



Past and future trends of vehicle emissions in Tianjin, China, from 2000 to 2030

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ABSTRACT

The rapid growth of the vehicle population was regarded as an important factor that contributed to the urban air pollution in China during the past decades. We used Tianjin, a typical megacity facing vehicle pollution problems, as the study domain to investigate a comprehensive estimation of vehicle emissions, including carbon monoxide (CO), volatile organic compounds (VOCs), nitrogen oxides (NO_x), inhalable particles (PM₁₀), carbon dioxide (CO₂) and sulphur dioxide (SO₂), from 2000 to 2030. The Computer Programme to calculate Emissions from Road Transport (COPERT) model was used to simulate the vehicle emission factors. Historical simulations show that the total emissions of CO, VOCs, NO_x, PM₁₀, CO₂, and SO₂ changed from 545.1 Gg, 70.04 Gg, 60.19 Gg, 6.57 Gg, 6.82 Tg and 12.88 Gg to 259.11 Gg, 34.01 Gg, 55.14 Gg, 3.42 Gg, 25.30 Tg and 0.16 Gg from 2000 to 2016, respectively. Passenger cars (PC) and light-duty vehicles (LDV) were the main contributors to the CO and VOCs emissions. Heavy-duty trucks (HDT) and buses (BUS) were the important contributors to NO_x and PM₁₀. PC was the major contributor to CO₂ and SO₂. With respect to the future, four Single Control Policy Scenarios (SCPS), including Passenger car Population Regulation (PPR), Emission Standard Updating (ESU), Public Transportation Promotion (PTP) and Electric Vehicle Popularity (EVP), and Integrated Scenarios (IS), were assembled to describe the impact of future policies on vehicle pollution from 2017 to 2030. Among all SCPS, the results show that the ESU is the more effective policy to control emissions of CO, NO_x and PM₁₀, while PPR is the more effective way to reduce emissions of VOCs, CO₂, and SO₂.

1. Introduction

The rapid growth of the vehicle population brings the challenges of air quality issues to megacities, which has been recognized as an important source of atmospheric pollution (Lang et al., 2014; Song et al., 2017; Wu et al., 2011). Cai et al. (2010) identified the major VOCs sources in the megacities of China using the positive matrix factorization (PMF) method and found that the most important source was vehicle related emissions. Zhao et al. (2013) noted that transportation was the important source of NO_x emissions in China based on a multi-year NO_x emission inventory. Wang et al. (2018) reported that the transportation sector could be an important contributor to secondary organic aerosol (SOA) in China, especially in winter, when haze pollution frequently occurs, by using the Community Multiscale Air Quality (CMAQ)

model based on Regional Emission inventory in ASia v2.1 (REAS2). Zheng et al. (2015) suggested that the constant increase in the vehicle population consumed massive amounts of fuel and emitted large amounts of greenhouse gases (GHG), which made vehicles become a difficult sector to reduce GHG emissions in China. In general, vehicle emissions have become a major concern for air pollution control (He et al., 2016). Therefore, it is necessary to estimate vehicle emissions for a more efficient design of pollution control policy.

Vehicle emission inventory is important to understand vehicle pollution and to formulate control policies (Sun et al., 2016). It can be utilized to investigate the current situation or historical trends of vehicle emissions. A number of vehicle emission inventories have been developed in different countries and regions, such as Hiroshima (Nurrohim and Sakugawa, 2005), Hanoi (Tung et al., 2011), Mauritius

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(Sookun et al., 2014), Greece (Fameli and Assimakopoulos, 2015) and Fortaleza (Policarpo et al., 2018). In China, a series of vehicle emission inventories have also been developed at national, regional and city levels. Cai and Xie (2007) developed a multi-year inventory of vehicular emissions in China from 1980 to 2005 based on provincial statistical data and emission factors that were calculated by the COPERT model. The results show that over three-quarters of the vehicle emissions were concentrated in developed regions. Lang et al. (2012) analysed vehicular emissions trends during 1999 to 2010 in the Beijing-Tianjin-Hebei (BTH) region and found that the emissions of CO and VOCs have decreased, and emissions of NO_x and PM₁₀ have been constantly increasing. Jing et al. (2016) established a vehicle emission inventory with high spatiotemporal resolution using local emission factors and near-real-time (NRT) traffic data for the urban area of Beijing in 2013. The study found that vehicle emissions show consistent temporal and spatial variation trends with anthropogenic activities.

Some studies also investigated future vehicle emissions to evaluate the impacts of different control policies by using scenario analysis. Yan and Crookes (2009) designed two scenarios to estimate the reduction potentials of energy demand and GHG emissions in the road transportation sector in China up to 2030. Private vehicle control, fuel economy regulation and fuel tax were recognized as effective policies to reduce energy demand and GHG emissions in the study. Liu et al. (2015) predicted energy consumption and GHG emissions from passenger vehicles in China through 2050 and noted that GHG emissions will peak in 2027 under the BAU scenario. The above two studies emphasized the relationship between energy, GHG and road transportation, while some other studies focused on the regulated pollutants such as CO, NO_x, and PM₁₀ emitted from vehicles. Zhang et al. (2014) assessed emissions of CO, THC, NO_x and PM_{2.5} from the Beijing vehicle fleet between 2010 and 2020 under the “license control” and “without license control” scenarios. Their results show that the license control policy was an effective way to mitigate vehicle emissions in the future. Guo et al. (2016) built a baseline scenario and five control scenarios to analyse the reduction potentials of vehicle emissions, including PM₁₀, NO_x, CO, and HC, under different control policies in the BTH region from 2011 to 2020. The updating of vehicle emission standards and eliminating high-emission vehicles are two policies to reduce emissions more effectively.

The previous studies have provided some perspectives of vehicle emissions and meaningful references for making pollution control policies in China. However, the results of these studies need to be updated because a wide range of control policies was newly implemented during recent years. Thus, the estimation of vehicle emissions and the evaluation of control policy effects need to incorporate the impacts of these new policies. Furthermore, most existing studies in the region of Beijing-Tianjin-Hebei (BTH), which is a key area for air pollution control in China, only focused on Beijing, the capital of China. However, the other megacity in the region, Tianjin (see Fig. 1), is also threatened by severe air pollution from vehicles.

Tianjin is one of the four municipalities in China. The Gross Domestic Product (GDP) of the city was \$265.53 billion, which ranked fifth in all cities in China (NBSC, 2016a). Vehicle population has experienced a rapid growth, along with economic growth, during the past decades and has become an important source of air pollution in this city (Liu et al., 2017a). Although Tianjin is a representative city that is faced with vehicle pollution, special studies are still lacking. Therefore, it is critical to investigate historical trends and future changes in vehicle emissions in this area.

The aim of this work is to estimate the historical trends (from 2000 to 2016) of vehicle emissions and to evaluate the reduction effects (from 2017 to 2030) of different control policies in Tianjin. Six types of vehicle pollutants were included in this study: CO, VOCs, NO_x, PM₁₀, CO₂, and SO₂. Vehicles were divided into five types: passenger cars (PC), light-duty vehicles (LDV), buses (BUS), heavy-duty trucks (HDT) and motorcycles (MC). Vehicle emission factors for different pollutants and vehicle types were simulated by the COPERT model.

2. Method

2.1. Estimation of vehicle emission

2.1.1. Emission estimation method

Vehicle emissions were estimated by vehicle populations (VP), annual average vehicle kilometres travelled (VKT) and vehicle emission factors (EF) using the following equation:

$$E_{p,t} = \sum_i \sum_j VP_{i,j,t} \times VKT_{i,t} \times EF_{i,j,p} \quad (1)$$

where E is the vehicle emission for each year; p is a specific pollutant (six pollutants such as CO, NO_x, VOCs, PM₁₀, CO₂, and SO₂); t represents the estimated year (from 2000 to 2030); i means the vehicle type (five types, including PC, LDV, BUS, HDT, and MC); and j is national vehicular emission standards (from Pre-State I to State VI).

