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ORIGINAL PAPER

# The dynamic analysis of a vehicle pollutant emission reduction management model under economic means

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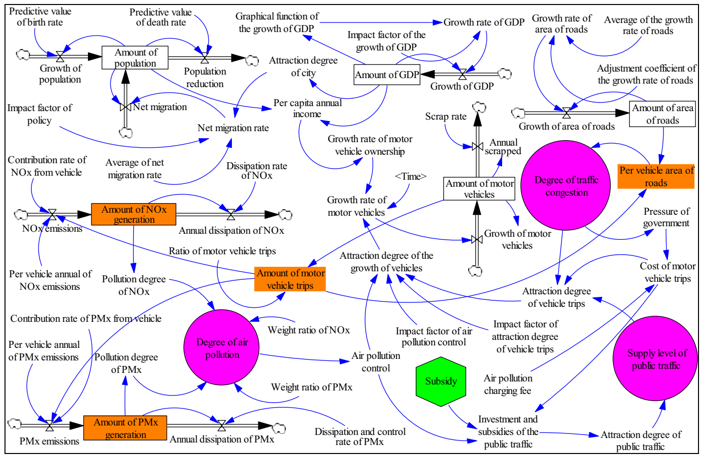
## Abstract

Aimed at the problem of traffic congestion and vehicle pollutant emissions, this paper utilized a system dynamics approach to construct an air pollution charging fee management model from the perspective of social and environmental benefits. The gray system theory was used to determine the major parameters and equations. On this basis, taking Beijing as a case study, simulation analysis of the major variables was conducted using the sensitivity analysis principle. Moreover, a reasonable range for air pollution charging fee was determined using the principle of marginal utility. Lastly, the different combinations of subsidy and air pollution charging fee were compared to explore their respective ranges and obtain the following conclusions: (1) To a certain extent, the amount of PMx generation, degree of air pollution, amount of motor vehicle trips, and degree of traffic congestion declined with the increase in the air pollution charging fee. However, the air pollution charging fee policy implementation influenced modes of transport, as some citizens turned to public transportation, which increased the burden on public transport. Therefore, we needed to consider a subsidy policy to improve the supply level of public traffic. (2) A single subsidy policy will limit the magnitude of the degree of traffic congestion, amount of PMx generation, and degree of air pollution reductions. (3) There were three effects to combining the subsidy policy with the air pollution charging fee: it relieved the degree of traffic congestion and reduced PMx emissions, inhibited the intensity of "haze pollution," and improved the supply level of public traffic. (4) Compared with a low air pollution fee of 2 yuan/day*vehicle, our model projects that by 2025, a policy combining a higher air pollution fee (50 yuan/day*vehicle) with a public transportation subsidy will reduce air pollution about 19% and increase the supply of public transportation by about 88%.

**Electronic supplementary material** The online version of this article (https://doi.org/10.1007/s10098-018-1631-2) contains supplementary material, which is available to authorized users.

Extended author information available on the last page of the article

## Graphical abstract




**Keywords** System dynamics · PMx emission · Traffic congestion · Subsidy policy · Combination schemes

## Introduction

The serious consequences of increased motor vehicle use include, but are not limited to, increasing traffic congestion and severe air pollution due to motor vehicle exhaust emissions (Qiu and Peng 2015; Reşitoğlu et al. 2015). These pollution problems exist in many cities of China, particularly high ambient $PM_{2.5}$ concentrations, and increase the pressure to accelerate efforts to reduce vehicle emissions (Wu et al. 2017). Vehicle emissions have been a critical contributor to air pollution in Chinese cities (Hao et al. 2000; Yang et al. 2011; Cui et al. 2015). Zíková et al. (2016) used a positive matrix factorization method to estimate a 25% traffic contribution to $PM_{2.5}$ levels in Beijing. In addition, traffic-related emissions (NOx, $PM_{2.5}$, PM10, etc.) are a major source of haze–fog pollution, especially in major metropolitan areas (such as Beijing and Shanghai). It has a large adverse impact on human health (Zhang et al. 2014; Requia et al. 2017). Taking "single and double number limit policy" in Beijing as an example, it did not relieve traffic congestion and pollution, but increased them in the long-term, while the effects are obvious in the beginning. In other words, although that policy relieved traffic congestion and pollution in the short term, it made them worse in the long term. Hence, the urban traffic congestion and the emission of vehicle exhaust pollutants have become a problem that hinders the efficient management of city traffic and urgently needs to be addressed.

Regarding vehicle exhaust emissions, some scholars addressed transport emissions (Shahbaz et al. 2015), while others researched the problems of energy efficiency and emission reductions (Iftikhar et al. 2016). Diao et al. (2016) studied the intangible cost of traffic policies between battery electric vehicles and conventional vehicles by using the life-cycle cost method. The results indicated that electric vehicles were not currently economically competitive compared with conventional vehicles, and both local and national subsidies were necessary for battery operated electric vehicles. Additionally, it was unclear whether fleet electrification can deliver substantial environmental benefits, since coal-based electricity dominates the power market in many regions of North China (Shen et al. 2014). Liu et al. (2017) summarized vehicle emission inventories include NOx, $PM_{2.5}$ and $PM_{10}$ emissions in the Guangdong Province from 1994 to 2014. Huo et al. (2015) calculated the average emission factors in China for NOx and $PM_{2.5}$ for the period between 2000 and 2012. Wu et al. (2016) assessed the first 15 years (1998–2013) of China's efforts to control vehicle emissions, based on national-scale total annual vehicle emission data for NOx and $PM_{2.5}$. Wang et al. (2010) established and analyzed NOx and $PM_{10}$ vehicle emission trends for Beijing, Shanghai, and Guangzhou from 1999 to 2005. In addition, there are many studies in traffic congestion charges around the world, including Singapore (Olszewski and Xie 2005; Phang and Toh 1997), London (Santos 2005; Wen et al. 2014), Stockholm (Eliasson et al. 2013; Eliasson 2014), Gothenburg (Börjesson et al. 2016), USA (Zmud 2008), and Malaysia (Almselati et al. 2015).

However, the existing literature pays scant attention to the dynamic property of the urban traffic system and interactions with critical variables when evaluating its societal and environmental performance. To this end, from the perspective of alleviating traffic congestion and reducing air pollution, this paper established an air pollution charging fee and vehicle emission reductions management model, based on an approach that integrates system dynamics with gray theory. It is essential that the air pollution charging fee use the charge mechanism to gain economic leverage. Additionally, motorists should be encouraged to alter their trip mode, and public transport (such as the subway, bus, and bicycle sharing) should be promoted as a cleaner and more sustainable mode of transport. Given the decline in the supply level of public traffic, this paper further introduces a subsidy mechanism to improve its service quality.

The rest of this paper is organized as follows: "Methodology" section utilizes the system dynamics method to construct vehicle pollutant emission reduction management model and uses the gray system theory and regression analysis method to determine the major parameters and equations; "Simulation results and discussion" section analyzes the results and discusses the impacts of the major variables under different combination policies of subsidy and air pollution charging fee; and "Conclusions" section summarizes the main conclusions.

