.8:0.2. Under different scenarios, the best points have changed, and the specific changes are shown in Table 8.

From the data in Table 8, it can be seen that the maximum fluctuation of the optimal point is 0.4% and the minimum is 0.02%, none of which exceeds 1%. It indicates that under the current situation, the change in the number of different types of vehicles will not significantly affect the optimal vehicle allocation plan with the objective of minimizing economic and environmental costs. In addition, row 0 represents the result of model solution, and row 1~9 represent the fluctuation of the optimal point under different scenarios, respectively. Based on comprehensive analysis of multiple scenarios, the quantity of traditional energy vehicles, pure electric vehicles and plug-in hybrid vehicles in Beijing accounts for about 64%, 32.5% and 3.5%, respectively, which can obtain better economic and environmental benefits.

Meanwhile, this paper compares the model-optimized proportions of Beijing, Shanghai and Guangzhou, and the specific results are shown in Table 9. The proportion of new energy vehicles in Beijing reaches 36% to achieve the model target, which is consistent with the results of sensitivity analysis. The proportion of new energy vehicles in Shanghai and Guangzhou is about 57% and 46% to achieve the model target, which can maximize the reduction of pollutant emissions and give full play to the emission reduction effect of new energy vehicles.

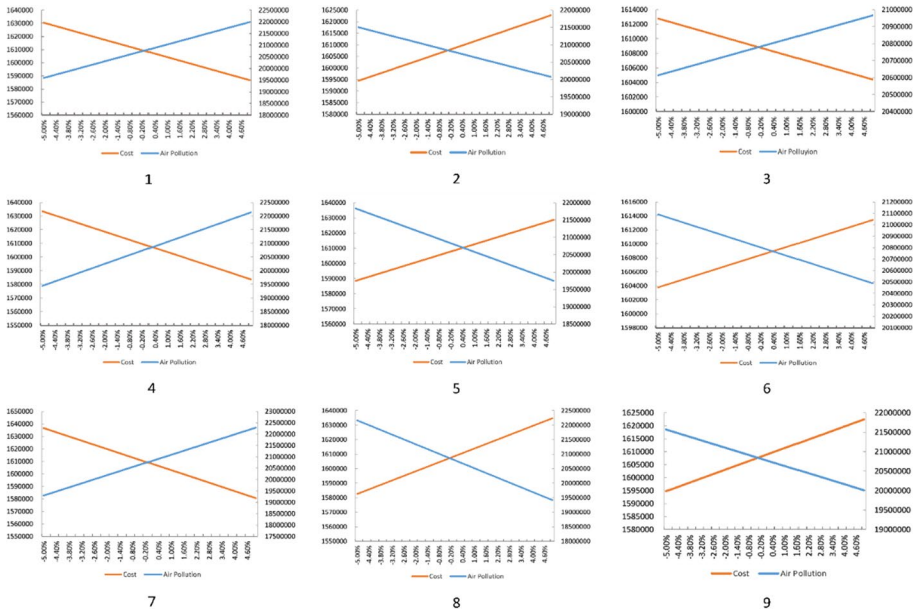


Fig. 7 Three kinds of vehicles change in a fixed proportion

Table 8 Optimal point fluctuations under fixed proportional changes

| Scenarios | N_1 | N_2 | N_3 |
|-----------|-----------------|-----------------|----------------|
| 0 | 64.02% | 32.53% | 3.45% |
| 1 | 63.92% (↓0.1%) | 32.55% (↑0.02%) | 3.53% (↑0.08%) |
| 2 | 64.06% (↑0.04%) | 32.33% (↓0.2%) | 3.61% (↑0.16%) |
| 3 | 64.08% (↑0.06%) | 32.77% (↑0.24%) | 3.15% (↓0.3%) |
| 4 | 64.32% (↑0.3%) | 32.38% (↓0.15%) | 3.30% (↓0.15%) |
| 5 | 63.82% (↓0.2%) | 32.93% (↑0.4%) | 3.25% (↓0.2%) |
| 6 | 63.82% (↓0.2%) | 32.33% (↓0.2%) | 3.85% (↑0.4%) |
| 7 | 63.92% (↓0.1%) | 32.61% (↑0.08%) | 3.47% (↑0.02%) |
| 8 | 64.18% (↑0.16%) | 32.33% (↓0.2%) | 3.49% (↑0.04%) |
| 9 | 64.34% (↑0.32%) | 32.61% (↑0.08%) | 3.05% (↓0.4%) |