2.1.2. Vehicle population

The historical data (from 2000 to 2016) of the vehicle population and the vehicle type composition were obtained from the China Statistical Yearbook (NBSC, 2001–2017). The future trends (from 2017 to 2030) of the vehicle fleet were predicted by elastic coefficient method (He et al., 2005; Liu et al., 2017b). Tianjin has already implemented the control policy on vehicle population since 16 December 2013, which was taken into consideration in the prediction.

The percentage of vehicles meeting the specific emission standards (from Pre-State I to State VI) is also important for estimating vehicle emissions because the vehicle emission factors are given according to the stage of vehicular emission standards, as presented by Eq. (1). With the fast upgrade of vehicular emission standards in China during the past decades, the compositions of emission standards became the key parameter relating to the estimation of vehicle emissions. However, the data of the compositions cannot be directly acquired from official statistics. In this study, emission standards compositions were simulated based on the age distribution of the vehicle fleet and the implementation year of a specific emission standard (see Table S1). The age distribution can be evaluated by the following equation (Gong et al., 2017):

$$SVP_{n,t} = R_n \times S_{n,t-n} \quad (2)$$

where n represents the year of newly registered vehicles, t is the estimated year, $t-n$ means the vehicle age, SVP is the survived vehicle population, R is the new vehicle registrations, and S represents the survival rate. The survival rate is defined as the proportion of vehicles registered in a previous given year that is still in operation at the estimated year (Huo and Wang, 2012).

The data of new vehicle registrations (see Table S2) were collected from National Data (NBSC, 2016b). The survival rate for each vehicle type, except MC, were provided by Hao et al. (2011a) and are presented in Fig. 2. According to the national average (MOC, 2002), the motorcycle lifespan and scrappage rate were assumed to be 10 years and 10% for each year, respectively.

The new registration of vehicles in a given year is assumed to meet the up-to-date emission standards (Lang et al., 2012). Consequently, for each vehicle type, the compositions of vehicular emission standards (see Fig. S1) was estimated based on the age distribution of the vehicle fleet and the implementation timetable of emissions standards.

2.1.3. Annual average vehicle kilometres travelled

The VKT has a direct influence on the calculation of the vehicle emissions. However, the VKT data could not be obtained from official records directly. Thus, the VKT data in Tianjin from 2000 to 2016 were estimated based on the collected data and previous studies (Guo et al., 2016; Lang et al., 2012). This study also assumed that the trends of VKT from historical data will continue in the near future and, therefore, the predicted VKTs between 2017 and 2030 were estimated by using the

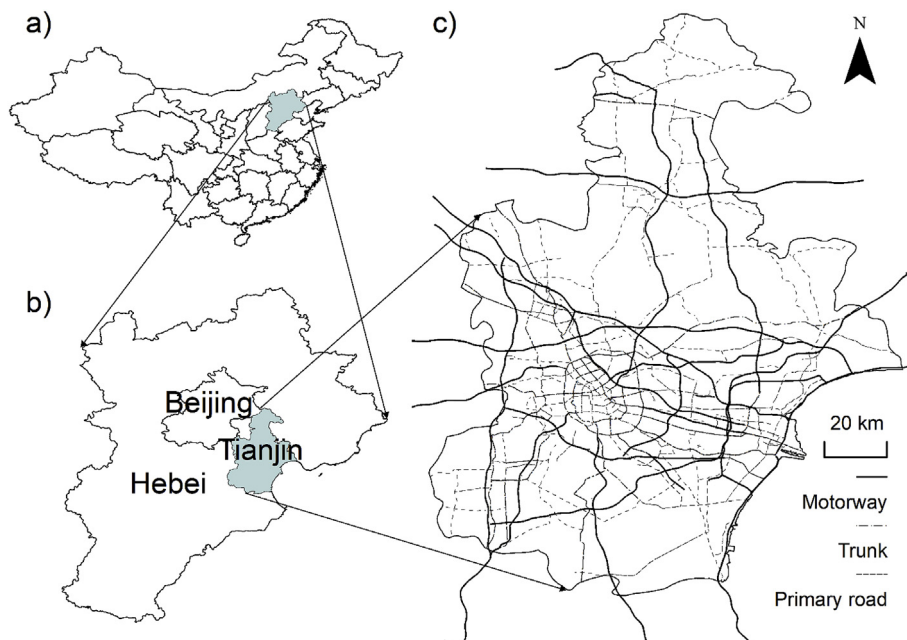


Fig. 1. Location of Tianjin in China.

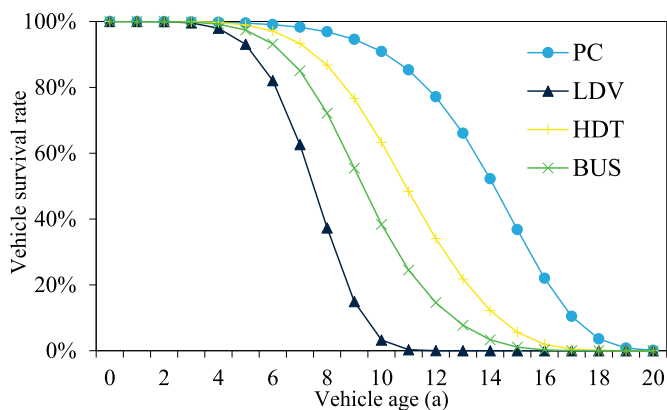


Fig. 2. Vehicle survival rates for PC, LDV, HDT and BUS in Tianjin.

trend extrapolation method (Wang et al., 2007).

2.1.4. Emission factors

The vehicle emission factors were simulated by the COPERT model in this study. The previous studies reported that the COPERT model, which was developed to estimate vehicle emissions in Europe, can also be used in China (Lang et al., 2016; Xie et al., 2006). The vehicle emission factors were calculated by speed-dependent equations in the COPERT model (EEA, 2000). Average speeds (see Table S3) were affected by a range of factors, such as vehicle type, road type, and city size. The COPERT model also needs the input of fuel quality and meteorological condition, which are listed in Fig. S2 and Table S4,

respectively. The calculation results of emission factors are presented in Fig. S3.

2.2. Scenario analysis for vehicle emission reduction

2.2.1. Definition of vehicle emission reduction scenarios

Several policies, such as limitations on new vehicle registrations, stringent vehicular emissions standards and elimination of high-emission vehicles, have been introduced in the megacities of China to control vehicle pollution (Guo et al., 2016). In Tianjin, some vehicle pollution control policies have also been introduced, such as Passenger car Population Regulation (PPR) and Emission Standard Updating (ESU), which have achieved some positive effects. Public Transportation Promotion (PTP) and Electric Vehicle Popularity (EVP) are two important control policies of vehicle pollution in the future. Public transportation was recognized as an effective policy to ease congestion and reduce vehicle pollution in urban areas. The government has set targets for improving public transportation in China both at the national level and city level (Peng et al., 2015). In the next several decades, the electric vehicle population will rapidly increase (Ou et al., 2010), which will bring a great reduction potential for vehicle emissions.

To analyse the impacts of different possible policies on vehicle pollution control in the future, this study established five vehicle emission reduction scenarios, including PPR, ESU, PTP, EVP and Integrated Scenarios (IS). The Business as Usual (BAU) scenario is a reference scenario, in which vehicle emission control policies remain at the same level in 2016. Five reduction scenarios had been defined by incorporating some additional policies. The implementation of the control policies will be expected to achieve their designated effects,

Table 1
Specific definitions of vehicle emission reduction scenarios from 2017 to 2030 in Tianjin.