## Methodology

System dynamics (SD), which was introduced by Jay Forrester, provides an effective tool to make system structure and functional analysis as well as simulations of dynamic behavior (Zhao et al. 2011). It is suitable for researching and planning the future behavior of complex socioeconomic systems and aids with the corresponding strategic decisions (Forrester 1973). For the SD model to simulate and model for application purposes, it requires constructing of "causal loop diagrams" or the "stock and flow diagram" (Dyson and Chang 2005). There are a variety of applications that system dynamics can be utilized for. Procter et al. (2017) established a SD model to simulate how light rail transit, and concurrent policies could help or hinder these sustainable growth goals. Crookes et al. (2013) adopted a SD approach to assess economic viability and risk trade-offs for ecological restoration in South Africa. Chang et al. (2013) researched the government subsidy policy effects on solar water heater installations in Taiwan because solar energy can provide a clean, non-polluting, renewable energy source and thus contributes significantly to relieving the energy and environment crises.

### Model development

The VENSIM software was proposed to generate the stock–flow diagram for vehicle pollutant emission reductions management model, as shown in Fig. 1. The descriptions of the main variables and equations are shown in online Appendix C. It contains three negative loops, and the specific descriptions are outlined in Fig. 2.

Loop 1 is a negative feedback loop, meaning an increase in the degree of traffic congestion would eventually affect itself in a negative way. In this loop, an increase in degree of traffic congestion will increase the pressure on the government, which leads to larger costs for motor vehicle trips, which will decrease the attraction of vehicle trips. Ultimately, this will reduce the growth rate of motor vehicles, which in turn will decrease the number of vehicles on the roads, and the amount of motor vehicle trips. Reduced amount of motor vehicle trips will lead to a larger per vehicle area of roads, which finally leads back to a smaller degree of traffic congestion.

Loop 2 is similar to Loop 1 in that it is also a negative feedback system, but with the addition that it introduces a subsidy policy. Loop 3 utilizes the subsidy policy to improve the growth of supply level of public traffic. Assuming there is an increase in the degree of air pollution, the air pollution control as well as the investment and subsidies of the public traffic will rise. A larger investment and subsidies of the public traffic will increase the attraction degree of public traffic and supply level of public traffic, reducing the number of vehicle trips, and will eventually influence growth rate of motor vehicles. With fewer motor vehicles and amount of motor vehicle trips, this will reduce the amount of PMx generation and amount of NOx generation, with the consequence of reducing the degree of air pollution.

Setting: INITIAL TIME = 2009, FINAL TIME = 2025, TIME STEP = 1, UNIT OF TIME: Year.

**Assumption** In the perspective of the emission-reducing effect, this paper focused on the PMx, and NOx, where PMx mainly includes $PM_{2.5}$ and $PM_{10}$, and NOx mainly refers to $NO_2$ and NO. In particular, (Air pollution charging fee, Subsidy) = (APCF, Subsidy) = (A, S), and the units are yuan/day*vehicle.

### Data sources

The data source mainly includes the existing literatures (Method 1), official statistical data (Method 2), and indirect data through calculations (Method 3).

*Method 1* Data from existing literatures.

According to existing literatures and the actual situation, we can obtain the following variables. See Table 1 for specific results.

Net migration $\text{rate}_{2009} = 0.00603$, net migration $\text{rate}_{2010} = 0.00556$, net migration $\text{rate}_{2011} = 0.00641$, net migration $\text{rate}_{2012} = 0.00517$, net migration $\text{rate}_{2013} = 0.00519$, net migration $\text{rate}_{2014} = 0.00347$. So, net migration $\text{rate}_{\text{mean value}} = 0.00531 = 5.31‰$. The trend is falling due to the influence of Beijing population policy, and net migration $\text{rate}_{\text{mean value}} >$ net migration $\text{rate}_{2014}$; hence, it needs to be adjusted. Therefore, let net migration rate = net

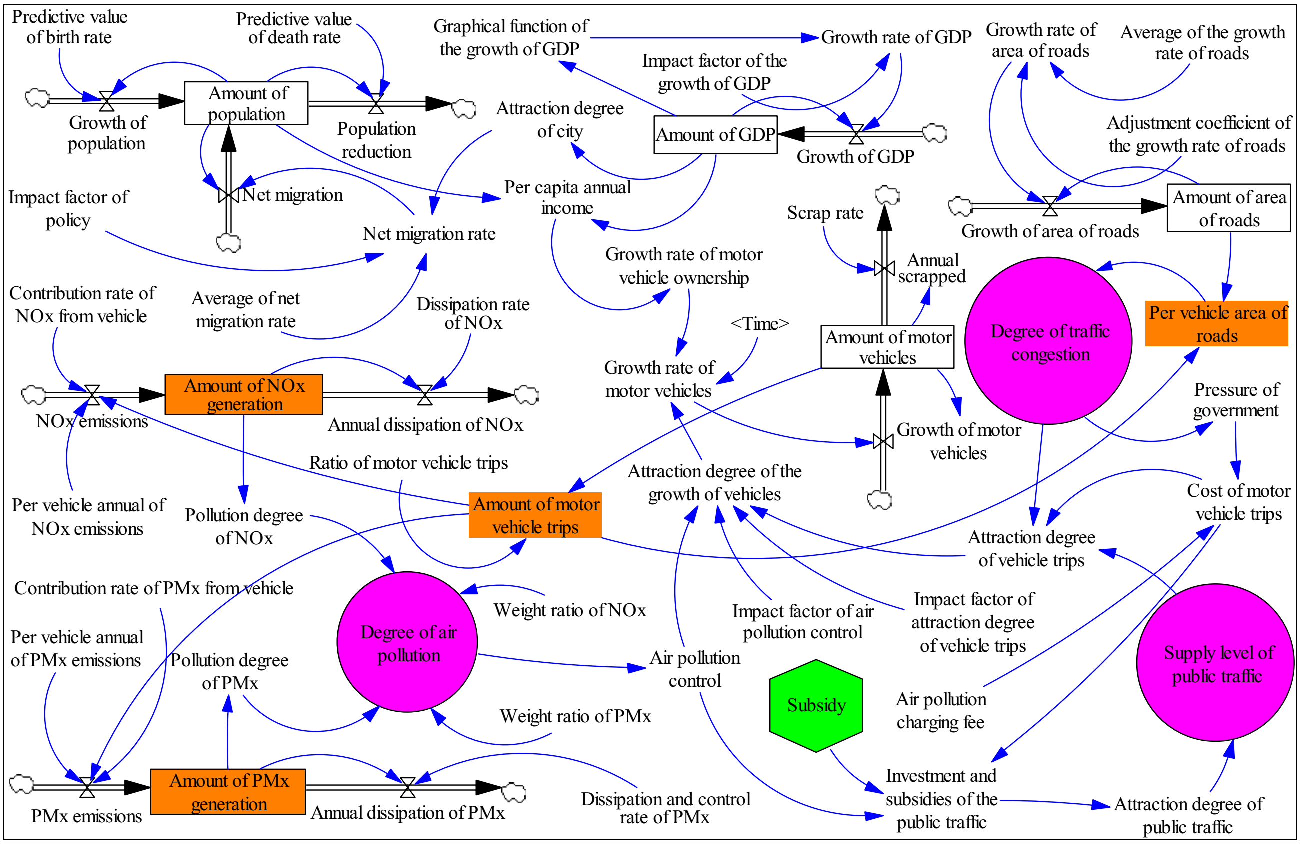



**Fig. 1** The stock–flow diagram for vehicle pollutant emission reductions management model

migration rate$_{\text{mean value}}$ × attraction degree of city$^a$, and by the calculation, it is closer to the actual value when $a = 1.5$.