() indicates the change in the proportion of this optimal point compared to the model results, ↑ indicates an increase, ↓ indicates a decrease, ~ indicates no change

6 Conclusions

The goal of carbon neutrality and carbon peak will inevitably promote the construction of low-carbon cities. As one of the main industries with carbon emissions, the transportation industry also needs to accelerate the process of cleaning. Therefore, it is very important to study how to reasonably plan the proportion of traditional fuel vehicles and new energy vehicles. Therefore, this paper constructs a multi-objective optimization

Table 9 Comparison of model optimization ratios in Beijing, Shanghai and Guangzhou

| | N_1 (%) | N_2 (%) | N_3 (%) |
|---------------|-----------|-----------|-----------|
| Beijing2020 | 92.1 | 6.7 | 1.2 |
| Beijing* | 64.0 | 32.5 | 3.5 |
| Beijing2050 | 0 | 90.4 | 9.6 |
| Shanghai2020 | 92.9 | 6.0 | 1.1 |
| Shanghai* | 42.8 | 36.9 | 20.3 |
| Shanghai2050 | 0 | 64.5 | 35.5 |
| Guangzhou2020 | 91.4 | 7.2 | 1.3 |
| Guangzhou* | 53.6 | 34.8 | 11.6 |
| Guangzhou2050 | 0 | 75.0 | 25.0 |

2020 denotes the current proportion of each city

*Denotes the optimized proportion, and 2050 refers to the relative proportion of new energy vehicles after the retirement of traditional energy vehicles

model considering social and economic benefits and environmental benefits to study Beijing, Shanghai and Guangzhou. The results are as follows:

- (1) Under the current background, when the proportion of new energy vehicles in Beijing, Shanghai and Guangzhou reaches about 36%, 57% and 46%, they can obtain better energy conservation, emission reduction and economic effect.
- (2) The overall carbon emissions of society will rise significantly if the policies of prohibiting the sale and delisting of traditional energy vehicles are promulgated in 2030 and 2050, respectively, based on the model calculation. Compared with 2030, Beijing, Shanghai and Guangzhou can achieve emission reductions of 320,000 tons, 200,000 tons and 250,000 tons, respectively, in 2050.
- (3) Through model verification and comparative analysis, it can be seen that the optimized results of Beijing, Shanghai and Guangzhou in the model framework of this paper can achieve greater emission reduction effects, which shows that this model can effectively analyze the optimal proportion of urban traditional vehicles and new energy vehicles. It can provide a basis for the policy formulation of various cities and achieve better emission reduction effects.

Based on the above conclusions, this paper makes the following recommendations. Firstly, in the planning of private vehicles in cities, full consideration should be given to increasing the proportion of new energy vehicles in order to give full play to the advantages of new energy vehicles. Moreover, the corresponding subsidy mechanism for the purchase of new energy vehicles should be formulated, which could actively stimulate the residents' consumption of new energy vehicles. Additionally, in order to achieve the optimal proportion as soon as possible, the government can promulgate a series of policies to achieve the goal. For example, it can reduce the proportion of traditional energy vehicles by forcing them to be scrapped. Finally, the government should invest in infrastructure such as charging piles and charging stations to improve the convenience of using new energy vehicles, which in turn will encourage more residents to buy new energy vehicles.

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