Scenarios	Specific definition
BAU	Take 2016 as the base year, vehicle emission controls are maintained at the level in 2016
PPR	From the base year, the growth of PC population will be limited to under 180 thousand, 170 thousand and 160 thousand until 2020, 2025 and 2030 in each year
ESU	State V for LDV will be implemented in 2018, and State VI for all vehicle types, except MC, will be implemented in 2020
PTP	PC VKT will be decreased by 1000 km in 2020 and 2500 km in 2030 compared with 2016
EVP	The stock share of electric vehicles in PC, LDV, and BUS will be 2.5% in 2020 and 10% in 2030
IS	Integrated the reduction policies in the PPR, ESU, PTP and EVP scenario

which are described in Table 1. To evaluate reduction effects with different control policies separately, this study focused on a Single Control Policy Scenario (SCPS), which is defined as a reduction scenario, including a single control policy. The SCPS in this study are PPR, ESU, PTP, and EVP.

2.2.2. Evaluation of reduction effects for scenarios

The reduction effects under different control scenarios were evaluated by two metrics. The first one is vehicle emission change rates between the base year (2016) and the end (2030) of the prediction period. The other one is the Average Reduction Rates of vehicle emissions compared with BAU (ARRB) given by the following equation:

$$ARRB_{VERS,p} = \frac{\sum_t \frac{E_{BAU,p,t} - E_{VERS,p,t}}{E_{BAU,p,t}}}{LPP} \quad (3)$$

where *VERS* means the vehicle emission reduction scenario (five scenarios, including PPR, ESU, PTP, EVP and IS); *p* is a specific pollutant; *t* represents the evaluated year (from 2017 to 2030); *E* is the vehicle emissions; and *LPP* means the length of the prediction period (14 years between 2017 and 2030).

3. Results and discussion

3.1. Trends of vehicle population and VKT

3.1.1. Vehicle population

As shown in Fig. 3, the vehicle population increased from 0.91 to 2.74 million between 2000 and 2016 and will reach to 3.36 million in 2030. The vehicle population was increasing fast from 2000 to 2013, with annual average increasing rate of 8.94%. However, the annual increasing rate dropped from 17.00% to 4.20% in 2014 due to the vehicle population control policy. After 2014, the annual increasing rate remained low at an average of 0.75%.

The shares of PC, LDV, HDT, BUS and MC were 24.39%, 16.94%, 6.38%, 3.39% and 48.89% in 2000 and 86.97%, 8.23%, 2.52%, 1.42% and 0.88% in 2016, respectively. The fastest growing vehicle type was PC (increased 9.71 times from 2000 to 2016), which has replaced MC as the dominant vehicle type. The populations of LDV, HDT, and BUS increased 0.46, 0.18 and 0.25 times during the same period, respectively. In contrast, the MC population show a downward trend (decreasing rate of 94.62% from 2000 to 2016), due to the increasingly stringent restriction for MC in megacities (Cai and Xie, 2013).

Considering the new variation in vehicle population in recent years and predicted values of GDP up to 2030 (see Fig. S4), this study predicted that the population of PC, LDV, HDT, BUS, and MC will change to 2835.37 thousand, 369.29 thousand, 100.11 thousand, 42.86 thousand and 8.50 thousand in 2030, respectively. Consequently, the total amounts of vehicles will tend to be stable in the near future. PC will continue to play a significant role for a long time, accounting for

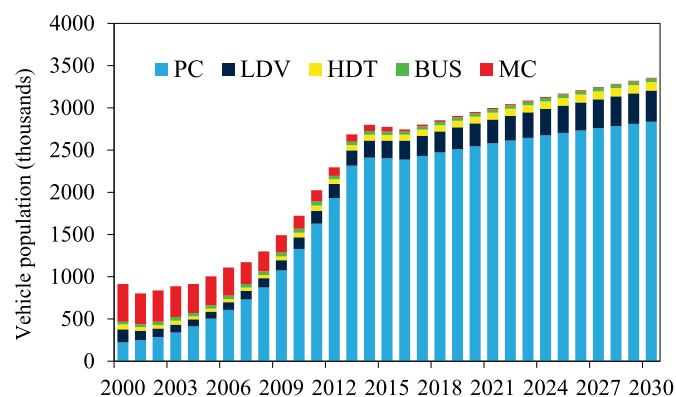


Fig. 3. Vehicle population of different types in Tianjin from 2000 to 2030.

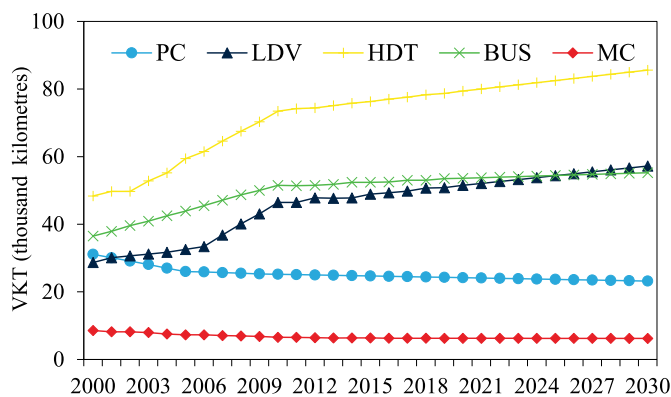


Fig. 4. Annual average vehicle kilometres travelled in Tianjin from 2000 to 2030.

85.60% between 2017 and 2030, followed by LDV (9.85%), HDT (2.78%), BUS (1.33%), and MC (0.44%). The population of LDV, HDT, and BUS will increase slowly and steadily, according to their historical trends. The MC population will continue to decrease because restriction policies for MC are still in force.

3.1.2. Annual average vehicle kilometres travelled

Fig. 4 shows that the VKTs of PC, LDV, HDT, BUS, and MC were 31.10, 28.67, 48.36, 36.50 and 8.57 thousand kilometres in 2000 and will change to 23.18, 57.23, 85.60, 55.24 and 6.22 thousand kilometres in 2030, respectively. The VKT trends for different vehicle types were variable (Lang et al., 2012). The VKT for PC has decreased in recent years with the popularization of private cars (Huo et al., 2012). Since MC in China was mainly (and widely) used in the countryside areas, its VKT slowly decreased with the urbanization process (Cai and Xie, 2013). There is a positive correlation between business activities and VKTs of LDV, HDT, and BUS (Guo et al., 2016). As a result, the VKTs for these vehicle types increased with the economic growth in Tianjin during the past ten years.

3.2. Historical trends of vehicle emissions

3.2.1. CO and VOCs emissions

As shown in Fig. 5, both CO (from 545.10 Gg to 259.11 Gg) and VOCs emissions (from 70.04 Gg to 34.01 Gg) have significantly decreased, due to the increasingly strict vehicular emission standards and old vehicles elimination policy (Wu et al., 2017) from 2000 to 2016. PC and LDV were the major contributors to CO and VOCs emissions, with the average contribution percentages of 61.29% and 24.28% for CO, respectively, and 62.10% and 17.68% for VOCs in this period, respectively. Larger reductions were observed in LDV and MC, which reduced by 129.97 Gg and 100.87 Gg for CO, respectively, and 13.07 Gg and 13.77 Gg for VOCs, respectively.