*Method 2* Official statistical data (see online Appendix A).

*Method 3* Indirect data through calculations.

On the one hand, gray accumulation of data weakens the randomness of the original sequence, which helps to reveal the characteristics of the system. Even in the absence of data, the gray prediction theory can excavate hidden information (Liu et al. 2014). On the other hand, SD is good at dealing with long-term problems. Hence, the SD-GM theory possesses the advantages of both approaches and can describe the dynamic trend of variables more accurately. Detailed descriptions are given in online Appendix B.

## Model validity

**Definition 1** Assume the images of a zero starting point for the two behavioral sequences (Jia et al. 2017)

$$X_i = \left(x_i(1), x_i(2), \ldots, x_i(n)\right), X_j = \left(x_j(1), x_j(2), \ldots, x_j(n)\right) \tag{1}$$

are

$$X_i^0 = \left(x_i^0(1), x_i^0(2), \ldots, x_i^0(n)\right), X_j^0 = \left(x_j^0(1), x_j^0(2), \ldots, x_j^0(n)\right). \tag{2}$$

Assume that $X_i'$ and $X_j'$ are the initial images of $X_i$ and $X_j$, the images of zero starting point of the two behavioral sequences $X_i', X_j'$ are $X_i'^0$ and $X_j'^0$, then

$$\begin{aligned} \varepsilon_{ij}^{\left(\frac{1}{\sqrt{n}},2\right)} = {} & \left[1 + \left|\sum_{k=2}^{n-1} x_i^0(k) + \frac{1}{2}x_i^0(n)\right| + \left|\sum_{k=2}^{n-1} x_j^0(k) + \frac{1}{2}x_j^0(n)\right|\right] \times \left[1 + \left|\sum_{k=2}^{n-1} x_i^0(k) + \frac{1}{2}x_i^0(n)\right|\right. \\ & \left.\left|\sum_{k=2}^{n-1} x_j^0(k) + \frac{1}{2}x_j^0(n)\right| + \left|\sum_{k=2}^{n-1}\left[x_i^0(k) - x_j^0(k)\right] + \frac{1}{2}\left[x_i^0(n) - x_j^0(n)\right]\right| + \frac{1}{\sqrt{n}} \cdot \left(\sum_{k=1}^{n}\left|x_i^0(k) - x_j^0(k)\right|^2\right)^{\frac{1}{2}}\right]^{-1} \end{aligned} \tag{3}$$

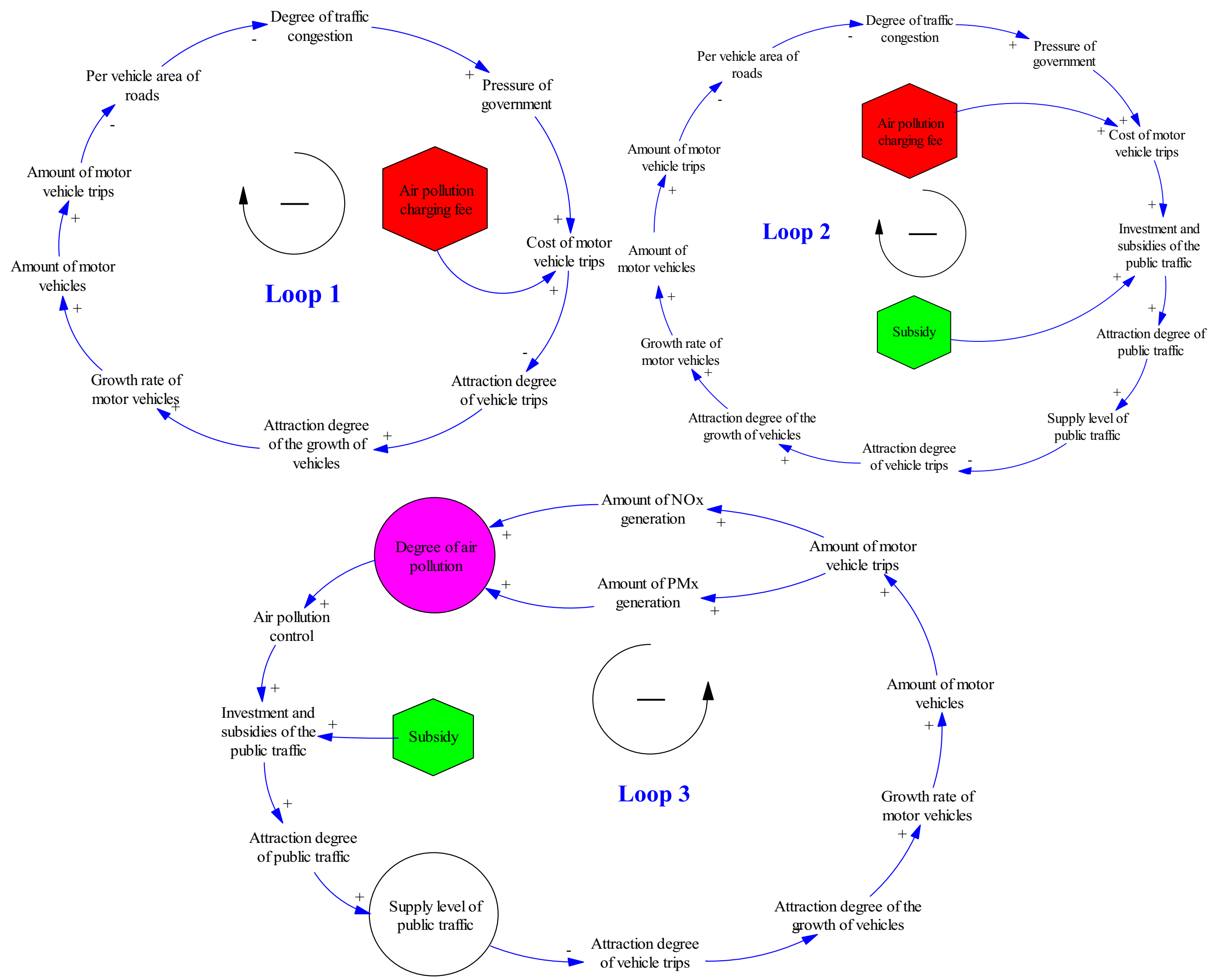



**Fig. 2** The causal loop diagrams for the SD model. Loop 1: Traffic congestion subsystem—the single policy of air pollution charging fee. Loop 2: Traffic policy subsystem—the combinations policy of subsidy and air pollution charging fee. Loop 3: Environment subsystem—the single policy of subsidy

**Table 1** Descriptions of the major variables in Method 1

| Variable | Value | Unit | Existing literatures |
|---|---|---|---|
| Per vehicle annual of NOx emissions | 0.02 | t/vehicle*year | Yang et al. (2014) and Wang et al. (2008) |
| Contribution rate of NOx from vehicle | 0.8 | – | Zhu (2013) |
| Contribution rate of PMx from vehicle | 0.6 | – | Zhu (2013) |
| Dissipation rate of NOx | 0.2 | – | Yang et al. (2014) and Wang et al. (2008) |
| Per vehicle annual of PMx emissions | 0.04 | t/vehicle*year | Zhu (2013) |
| Dissipation and control rate of PMx | 0.4 | – | Zhu (2013) |
| Attraction degree of city | 0.7056 | – | Jia et al. (2017) |
| Ratio of motor vehicle trips | 0.55 | – | Zhu (2013) |
| Scrap rate | 0.067 | – | Yang et al. (2014) and Wang et al. (2008) |

