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Research article

Least-cost control strategy optimization for air quality attainment of Beijing–Tianjin–Hebei region in China

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ABSTRACT

Control strategies can be optimized to attain air quality standards at minimal cost through selecting optimal combinations of controls on various pollutants and regional sources. In this study, we developed a module for least-cost control strategy optimization based on a real-time prediction system of the responses of pollution concentrations to emissions changes and marginal cost curves of pollutant controls. Different from other method, in this study the relationship between pollution concentrations to and precursor emissions was derived from multiple air quality simulations in which the nonlinear interactions among different precursor emissions can be well addressed. Hypothetical control pathways were designed to attain certain air quality goals for particulate matter ($PM_{2.5}$) and ozone (O_3) in the Beijing–Tianjin–Hebei region under the 2014 baseline emission level. Results suggest that reducing local primary PM emissions was the most cost-efficient method to attain the ambient $PM_{2.5}$ standard, whereas for O_3 attainment, reducing regional emission sources of gaseous pollutants (i.e., SO_2, NO_x, and volatile organic compounds (VOCs)) exhibited greater effectiveness. NH_3 controls may be cost-efficient in achieving strengthened $PM_{2.5}$ targets; however, they might not help in reducing O_3. To achieve both $PM_{2.5}$ ($< 35\,\mu g\,m^{-3}$) and O_3 (daily 1-h maxima concentration < 100 ppb) targets in Beijing, the reduced rates in BTH regions of NO_x, SO_2, NH_3, VOCs and primary PM are 75%, 75%, 5%, 55%, and 85%, respectively from the emission levels in the year of 2014. Local reduction is the most effective method of attaining moderate $PM_{2.5}$ and O_3 targets; however, to achieve more aggressive air quality goals, the same level of reductions must be conducted across the whole Beijing–Tianjin–Hebei region.

1. Introduction

Airborne fine particles ($PM_{2.5}$) are responsible for the haze and severely impaired visibility in cities across China. Since late 2000s, substantial measures have been taken to reduce SO_2, NO_x, and primary particulate matter (PM) emissions. Particularly, since the Action Plan on Prevention and Control of Air Pollution was implemented in 2013, noticeable improvements have been observed in ambient $PM_{2.5}$ concentrations, which have exhibited declining trends in three key regions in China. $PM_{2.5}$ levels in the Beijing–Tianjin–Hebei (BTH), Yangtze–River–Delta (YRD) and Pearl–River–Delta (PRD) regions decreased from 110, 70, and 48 $\mu g\,m^{-3}$ in 2013 to 85, 55 and 34 $\mu g\,m^{-3}$ respectively in 2015 (Wang et al., 2017). However, 75.1% of China's 338 cities at the prefecture or higher level still exceeded the national annual averaged $PM_{2.5}$ standard of 35 $\mu g\,m^{-3}$ in 2016 (Environment Bulletin of China). With further plans to strengthen abatement of SO_2, NO_x, and primary PM emissions, ambitious control policies for VOC and NH_3 must be enforced to further reduce ambient $PM_{2.5}$ concentrations in China (Huang et al., 2014; Fu et al., 2017). NH_3 emission controls can be a cost-efficient strategy to reduce $PM_{2.5}$ (Pinder et al., 2007; Winiwarter and Klimont, 2011); however, few NH_3 emission control measures have been implemented in China to date (Wang et al., 2017). Relevant modeling studies have demonstrated the importance of VOC controls in reducing $PM_{2.5}$ with improved secondary organic aerosols

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(SOA) simulation modules (Zhao et al., 2015a, b, ; Zhao et al., 2017a,b). VOC emission controls have also been suggested for their control effectiveness in reducing O_3, which tends to be slightly enhanced in urban areas where NO_x is abundant (VOC–limited regime). For example, some cities in the PRD regions present an increasing O_3 trend accompanied by effective controls on $PM_{2.5}$ through reducing NO_x (Li et al., 2014). Optimizing the control ratios for all pollutants is a major policy challenge in attaining the objectives for both $PM_{2.5}$ and O_3.