3.2.2. NO_x and PM₁₀ emissions

Emissions of NO_x and PM₁₀ show evident fluctuation. NO_x and PM₁₀ emissions were 60.19 Gg and 6.57 Gg in 2000, locally peaked at 69.32 Gg and 5.31 Gg approximately 2011 and then decreased to 55.14 Gg and 3.42 Gg in 2016, respectively. From 2000 to 2016, the rate of decrease in NO_x (8.39%) emissions was less than CO (52.47%), VOCs (51.44%) and PM₁₀ (47.90%) emissions because the emission factors of CO, VOCs, and PM₁₀ in China have been significantly reduced with more stringent emission standards (see Fig. S3) (Shen et al., 2015). HDT and BUS were the major contributors of these two pollutants, with the average fractional contributions of 34.12% and 38.29% for NO_x, and 45.80% and 27.85% for PM₁₀ in the study period, respectively. From 2000 to 2016, LDV (decreased 9.76 Gg) was the major contributor to NO_x reductions, and HDT (decreased 3.04 Gg) has a significant

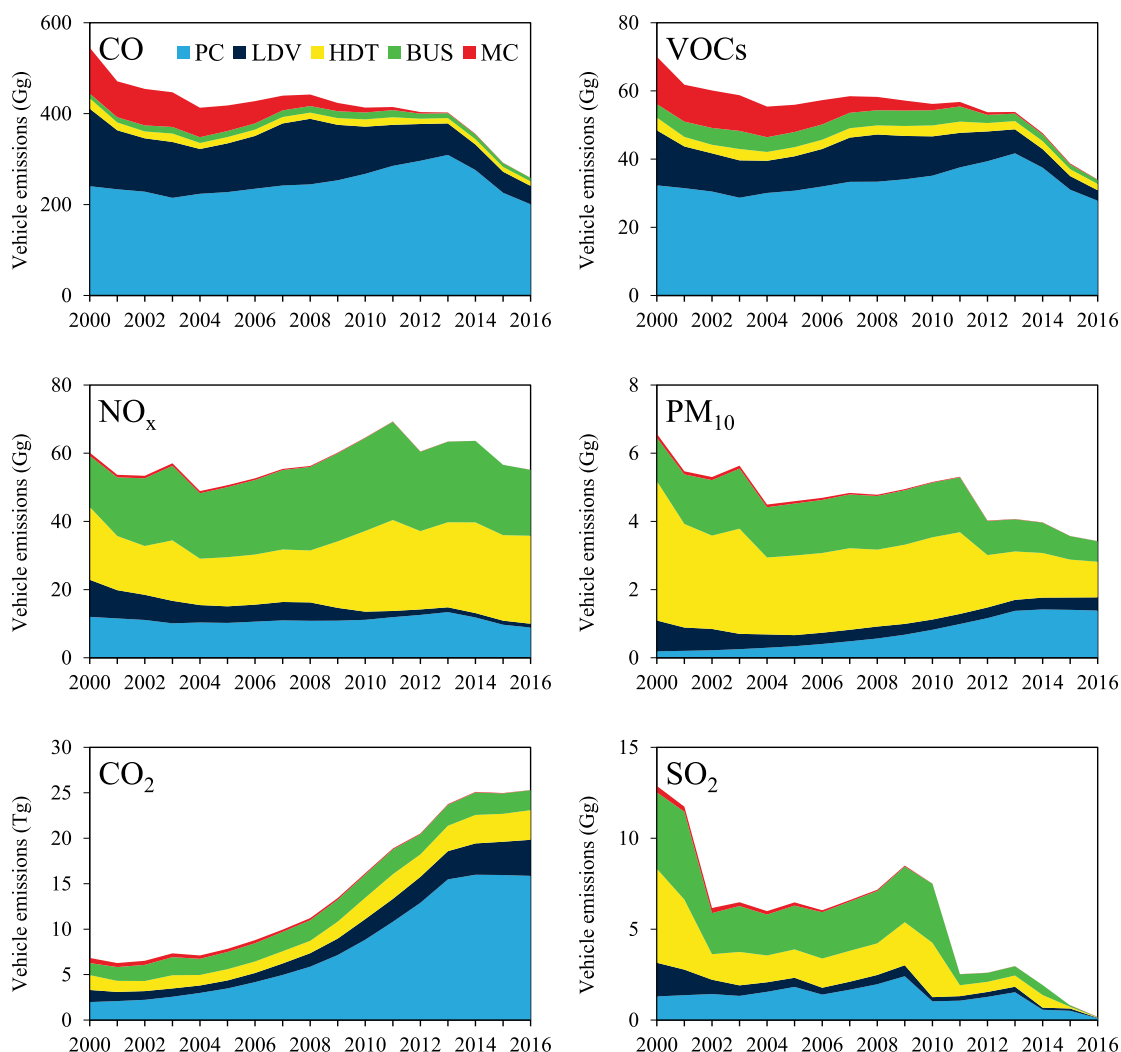


Fig. 5. Total vehicle emissions in Tianjin from 2000 to 2016.

contribution for PM_{10} reductions.

3.2.3. CO_2 emissions

The CO_2 emissions maintained rapid growth, which is different from other pollutants. The CO_2 emissions increased from 6.82 Tg in 2000 to 25.30 Tg in 2016. The unconstrained increase in CO_2 emissions can be mainly attributed to the insufficient improvement of fuel economy under current policies (Zheng et al., 2015). PC was the major contributor of CO_2 , with an average contribution of 50.04% from 2000 to 2016. Most of the carbon in fuel is converted to CO_2 during vehicle driving; therefore, CO_2 emissions have a strong relationship with the vehicle population. This led PC, which has the largest rate of increase, to become the most important source of CO_2 .

3.2.4. SO_2 emissions

The SO_2 emissions decreased approximately 98.74% from 2000 to 2016 (from 12.88 Gg to 0.16 Gg), due to the improvement of fuel quality standards, which limited sulphur content in vehicle fuel during the past decades (Lang et al., 2016). For the entire study period, PC (31.55%), HDT (26.12%) and BUS (31.35%) were important contributors to SO_2 emissions. Specifically, PC has become the major contributor (as high as 62.90% in 2016) to SO_2 emissions in recent years, due to the rapidly increasing PC population. HDT and BUS (decreased 5.15 Gg and 4.19 Gg, respectively) were major contributors to SO_2 reductions from 2000 to 2016 because the sulphur content in diesel significantly reduced from 5000 ppm to 10 ppm during this period (see

Fig. S2).

3.3. Future trends of vehicle emissions

3.3.1. Vehicle emissions under the BAU scenario

Fig. 6 shows the future vehicle emissions (from 2017 to 2030) under the BAU scenario. If the situation of emission control policy in 2016 is to be maintained until 2030, emissions of CO and VOCs still can be controlled in the future, with declines of 53.16% and 60.86% in 2030 compared with 2017, respectively. However, the NO_x and PM_{10} emissions will have long-term, stable trends that first slightly decrease and then increase, with 54.55 Gg and 3.35 Gg in 2017 and 55.27 Gg and 3.44 Gg in 2030, respectively. CO_2 and SO_2 emissions will constantly increase, with rates of increase reaching 28.48% and 28.46%, respectively, from 2017 to 2030.

The major contributors to each pollutant are similar to the historical estimation results from 2000 to 2016). PC and LDV are the main sources of CO and VOCs, with average contributions of 61.42% and 28.51% to CO, and 81.73% and 11.70% to VOCs, respectively, from 2017 to 2030. The annual contribution of LDV to CO (from 15.18% to 45.86%) and VOCs (from 7.68% to 19.60%) rapidly increase during the period, due to the increasing LDV population (Hao et al., 2011b). HDT and BUS are important contributors to NO_x , with the average contributions of 54.64% and 31.63%, respectively.