**Table 2** Reference list of accuracy test grade (Liu et al. 2014)

| Accuracy grade | Grade 1 | Grade 2 | Grade 3 | Grade 4 |
|---|---|---|---|---|
| Degree of gray incidence $\varepsilon_0$ | 0.90 | 0.80 | 0.70 | 0.60 |

and

$$r_{ij}^{\left(\frac{1}{\sqrt{n}},2\right)} = \left[1 + \left|\sum_{k=2}^{n-1} x_i'^0(k) + \frac{1}{2}x_i'^0(n)\right| + \left|\sum_{k=2}^{n-1} x_j'^0(k) + \frac{1}{2}x_j'^0(n)\right|\right] \times \left[1 + \left|\sum_{k=2}^{n-1} x_i'^0(k) + \frac{1}{2}x_i'^0(n)\right| \right. \\ \left. \left|\sum_{k=2}^{n-1} x_j'^0(k) + \frac{1}{2}x_j'^0(n)\right| + \left|\sum_{k=2}^{n-1}\left[x_i'^0(k) - x_j'^0(k)\right] + \frac{1}{2}\left[x_i'^0(n) - x_j'^0(n)\right]\right| + \frac{1}{\sqrt{n}}\cdot\left(\sum_{k=1}^{n}\left|x_i'(k) - x_j'(k)\right|^2\right)^{\frac{1}{2}}\right]^{-1} \tag{4}$$

are, respectively, called the quasi-"Euclidean" absolute degree of incidence (Q-EUGAID) and the quasi-"Euclidean" relative degree of incidence(Q-EUGRID), then

$$\rho_{ij}^{\left(\frac{1}{\sqrt{n}},2\right)} = \sigma_1^{\left(\frac{1}{\sqrt{n}},2\right)}\xi_{ij}^{\left(\frac{1}{\sqrt{n}},2\right)} + \sigma_2^{\left(\frac{1}{\sqrt{n}},2\right)}\gamma_{ij}^{\left(\frac{1}{\sqrt{n}},2\right)} \tag{5}$$

is called the quasi-"Euclidean" synthetic degree of incidence (Q-EUGSID) of $X_i$ and $X_j$, where

$$\sigma_1^{\left(\frac{1}{\sqrt{n}},2\right)} > 0, \sigma_2^{\left(\frac{1}{\sqrt{n}},2\right)} > 0, \sigma_1^{\left(\frac{1}{\sqrt{n}},2\right)} + \sigma_2^{\left(\frac{1}{\sqrt{n}},2\right)} = 1. \tag{6}$$

**Definition 2** Qualified verification of the degree of gray incidence.

Assume that $X^{(0)}$ is the original sequence, $\hat{X}^{(0)}$ is its simulation sequence, and $\varepsilon$ is the Q-EUGSID between $X^{(0)}$ and $\hat{X}^{(0)}$, if $\exists\varepsilon_0 > 0$, when $\varepsilon > \varepsilon_0$, it is defined as the qualified verification of the degree of gray incidence. See Table 2 for the accuracy test grade. In particular, qualified verification of the degree of gray incidence is different from mean absolute percent error (MAPE), it is more focused on the long-term of testing, and it will overcome the deficiency of partial validation (such as MAPE).

(a) Qualified verification of the Q-EUGSID for the amount of motor vehicles.

The original sequence and its simulation sequence are, respectively,

$$X_0 = \begin{bmatrix} x_0(1) \\ x_0(2) \\ x_0(3) \\ \vdots \\ x_0(7) \end{bmatrix} = \begin{bmatrix} 4.019e+006 \\ 4.809e+006 \\ 4.983e+006 \\ 5.200e+006 \\ 5.437e+006 \\ 5.591e+006 \\ 5.619e+006 \end{bmatrix},$$

$$X_1 = \begin{bmatrix} x_1(1) \\ x_1(2) \\ x_1(3) \\ \vdots \\ x_1(7) \end{bmatrix} = \begin{bmatrix} 4.01900e+006 \\ 4.65222e+006 \\ 5.16324e+006 \\ 5.28475e+006 \\ 5.35856e+006 \\ 5.35578e+006 \\ 5.33975e+006 \end{bmatrix},$$

and the images of zero starting point of the two sequences are

$$X_0^0 = \begin{bmatrix} x_0^0(1) \\ x_0^0(2) \\ x_0^0(3) \\ \vdots \\ x_0^0(7) \end{bmatrix} = \begin{bmatrix} 0 \\ 7.900e+005 \\ 9.640e+005 \\ 1.181e+006 \\ 1.411e+006 \\ 1.572e+006 \\ 1.600e+006 \end{bmatrix},$$

$$X_1^0 = \begin{bmatrix} x_1^0(1) \\ x_1^0(2) \\ x_1^0(3) \\ \vdots \\ x_1^0(7) \end{bmatrix} = \begin{bmatrix} 0 \\ 6.33220e+005 \\ 1.14424e+006 \\ 1.26575e+006 \\ 1.33956e+006 \\ 1.33678e+006 \\ 1.32075e+006 \end{bmatrix},$$

and the initial images of sequences are

$X_0' = (1, 1.1966, 1.2399, 1.2939, 1.3511, 1.3911, 1.3981)$,

$X_1' = (1, 1.1576, 1.2847, 1.3149, 1.3333, 1.3326, 1.3286).$

Hence, their Q-EUGAID and Q-EUGRID are, respectively,

So, $\exists\varepsilon_0 = 0.9$, making

$$\varepsilon_{01} = \rho_{01}^{\left(\frac{1}{\sqrt{n}},2\right)} = \sigma_{01-1}^{\left(\frac{1}{\sqrt{n}},2\right)}\xi_{01}^{\left(\frac{1}{\sqrt{n}},2\right)} + \sigma_{01-2}^{\left(\frac{1}{\sqrt{n}},2\right)}\gamma_{01}^{\left(\frac{1}{\sqrt{n}},2\right)} = 0.9669 > 0.9 = \varepsilon_0,$$

$$\begin{aligned}\xi_{01}^{\left(\frac{1}{\sqrt{n}},2\right)} = & \left[1 + \left|\sum_{k=2}^{6} x_0^0(k) + \frac{1}{2}x_0^0(7)\right| + \left|\sum_{k=2}^{6} x_1^0(k) + \frac{1}{2}x_1^0(7)\right|\right] \times \left[1 + \left|\sum_{k=2}^{6} x_i^0(k) + \frac{1}{2}x_i^0(7)\right| + \right.\\ & \left. + \left|\sum_{k=2}^{6} x_1^0(k) + \frac{1}{2}x_1^0(7)\right| + \left|\sum_{k=2}^{6} [x_0^0(k) - x_1^0(k)] + \frac{1}{2}[x_0^0(7) - x_1^0(7)]\right| + \frac{1}{\sqrt{7}} \cdot \left(\sum_{k=1}^{7} \left|x_0^0(k) - x_1^0(k)\right|^2\right)^{\frac{1}{2}}\right]^{-1}\\ = & \frac{1 + 6718000 + 6319925}{1 + 6718000 + 6319925 + 338075 + \frac{1}{\sqrt{7}} \times 450179.60083} \approx 0.9626\end{aligned}$$