PC, HDT, and LDV will be the major sources of PM_{10} , with the average contributions of 44.65%, 26.54% and 17.44%, respectively.

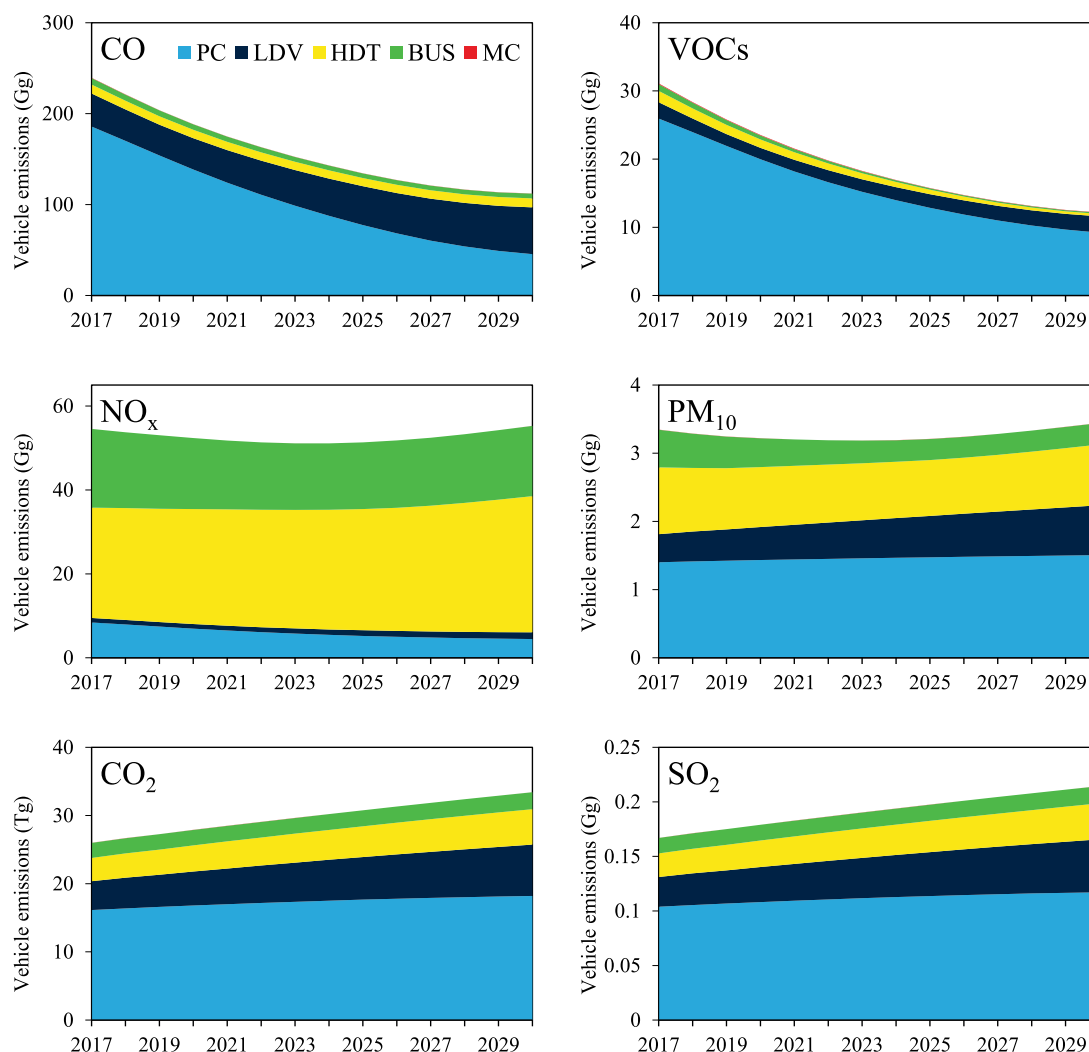


Fig. 6. Total vehicle emissions in Tianjin from 2017 to 2030 under the BAU scenario.

The concern is that the contribution of PC and LDV to PM₁₀ emissions will continue to increase in the future, which means these two vehicle types should gain more attention when controlling the particulate pollution. The compositions of vehicle contribution to CO₂ and SO₂ emissions are similar. A major source of CO₂ and SO₂ emissions is PC, and the average contributions are 58.22% and 58.41%, respectively, from 2017 to 2030. Because sulphur content in fuel will maintain a steady level, as in 2016, during the forecasting period according to assumptions, emissions of CO₂ and SO₂ are mainly affected by vehicle fuel consumptions, leading to similar variations in these two pollutants.

Since vehicle emissions are not controlled (emissions of NO_x, PM₁₀, CO₂, and SO₂ all increase compared to the base year) under the BAU scenario, effective control policies should be implemented for the comprehensive prevention of vehicle pollution. In the next section, this study will discuss the reduction effects of vehicle emissions when different control policies are implemented in the future.

3.3.2. Vehicle emissions under different reduction scenarios

Fig. 7 shows future vehicle emissions (from 2017 to 2030) under different reduction scenarios. The results of the change rates in vehicle emissions and the ARRB are shown in Table 2 and Table 3, respectively. The vehicle pollution will be controlled to various levels under different reduction scenarios. Among all these scenarios, IS has the most significant reduction, with AARB of 22.99%, 13.30%, 35.52%, 11.95%, 14.61% and 14.65% for CO, VOCs, NO_x, PM₁₀, CO₂, and SO₂, respectively.

The most effective SCPS for different pollutants are various. For CO emissions, the highest ARRB is 14.30% under ESU, which means the implementation of strict vehicle emissions standards is an effective way to control CO emissions. PPR and EVP also play important roles in reducing CO emissions, with an ARRB of 3.55% and 4.80%, respectively. To reduce VOCs emission, the PPR and EVP are two more effective policies, with an AARB of 5.58% and 4.96%, respectively. This suggests that the key to control VOCs emissions in the future is to restrict vehicle population. However, the ESU has a limited reducing effect on VOCs emissions (ARRB of 1.24%) in comparison with CO emissions (ARRB of 14.30%).

The ESU has an overwhelming effect on the reduction of NO_x emissions, with ARRB of 33.40%, while PPR, PTP, and EVP have limited effects on the mitigation of the pollutant emissions and ARRB values of 0.66%, 0.32% and 2.26%, respectively. The results show that the ESU is an effective way to control NO_x emissions (Guo et al., 2016), while reductions of other measures are not obvious. Although updating the emission standards has only a limited effect on vehicle NO_x emissions control according to the historical trends (from 2000 to 2016), the new emission standards will have a promising control effect on the NO_x pollution in the future, which is consistent with Wu et al. (2017).

The results indicate that PPR, ESU, and EVP have similar effects on the PM₁₀ emissions control. The ARRB are 3.17%, 4.20%, and 3.83%, and the change rates are -7.89%, -8.75% and -6.84% for PPR, ESU and EVP, respectively. In general, the ESU leads to relatively better performance for PM₁₀ reductions, but it is not a dominant policy to

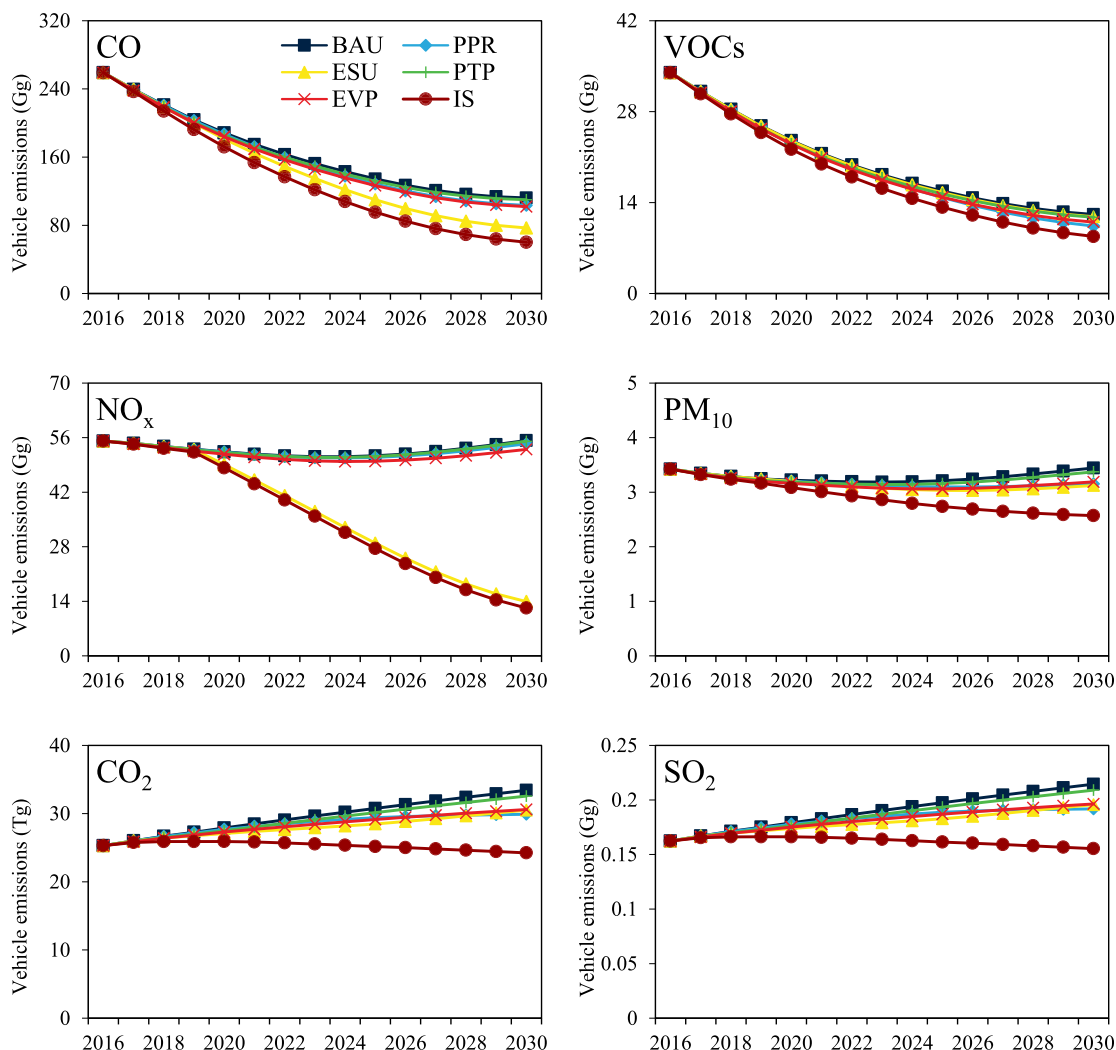


Fig. 7. Total vehicle emissions in Tianjin from 2016 to 2030 under different scenarios.

Table 2
Change rates of vehicle emissions under different scenarios in Tianjin from 2016 to 2030.

	BAU	PPR	ESU	PTP	EVP	IS
CO	-56.72%	-60.11%	-70.31%	-57.54%	-60.66%	-76.77%
VOCs	-64.21%	-69.45%	-65.24%	-65.48%	-67.67%	-74.17%
NO _x	0.24%	-1.32%	-74.75%	-0.14%	-3.90%	-77.74%
PM ₁₀	0.62%	-7.89%	-8.75%	-1.44%	-6.84%	-24.90%
CO ₂	32.11%	18.19%	20.57%	28.74%	20.95%	-4.19%
SO ₂	32.08%	18.12%	20.51%	28.70%	20.91%	-4.32%

Table 3
Average Reduction Rates of vehicle emissions compared with BAU (ARRB) under different reduction scenarios in Tianjin from 2017 to 2030.

	PPR	ESU	PTP	EVP	IS
CO	3.55%	14.30%	1.74%	4.80%	22.99%
VOCs	5.58%	1.24%	2.47%	4.96%	13.30%
NO _x	0.66%	33.40%	0.32%	2.26%	35.52%
PM ₁₀	3.17%	4.20%	1.37%	3.83%	11.95%
CO ₂	3.97%	5.46%	1.75%	4.41%	14.61%
SO ₂	3.98%	5.48%	1.76%	4.42%	14.65%

control the pollutant. The ESU should combine with other control policies to achieve the goal in PM₁₀ pollution control.

The CO₂ emissions continue to increase in all SCPS. The minimum change rate is 18.19% under PPR because the limitation of vehicle population can reduce fuel consumption, which is closely related to CO₂ emissions. Even though it is difficult to control vehicle GHG emissions, the PPR is the relatively effective way to reduce energy use and GHG emissions in future decades (Peng et al., 2015). However, the AARB of PPR (3.97%) is lower than ESU (5.46%) and EVP (4.41%). The reason is that the annual CO₂ emissions reduction rates compared with BAU (see Fig. S5) for ESU and EVP are higher than PPR in the early and middle stages of the evaluation period. It also shows that implementing new emission standards leads to an increase in fuel efficiency and a decrease in GHG emissions (EP, 2007). The future trends of SO₂ emissions under different scenarios are similar to CO₂, and PPR is also recognized as the most effective SCPS in the pollutant emissions, with a change rate of 18.12%. SO₂ emissions are mainly influenced by two factors: the fuel sulphur content (it stays at the same level as 2016) and the fuel consumption. Thus, emissions of CO₂ and SO₂ are influenced by fuel consumptions, which lead to similar trends in these two pollutants.

The analysis of SCPS could provide a new perspective on establishing control policy. To summarize, the ESU is the most effective policy to control CO, NO_x and PM₁₀, and the PPR has significant effects on VOCs. And no SCPS could reduce the emissions of CO₂ and SO₂ significantly, which means to control these two pollutants requires implementing a variety of policies simultaneously. The EVP is the

Table 4
Comparison with other studies for the emissions of CO, VOCs, NO_x, and PM₁₀ (Gg).