and

$$\begin{aligned}\gamma_{01}^{\left(\frac{1}{\sqrt{n}},2\right)} = & \left[1 + \left|\sum_{k=2}^{6} x_0'^0(k) + \frac{1}{2}x_0'^0(7)\right| + \left|\sum_{k=2}^{6} x_1'^0(k) + \frac{1}{2}x_1'^0(7)\right|\right] \times \left[1 + \left|\sum_{k=2}^{6} x_0'^0(k) + \frac{1}{2}x_0'^0(7)\right| + \right.\\ & \left. + \left|\sum_{k=2}^{6} x_1'^0(k) + \frac{1}{2}x_1'^0(7)\right| + \left|\sum_{k=2}^{6} [x_0'^0(k) - x_1'^0(k)] + \frac{1}{2}[x_0'^0(7) - x_1'^0(7)]\right| + \frac{1}{\sqrt{7}} \times \left(\sum_{k=1}^{7} \left|x_0'(k) - x_1'(k)\right|^2\right)^{\frac{1}{2}}\right]^{-1}\\ = & \frac{1 + 1.67165 + 1.5874}{1 + 1.67165 + 1.5874 + 0.08425 + \frac{1}{\sqrt{7}} \times 0.1119749079} \approx 0.9711.\end{aligned}$$

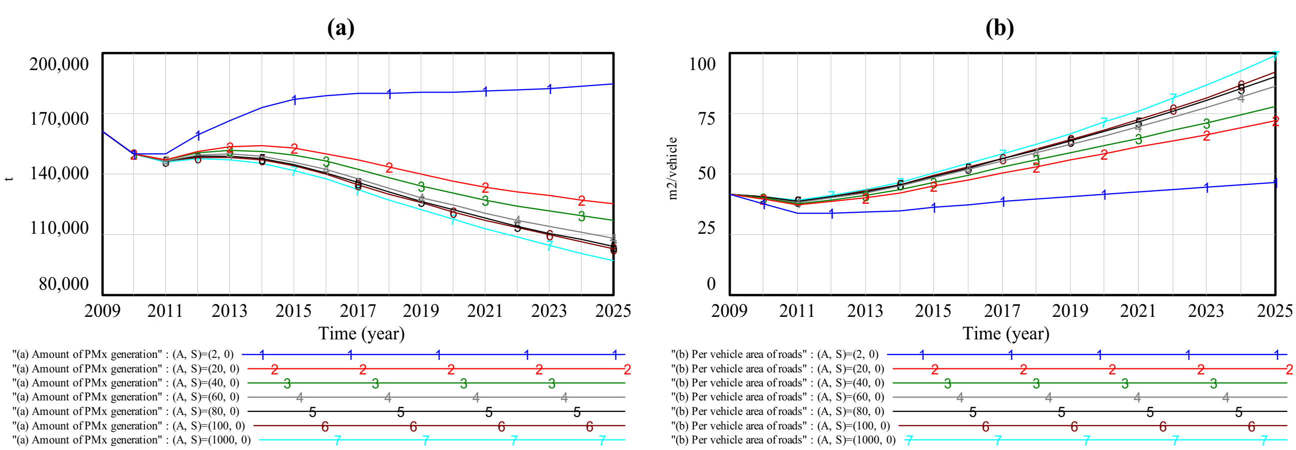



**Fig. 3** Sensitivity test and pricing analysis. **a** Amount of PMx generation; **b** per vehicle area of roads

**Table 3** The effects of amount of PMx generation and per vehicle area of roads under different air pollution charging fees (in 2025)

| Air pollution charging fee | Amount of PMx generation (t) | Marginal change | Per vehicle area of roads ($m^2$/vehicle) | Marginal change |
|---|---|---|---|---|
| 2 | 184,426 | – | 46.0986 | – |
| 20 | 125,130 | −32.1516% | 71.6662 | 55.4629% |
| 40 | 116,843 | −6.6227% | 77.8043 | 8.5648% |
| 60 | 107,809 | −7.7317% | 86.0470 | 10.5941% |
| 80 | 104,040 | −3.4960% | 90.1227 | 4.7336% |
| 100 | 102,710 | −1.2784% | 91.6673 | 1.7139% |