Year	CO	VOCs	NO _x	PM ₁₀
2000	545.10 ^a , 484.31 ^g	70.04 ^a , 70.23 ^g	60.19 ^a , 46.20 ^g	6.57 ^a , 5.81 ^g
2001	471.02 ^a , 461.86 ^g	61.83 ^a , 64.28 ^g	53.67 ^a , 43.10 ^g	5.47 ^a , 4.72 ^g
2002	454.42 ^a , 481.45 ^g	60.14 ^a , 63.93 ^g	53.40 ^a , 43.30 ^g	5.30 ^a , 4.16 ^g
2003	447.19 ^a , 453.84 ^g	58.76 ^a , 61.67 ^g	57.03 ^a , 49.22 ^g	5.63 ^a , 5.75 ^g
2004	413.05 ^a , 401.94 ^g	55.42 ^a , 53.61 ^g	48.89 ^a , 41.12 ^g	4.49 ^a , 4.53 ^g
2005	418.05 ^a , 381.31 ^g , 555.81 ⁱ	55.93 ^a , 50.99 ^g , 86.88 ⁱ	50.62 ^a , 39.28 ^g , 57.69 ⁱ	4.59 ^a , 4.00 ^g , 13.61 ⁱ
2006	427.63 ^a , 398.17 ^g	57.28 ^a , 51.53 ^g	52.65 ^a , 43.19 ^g	4.69 ^a , 4.64 ^g
2007	439.59 ^a , 384.37 ^g , 220.28 ^h	58.44 ^a , 49.70 ^g , 25.26 ^h	55.41 ^a , 44.24 ^g , 59.93 ^h	4.84 ^a , 4.69 ^g , 2.34 ^h
2008	442.11 ^a , 373.76 ^g	58.24 ^a , 47.23 ^g	56.26 ^a , 43.81 ^g	4.78 ^a , 4.53 ^g
2009	423.50 ^a , 303.00 ^f , 362.24 ^g	57.18 ^a , 69.00 ^f , 45.85 ^g	60.18 ^a , 102.00 ^f , 48.97 ^g	4.94 ^a , 9.00 ^f , 5.01 ^g
2010	413.31 ^a , 507.07 ^g , 350.41 ^g	56.17 ^a , 54.38 ^g , 44.25 ^g	64.59 ^a , 50.41 ^g , 51.65 ^g	5.16 ^a , 6.37 ^g , 5.18 ^g
2011	414.63 ^a , 431.40 ^h , 252.88 ^c , 556.26 ^c	56.75 ^a , 48.71 ^h , 41.68 ^c , 55.36 ^c	69.32 ^a , 52.69 ^h , 58.92 ^c , 66.53 ^c	5.31 ^a , 6.55 ^h , 1.72 ^c
2012	403.53 ^a , 469.92 ^h , 240.49 ^c	53.74 ^a , 51.31 ^h , 36.50 ^c	60.49 ^a , 51.88 ^h , 58.43 ^c	4.02 ^a , 6.50 ^h , 1.99 ^c
2013	402.57 ^a , 457.62 ^h , 234.28 ^c , 227.80 ^d	53.84 ^a , 50.09 ^h , 34.83 ^c , 52.90 ^d	63.42 ^a , 55.21 ^h , 58.42 ^c , 67.40 ^d	4.07 ^a , 6.46 ^h , 2.11 ^c , 3.20 ^d
2014	355.61 ^a , 457.20 ^h , 229.32 ^c	47.64 ^a , 50.47 ^h , 33.54 ^c	63.65 ^a , 55.31 ^h , 59.39 ^c	3.97 ^a , 6.11 ^h , 2.32 ^c
2015	292.15 ^a , 444.14 ^h , 218.17 ^c	38.73 ^a , 49.57 ^h , 28.72 ^c	56.61 ^a , 50.58 ^h , 54.52 ^c	3.57 ^a , 6.02 ^h , 2.21 ^c
2016	259.11 ^a , 411.47 ^h	34.01 ^a , 46.16 ^h	55.14 ^a , 49.93 ^h	3.42 ^a , 5.63 ^h

Notes: sources.

^a This study.

^b CVEMAR.

^c Jia et al. (2018).

^d Zhang et al. (2017).

^e Lang et al. (2014).

^f Cai and Xie (2013).

^g Lang et al. (2012).

^h Liu et al. (2008).

ⁱ Cai and Xie (2007).

second effective policy for all pollutants, indicating that the promotion of electric vehicles is a promising way to control vehicle pollution in the future.

3.4. Comparison with other studies and uncertainty analysis

From 2010, the Ministry of Ecology and Environment of the People's Republic of China (MEE) has released the China Vehicle Environmental Management Annual Report (CVEMAR) which is the official vehicle emission inventory (MEE, 2010–2017). And there were some previous studies focusing on Tianjin during the past decade. CVEMAR and most previous studies focused on the emissions of CO, VOCs, NO_x, and PM₁₀, and these results were summarized and compared to this study, as shown in Table 4. The emissions and trends of these four pollutants estimated by this study were close to CVEMAR and consistent with most previous studies. There are few studies on emissions of CO₂ and SO₂. The emissions and trends of these two pollutants in this study were close to Jia et al. (2018) and Cai and Xie (2007). The results in this study have proved reliable by comparison.

Since the predictions of vehicle emissions under different scenarios were various, the predicted emissions were only compared under BAU scenario. Guo et al. (2016) suggested that the emissions of PM₁₀, NO_x, CO, HC in Tianjin are increasing in the future. However, the emissions of these pollutants are decreasing (CO and VOCs) or remaining static (NO_x and PM₁₀) in this study. There were two reasons for the difference between this study and Guo et al. (2016): (1) the vehicle population was predicted by using elastic coefficient method and Gompertz method, respectively; (2) the base year in BAU scenario were 2016 and 2011, respectively.

The difference among the above studies indicated that the uncertainties are inevitable in the estimation of vehicle emissions. The most important reason is the estimation method simplifies the complex emission process in reality. For example, previous studies showed that vehicle emission factors are greatly influenced by driving conditions (Suarez-Bertoa et al., 2016), but it was difficult to take the variation into account when simulating the emission factors. Besides, the uncertainties also exist in the estimations of vehicle populations and VKT.

For example, the survival rates were obtained from the previous literature and were used to describe the law of car scrappage at the national level in the original article (Hao et al., 2011a). The VKT were gathered from summarizing various studies (Guo et al., 2016; Lang et al., 2012), which result in some uncertainties about describing vehicle activities in the study area. The survey data on driving conditions, survival rates and VKT in Tianjin could reduce these uncertainties.

Monte Carlo simulation, which were widely used in the uncertainty analysis of air pollutant emissions, are introduced to estimate the uncertainties about the estimation of vehicle emissions in this study. There are two basic parameters in Monte Carlo simulation: the probability distribution and the coefficients of variation (CV, the standard deviation divided by the mean). This study estimates vehicle emissions based on vehicle population, emission factors, and VKT, and the probability distribution and the CV were set for the three variables, respectively. In the historical simulation, the data on vehicle population were obtained from the official statistical yearbooks, and the uncertainty of which was low. Therefore, the normal distribution with CV of 5% was set for the historical vehicle population, and 10% was assumed for the future. The data on VKT were gathered from summarizing various studies, leading to higher uncertainty than the vehicle population. Consequently, the normal distribution with CV of 30% was set for VKT. The probability distribution and the CV are various for the emission factors of different pollutants according to the previous studies (Guo et al., 2016; Lang et al., 2016). For CO, CO₂, NO_x, and VOCs, the lognormal distributions with CV of 36% was set for Pre-State I and State I, and 17% for State II-State VI. For PM₁₀, the lognormal distribution with CV of 59% was assumed for Pre-State I and State I, and 34% for State II-State VI. For SO₂, the distribution was assumed to be uniform with change range of –10% to 20% for two reasons: (1) the SO₂ formation mechanism was simpler than other pollutants, leading to lower uncertainty; (2) COPERT takes the upper limit value as the sulphur content which may less than the actual value. Besides, the trial number also has a significant impact on prognosis in Monte Carlo simulation. It was set to 100,000 to ensure the accuracy of the simulation.