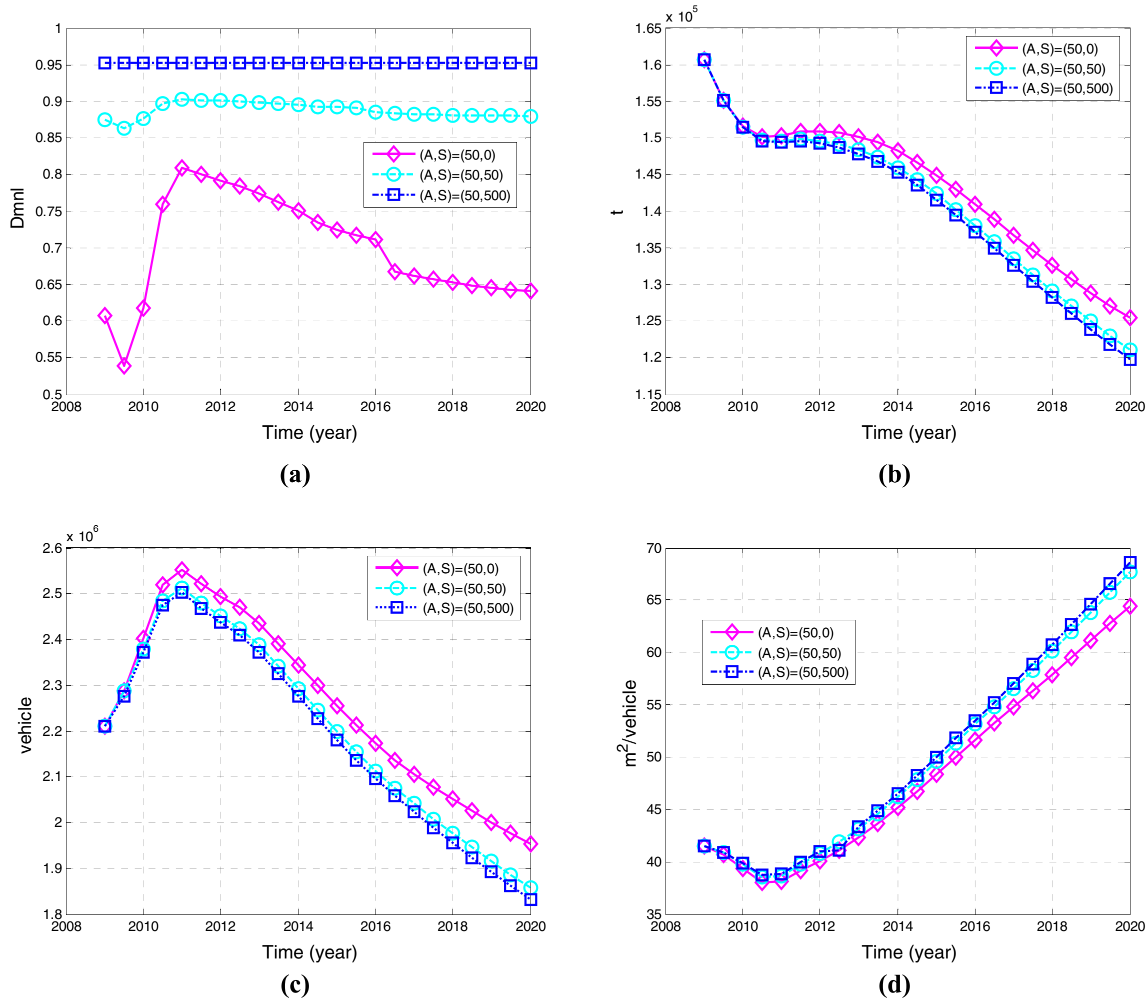



**Fig. 4** Realistic test, in which (APCF, subsidy) = (A, S). **a** Supply level of public traffic; **b** amount of PMx generation; **c** amount of motor vehicle trips; **d** per vehicle area of roads

where

$$\sigma_{01-1}^{\left(\frac{1}{\sqrt{n}},2\right)} = 0.5 = \sigma_{01-2}^{\left(\frac{1}{\sqrt{n}},2\right)}.$$

Therefore, according to Definition 2, this model is called the qualified verification of the degree of gray incidence.

(b) Qualified verification of the Q-EUGSID for amount of GDP.

**Table 4** The variation of the main variables under different subsidies (in 2025)

| Subsidy | Amount of PMx generation (t) | Marginal change | Supply level of public traffic | Marginal change |
|---|---|---|---|---|
| 0 | 112,158 | – | 0.758425 | – |
| 10 | 108,802 | −2.9922% | 0.828297 | 9.2128% |
| 20 | 106,687 | −1.9439% | 0.848857 | 2.4822% |
| 30 | 105,992 | −0.6514% | 0.867028 | 2.1406% |
| 40 | 105,391 | −0.5670% | 0.881511 | 1.7604% |
| 50 | 104,888 | −0.4773% | 0.896249 | 1.6719% |
| 60 | 104,383 | −0.4815% | 0.911206 | 1.6688% |
| 70 | 103,876 | −0.4857% | 0.926399 | 1.6674% |
| … | … | … | … | … |

The original sequence of the amount of GDP and its simulation sequence are, respectively,

$$X_{02}=\begin{bmatrix}x_{02}(1)\\x_{02}(2)\\x_{02}(3)\\\vdots\\x_{02}(7)\end{bmatrix}=\begin{bmatrix}1.21530e+012\\1.41136e+012\\1.62519e+012\\1.78794e+012\\1.98008e+012\\2.13308e+012\\2.30146e+012\end{bmatrix},X_2=\begin{bmatrix}x_{2}(1)\\x_{2}(2)\\x_{2}(3)\\\vdots\\x_{2}(7)\end{bmatrix}=\begin{bmatrix}1.21530e+012\\1.34341e+012\\1.55057e+012\\1.78565e+012\\1.97278e+012\\2.17044e+012\\2.34291e+012\end{bmatrix}.$$

In the same way, we can obtain

$\xi_{02}^{\left(\frac{1}{\sqrt{n}},2\right)}\approx 0.9799,\gamma_{02}^{\left(\frac{1}{\sqrt{n}},2\right)}\approx 0.9829.$

So, let $\sigma_{02-1}^{\left(\frac{1}{\sqrt{n}},2\right)}=0.5=\sigma_{02-2}^{\left(\frac{1}{\sqrt{n}},2\right)},\exists\varepsilon_0=0.9$, making

$\varepsilon_{02}=\rho_{02}^{\left(\frac{1}{\sqrt{n}},2\right)}=\sigma_{02-1}^{\left(\frac{1}{\sqrt{n}},2\right)}\xi_{02}^{\left(\frac{1}{\sqrt{n}},2\right)}+\sigma_{02-2}^{\left(\frac{1}{\sqrt{n}},2\right)}\gamma_{02}^{\left(\frac{1}{\sqrt{n}},2\right)}$
$=0.9814>0.9=\varepsilon_0.$

Therefore, according to Definition 2 and Table 2, this model is called the qualified verification of the degree of gray incidence and is reached as "first-class" precision.

## Simulation results and discussion

### The policy of air pollution charging fee

In Fig. 3a, the amount of PMx generation decreases continuously with the increase in air pollution charging fee (APCF). The changes in curves 6–7 indicate that the amount of PMx generation stays almost unchanged when air pollution charging fee is higher than 100 yuan/day*vehicle. The changes in Fig. 3b are similar to Fig. 3a.

Table 3 shows that the amount of PMx generation showed a downward trend along with the increase in air pollution charging fee; however, the air pollution charging fee increase exerted only a marginal decreasing effect on the other variables. In particular, when air pollution charging fee values were more than 60 yuan/day*vehicle, the decline in amount of PMx generation was slight. Therefore, the air pollution charging fee is not always "bigger means better." It had a better impact between 40 and 60 yuan/day*vehicle from the perspective of social and environmental benefits.

### Subsidy policy

In Fig. 4a, the value of supply level of public traffic is smallest when (A, S) = (50, 0), and is largest when (A, S) = (50, 500), and these results are considered within realistic standards. However, as time goes on, supply level of public traffic will show a downward trend when subsidy = 0. As shown in Fig. 4a–d, with the increase in subsidy, curves have changed most significantly when subsidy ∈[0, 50], buy only slightly when the subsidy was more than 50 yuan/day*vehicle. Therefore, the value of subsidy should not surpass 50 yuan/day*vehicle.

As shown in Table 4, with the increase in the subsidy, the amount of PMx generation decreased steadily, and the supply level of public traffic increased significantly. In particular, there were some significant changes when subsidy ranges between 10 and 30, and relatively large