Fig. 8 shows the results of Monte Carlo simulations. The average uncertainty ranges (at a 95% confidence level) for CO, VOCs, NO_x,

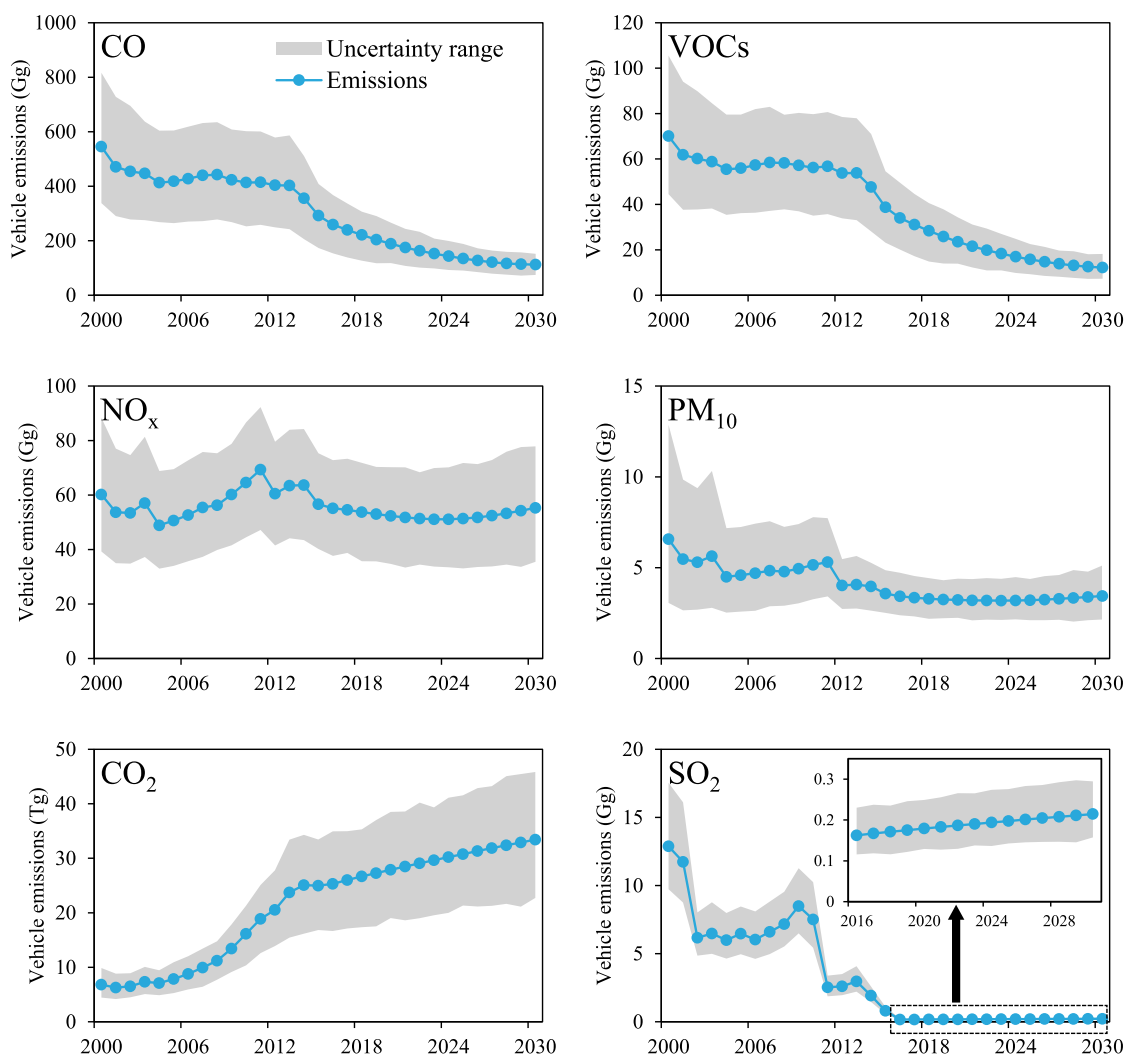


Fig. 8. Vehicle emissions with uncertainty ranges (at a 95% confidence level) in Tianjin from 2000 to 2030. Note: the emissions and the uncertainty ranges from 2017 to 2030 were illustrated under the BAU scenario.

PM₁₀, CO₂, and SO₂ were $-37.73\% \sim 42.33\%$, $-39.79\% \sim 44.86\%$, $-33.17\% \sim 36.75\%$, $-37.53\% \sim 48.10\%$, $-33.38\% \sim 36.26\%$, and $-26.78\% \sim 37.24\%$, respectively. The interval range of PM₁₀ was slightly larger than other pollutants, due to higher uncertainty in its emission factors. Although uncertainties are inevitable, the comprehensive estimation of vehicle emissions still provides a reference for environmental policy formulation, especially in a megacity like Tianjin.

4. Conclusion

This study made a comprehensive estimation of vehicle emissions, including CO, VOCs, NO_x, PM₁₀, CO₂, and SO₂, in Tianjin from 2000 to 2030. The study period was divided into two parts: the historical part (from 2000 to 2016) and the future part (from 2017 to 2030). The historical part focused on general changes and main contributors for each pollutant, and the future part intended to evaluate reduction effects of different control policies. The compositions of vehicular emission standards have been analysed based on the age distribution of the vehicle fleet and the implementation timetable of emission standards. The vehicle emission factors were simulated by the COPERT model, considering the main factors, such as driving speeds, fuel quality, and meteorological conditions.

The future trends of vehicle population and VKT were predicted based on the elastic coefficient method and trend extrapolation, respectively. In 2030, vehicle population of PC, LDV, HDT, BUS, and MC

are 2835.37 thousand, 369.29 thousand, 100.11 thousand, 42.86 thousand and 8.50 thousand, while those of VKT are 23.18, 57.23, 85.60, 55.24 and 6.22 thousand kilometres, respectively.

In the historical part, a multi-year vehicle emission inventory was developed. The results show that the emission trends for different pollutants were various. Total emissions of CO, VOCs, NO_x, PM₁₀ and SO₂ decreased from 545.1 Gg, 70.04 Gg, 60.19 Gg, 6.57 Gg, and 12.88 Gg to 259.11 Gg, 34.01 Gg, 55.14 Gg, 3.42 Gg, and 0.16 Gg from 2000 to 2016, respectively. However, CO₂ emissions increased from 6.82 Tg to 25.30 Tg during the same period. The emission contributions of each vehicle type for certain pollutants were different. PC and LDV were the main sources of CO and VOCs. HDT and BUS were the main contributors to NO_x and PM₁₀. PC was the major contributor to CO₂ and SO₂.

In the future part, the vehicle emissions were predicted under six scenarios, including BAU, PPR, ESU, PTP, EVP and IS. Under the BAU scenario, the vehicle emissions of CO, VOCs, NO_x, PM₁₀, CO₂ and SO₂ in Tianjin will change from 239.45 Gg, 31.10 Gg, 54.55 Gg, 3.35 Gg, 26.01 Tg and 0.17 Gg in 2017 to 112.15 Gg, 12.17 Gg, 55.27 Gg, 3.44 Gg, 33.42 Tg and 0.21 Gg in 2030, respectively. The main contributors to certain pollutants are similar to those in the historical part. The effects of different reduction scenarios were evaluated. The best reduction scenario is IS, with the AARB of 22.99%, 13.30%, 35.52%, 11.95%, 14.61% and 14.65% for CO, VOCs, NO_x, PM₁₀, CO₂, and SO₂, respectively. The most effective SCPS for different pollutants vary. The

ESU is the more effective policy to control emissions of CO, NO_x, and PM₁₀, while the PPR is the more effective way to reduce emissions of VOCs, CO₂ and SO₂. The EVP is also the effective policy for all pollutants, which means the promotion of electric vehicles is a promising way to control vehicle pollution in the future.

The estimations of vehicle emissions reported by CVEMAR and some previous studies were compared to this study. And the Monte Carlo simulation was introduced to analyse the uncertainty in the estimations. The average uncertainty ranges (at a 95% confidence level) for CO, VOCs, NO_x, PM₁₀, CO₂, and SO₂ were −37.73%~42.33%, −39.79%~44.86%, −33.17%~36.75%, −37.53%~48.10%, −33.38%~36.26%, and −26.78%~37.24%, respectively.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.atmosenv.2019.04.016>.

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