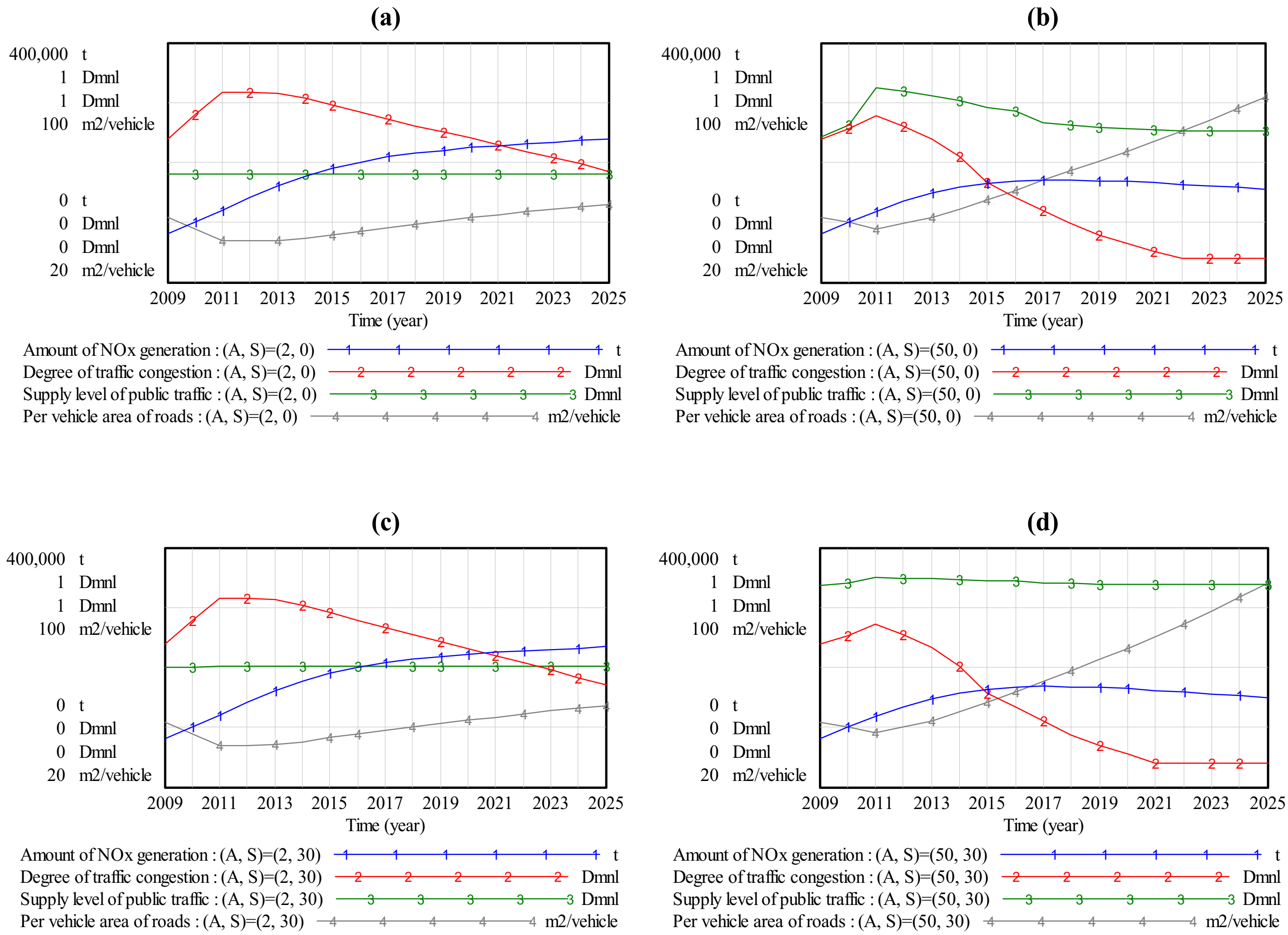



**Fig. 5** The trends of the major variables. **a** Low-APCF policy; **b** high-APCF policy; **c** low-APCF and high-subsidy policy; **d** high-APCF and high-subsidy policy

differences were observed when subsidy ∈[30, 50]. Nevertheless, there were almost no changes when subsidy was more than 50 yuan/day*vehicle. Therefore, the subsidy should range between 30 and 50 yuan/day*vehicle.

## The effects of combination polices

Figure 5a shows that when (A, S) = (2, 0), the growth rate was very slow, despite the per vehicle area of roads having constantly increased after 2011. Similarly, the decline of degree of traffic congestion (curve 2) was very limited. Although the growth rate of amount of NOx generation (curve 1) has slowed, the total of NOx generation kept rising and then led to a constant high level of degree of air pollution. These results revealed that the low-APCF policy cannot effectively reduce the degree of air pollution and degree of traffic congestion.

Figure 5b demonstrates that a high-APCF policy can promote an increase in per vehicle area of roads (curve 4) and reduce the degree of traffic congestion (curve 2) and amount of NOx generation (curve 1). However, after 2011, the supply level of public traffic (curve 3) began to decrease slowly with the increase in air pollution charging fee. A possible explanation for this may be the implementation of the air pollution charging fee policy prompted some vehicle travelers to change their travel mode to public transportation, which increased the burden of public transport and lowered the supply level of public traffic. Hence, the air pollution charging fee policy alone has certain limitations, and we should introduce the subsidy policy.

Figure 5a, c indicates that although a low-APCF and high-subsidy policy can effectively increase the supply level of public traffic (curve 3), the changes in amount of NOx generation (curve 1), per vehicle area of roads (curve 4), and degree of traffic congestion (curve 2) were not obvious. These results demonstrated that the subsidy policy has certain limitations, and for this reason, we should consider combing air pollution charging fee and subsidy.

In Fig. 5d, when (A, S) = (50, 30), curve 4 descended slowly at first and then quickly rose after 2011. This captured

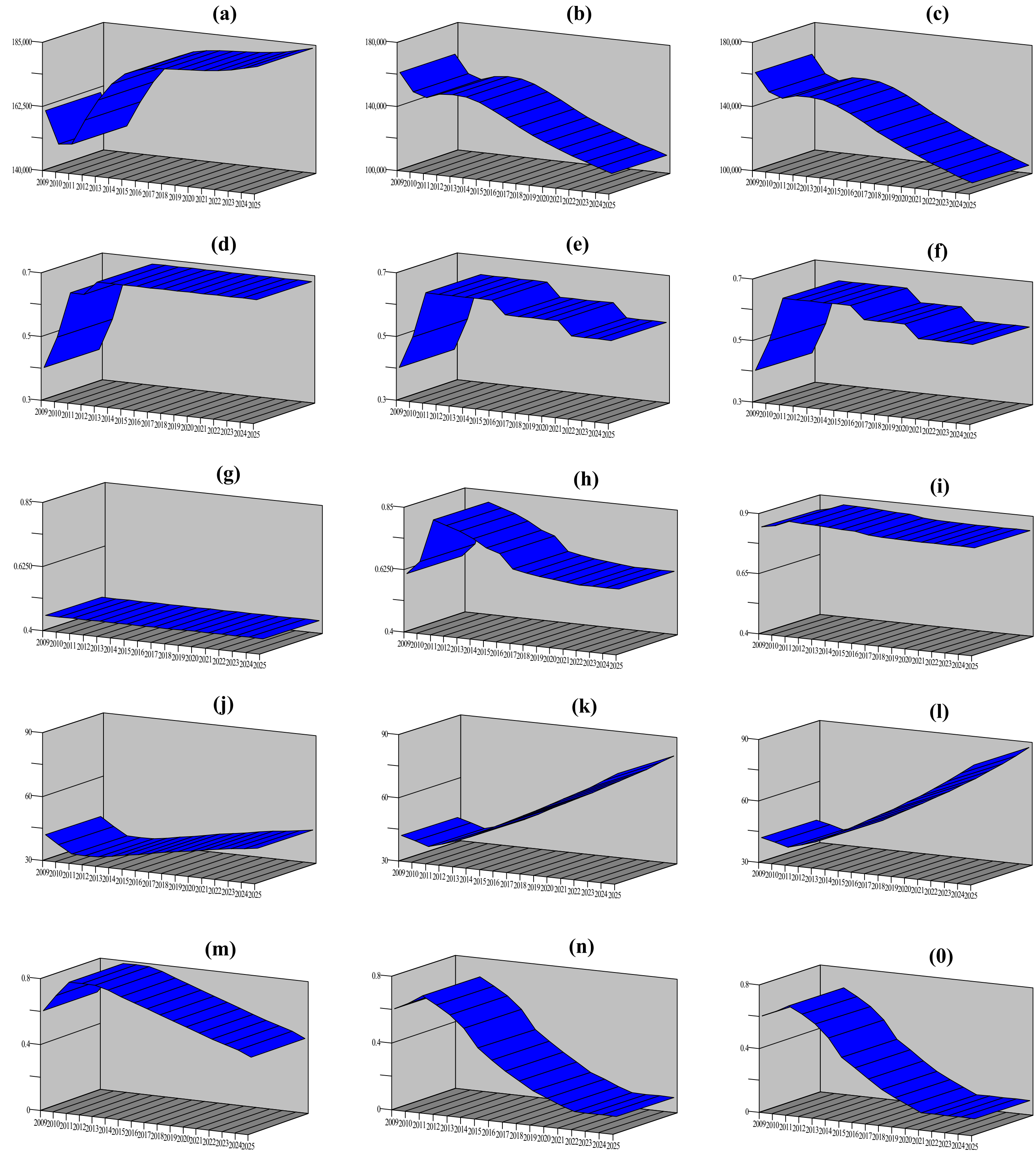



**Fig. 6** The effects of the main variables under different combination policies. **a** Amount of PMx generation (APMG): (A, S) = (2, 0); **b** APMG: (A, S) = (50, 0); **c** APMG: (A, S) = (50, 30); **d** degree of air pollution (DAP): (A, S) = (2, 0); **e** DAP: (A, S) = (50, 0); **f** DAP: (A, S) = (50, 30); **g** supply level of public traffic (SLPT): (A, S) = (2, 0); **h** SLPT: (A, S) = (50, 0); **i** SLPT: (A, S) = (50, 30); **j** per vehicle area of roads (PVAR): (A, S) = (2, 0); **k** PVAR: (A, S) = (50, 0); **l** PVAR: (A, S) = (50, 30); **m** degree of traffic congestion (DTC): (A, S) = (2, 0); **n** DTC: (A, S) = (50, 0); **o** DTC: (A, S) = (50, 30). There were three effects to combining the subsidy policy with the APCF: it relieved the degree of traffic congestion (see **j**–**o**) and reduced PMx emissions (see **a**–**c**), inhibited the intensity of "haze pollution" (see **d**–**f**), and improved the supply level of public traffic (see **g**–**i**)

**Table 5** The impacts of the major variables under different scenarios (in 2025)

| Variable | (Air pollution charging fee, Subsidy) = (A, S) | | Percent change (%) |
|---|---|---|---|
| | (A, S) = (2, 0) | (A, S) = (50, 30) | |
| Amount of PMx generation (t) | 184,426 | 105,992 | − 42.53 |
| Degree of air pollution | 0.6857 | 0.55712 | − 18.75 |
| Per vehicle area of roads ($m^2$/vehicle) | 46.0986 | 88.0859 | 91.08 |
| Supply level of public traffic | 0.449329 | 0.84524 | 88.11 |

the substantial increase to per vehicle area of roads, and accordingly the degree of traffic congestion declined significantly. In particular, the supply level of public traffic (curve 3) levels remained high, and the growth rate of amount of NOx generation (curve 1) slowed. These results revealed the high-APCF and high-subsidy policy had a triple effect: it can relieve traffic congestion and reduce NOx (PMx) emissions, it can inhibit the intensity of "haze" degree, and it can improve the supply level of public traffic.

### Comparison of the different policies

In Fig. 6a, when (A, S) = (2, 0), curve is still rising year by year. This indicated that low-APCF policy cannot effectively reduce the amount of PMx generation alone. On the contrary, Fig. 6c indicates that there was a dramatic decline when (A, S) = (50, 30). These results demonstrated that the combined high-APCF and high-subsidy policy could greatly decrease the amount of PMx generation. In the same way, Fig. 6d–f shows that high-APCF and high-subsidy policy can effectively reduce the degree of air pollution. In Fig. 6h, when (A, S) = (50, 0), the supply level of public traffic started falling slowly (after 2011) with the increase in air pollution charging fee. A proposed explanation was that some vehicle travelers turned to public transportation, which increased the burden of public transport. In Fig. 6i, when (A, S) = (50, 30), along with the increase in subsidy, the decline in supply level of public traffic will be negligible. Similarly, Fig. 6j–o reveals that high-APCF and high-subsidy policy cannot only reduce the degree of traffic congestion, but also improve the growth of per vehicle area of roads.

Table 5 shows that, compared with the low-APCF policy, (A, S) = (2, 0), the amount of PMx generation and degree of air pollution will be reduced by approximately 42.53% and 18.75% by 2025, respectively. The per vehicle area of roads and supply level of public traffic will increase by about 91.08% and 88.11% when (A, S) = (50, 30).

In summary, a low-APCF policy cannot effectively alleviate traffic congestion (Yang et al. 2014) and reduce vehicle pollutant emissions (Wu et al. 2017; Zhu 2013). Although high-APCF policy can significantly decrease the degree of traffic congestion, amount of PMx generation, and amount of NOx generation, the supply level of public traffic will decline. Hence, the implementation of the APCF policy in isolation has certain limitations. Conversely, the positive impacts of a combined high-subsidy and high-APCF policy are more obvious. It can not only decrease the degree of traffic congestion, amount of PMx generation, and amount of NOx generation, but also improve the growth of supply level of public traffic.

## Conclusions

To relieve urban traffic congestion and its resulting NOx (PMx) atmospheric pollution, we established the air pollution charging fee management model using a charge mechanism. Through simulations, tests, and validations, we found that although the air pollution charging fee can effectively relieve congestion and reduce environmental pollution, the supply level of public traffic would decline at the same time. To counter this, a subsidy mechanism to improve the original model was introduced. Simulation and policy analysis were carried out utilizing a combination of subsidy policy and air pollution charging fee and obtained the following conclusions:

To a certain extent, with an increase in air pollution charging fee, a decline can be observed in the amount of NOx generation, amount of PMx generation, amount of motor vehicle trips, degree of traffic congestion and a significant rise in per vehicle area of roads. However, the air pollution charging fee and subsidy are not always "bigger means better." We suggest that air pollution charging fee should be in the range of 40–60 yuan/day*vehicle, and the subsidy should range between 30 and 50 yuan/day*vehicle. Single subsidy and air pollution charging fee policies have deficiencies when implemented independently; therefore, it is necessary to consider combing policies. The combination scheme (especially high-subsidy and high-APCF policy) has triple effect; namely, it can not only alleviate traffic congestion and decrease NOx (PMx) emissions, but improve the growth of supply level of public traffic.

One major contribution of this article is the improvement of a dynamic model to assess vehicle pollutant emission reduction strategies under economic means, so that some optimizing management strategies could be identified before being implemented in practice. The measures, which are proposed based on the management strategies, can provide a valuable reference to reduce the intensity of haze pollution in Beijing. Furthermore, this model developed can function as a tool to effectively to determine the appropriate range of charging and subsidies. It can also be used by other regions intending to stimulate pollutant emission reduction through implementing an appropriate combination scheme. However, due to limited data, the model still has some limitations: The air pollution charging fee policy will lead to decline in supply level of public traffic. From this perspective, we should take other policies into full account, including the government subsidies on public transport, especially subway, bus and bike-share program in order to improve the supply level of public traffic.

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