Most relevant studies in China have adopted the concept of atmospheric environmental capacity to calculate the maximum permissible pollutant emissions when the air pollution concentration reaches the national ambient air quality standard (Xue et al., 2014; An et al., 2007; Li et al., 2013; Zhou and Zhou, 2017; Liu et al., 2017). However, the calculation of atmospheric environmental capacity is not straightforward if the concentration of pollutants (e.g., $PM_{2.5}$ and O_3) is contributed by various emission sources through nonlinear behavior (Cohan et al., 2005; Tsimpidi et al., 2008). In particular, regional sources play a critical role in $PM_{2.5}$ and O_3 concentrations in receptor region, suggesting the importance of joint regional controls (Wu et al., 2015; Xing et al., 2017a). With multiple factors involved, the atmospheric environmental capacity can only be calculated in an economically efficient manner, which is to be performed with optimization techniques (e.g., linear programming) based on receptor-oriented models and marginal cost curves. The optimized control strategy is supposed to select the best combination of controls to attain the air quality standard at minimal cost (Cass and McRae, 1981; Harley et al., 1989; Cohan et al., 2006).

Studies on least-cost control strategy optimization have been conducted for O_3 (Heyes et al., 1997; Cohan et al., 2006; Fu et al., 2006) and $PM_{2.5}$ (Harley et al., 1989; Amann et al., 2001; Carnevale et al., 2012), mostly in the United States and Europe. Cost–benefit analysis has become an essential module in integrated assessment modeling, such as in the Greenhouse gas Air pollution Interactions and Synergies model (GAINS; Amann et al., 2011a) developed by the International Institute for Applied Systems Analysis. In GAINS, the source–receptor relationships are based on reduced-form approximations derived from the unified European Monitoring and Evaluation Programme (EMEP) Eulerian model (Heyes et al., 1996). The GAINS model has been applied in Europe (Amann et al., 2011b), China (Amann et al., 2008), and India (Purohit et al., 2010). However, limitations were also recognized, such as the SOA and nonlinearity in the joint controls of pollutants not being addressed well (Amann et al., 2011a). Since 2012, a new policy-oriented integrated scientific assessment system, the Air Benefit and Cost and Attainment Assessment System (ABaCAS), has been continually developing by an international team of scientists from the United States and China, aims to provide the cost-efficient control strategy for policy makers (Xing et al., 2017b). In ABaCAS, the response surface model (RSM), an advanced statistical interpolation technique based on meta-simulation scenarios, has the ability to represent a nonlinear air quality response to emission perturbations, and thus make real-time predictions of the responses of pollution concentrations to emission changes (Xing et al., 2011; Wang et al., 2011; Zhao et al., 2015a,b). Since the RSM was built on multiple air quality simulations, the advantage of this system is that the nonlinear interactions among different precursor emissions can be well addressed without involving additional assumptions. The costs associated with certain control strategies were estimated by the International Cost Estimate Tool (ICET; previously Cost, the China Multi-Pollutant Control Cost Model) based on cost information of control technologies and was successfully applied in the YRD region (Sun et al., 2014). However, the optimization of control strategies between the ICET and RSM has not yet been developed. The design of a cost-efficient control strategy is expected to be straightforward after the application of the RSM with polynomial function (pf-RSM) developed recently which largely improves the computational efficiency in estimating the air quality response to the emission change (Xing et al., 2018).

In this study, the module of LEast-COst control strategy optimization (LE-CO) was developed based on a pf-RSM with marginal cost curves. The LE-CO was further implemented in the ABaCAS system and applied to a case study in China's BTH region.

2. Method

2.1. Framework design of LE-CO

The LE-CO module was designed to select the optimal combination of controls that can not only meet air quality standards but are also the most cost-efficient control strategy among all candidates. Generally, the air quality criteria represent the air quality standards. In this study, we selected the thresholds of annual mean of $PM_{2.5}$ and daily 1-h maxima of O_3 to be $35\,\mu g\,m^{-3}$ and 100 ppb respectively, which correspond to Class II of the National Ambient Air Quality Standard in China. Beijing city was chosen as the target region to represent the BTH, considering it is located in the center of the BTH region.

The real-time responses of $PM_{2.5}$ and O_3 to emission reduction ratios were calculated using a RSM that quantified the nonlinear relationship between $PM_{2.5}$ and O_3 concentrations to emissions of five pollutants including NO_x, SO_2, NH_3, volatile organic compounds (VOCs; i.e., VOC and intermediate VOC), and primary PM (including primary organic aerosol (POA) and other primary PM) in five regions over BTH, which included Beijing, Tianjin, northern Hebei (denoted as HebeiN), eastern Hebei (denoted as HebeiE), and southern Hebei (denoted as HebeiS). The reduction ratios of different pollutants and regions were calculated using LE-CO through optimization with the following nonlinear programming procedure:

Minimize

$$Cost_T = \sum_r \sum_p Cost_p^r \tag{E1}$$

Subject to

$$Cost_p^r = f_p^r(CtrR_p^r) \tag{E2}$$

$$Conc_{sp}^r = rsm_{sp}^r\left(CtrR_{\sum p}^r\right) \tag{E3}$$

$$Conc_{sp}^r \le obj\_Conc_{sp} \tag{E4}$$

Where $Cost_T$ is the total cost; $Cost_p^r$ is the cost for pollutant p (i.e., NO_x, SO_2, NH_3, VOCs, and primary PM) at region r (i.e., Beijing, Tianjin, HebeiN, HebeiE, and HebeiS); $CtrR_p^r$ is the control ratio of pollutant p at region r; f_p^r is the cost control ratio function of pollutant p at region r; rsm_{sp}^r is the function of concentration of pollutant sp (i.e., $PM_{2.5}$ and O_3) to $CtrR_p^r$ based on RSM; and obj_Conc_{sp} is the air quality criteria of pollutant sp (i.e., $PM_{2.5}$ and O_3).

The framework of LE-CO is displayed in Fig. 1. Since RSM has high efficiency in predicting the air quality responses under various emission reductions, the optimized $CtrR_p^r$ can be determined through the grid searching method to select the strategy that meets the environmental targets with minimal cost. First, the high-dimension sampling space was divided into grids with ten steps from 5% to 95% reductions for each pollutant, resulting in 10000 grid cells (control scenarios) with the combination of different reduction ratios of five pollutants. Second, the concentration responses for all control scenarios were estimated based on the RSM. Third, the total control costs associated with each control scenario were estimated based on the ICET. At last, the optimized control scenario will be selected from the candidate control scenarios which meets the ambient target with least control cost. One thing should be noted that the control scenarios are hypothetical, since the controls in reality cannot be implemented immediately. This study aims to conduct a counterfactual analysis to estimate what if we had better emission controls today and what would they cost.

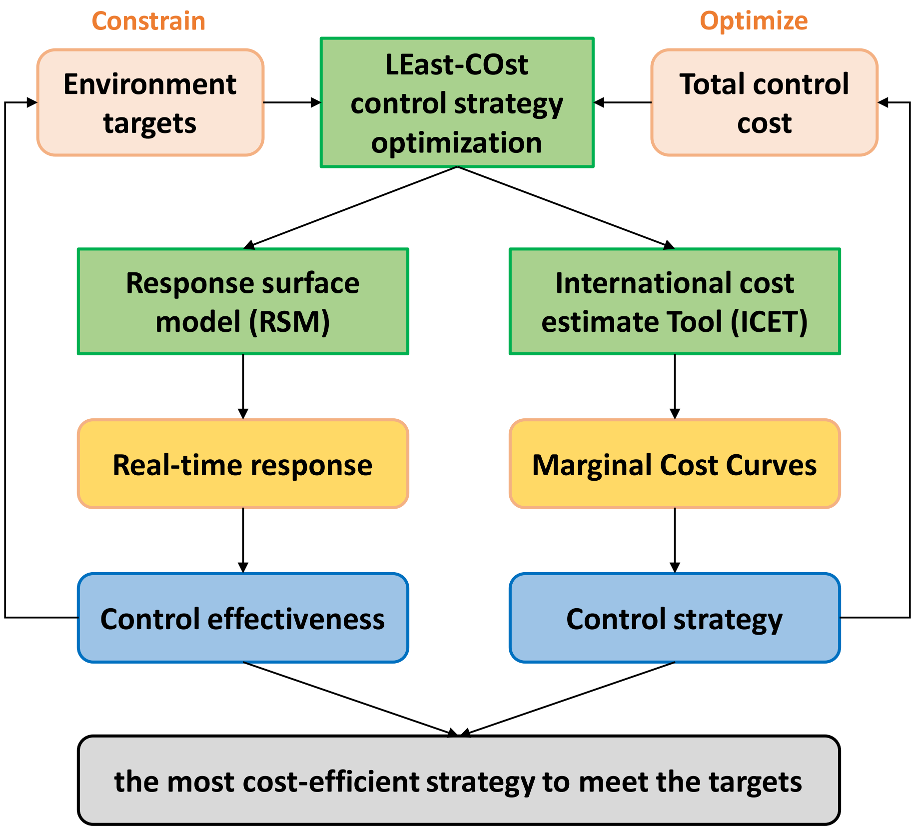

Fig. 1. Conceptual framework of the least-cost control stratege optimization (LE-CO) module.

2.2. Marginal abatement cost curves

The marginal abatement cost curves for pollutant emissions were established based on the ICET module in the ABaCAS system. The cost estimated in ICET refers to the cost associated with control technology application, while the social cost (e.g., subsidy to promote the control policy) was not considered in ICET in this study. For each pollutant in each region, the total cost under certain abatement targets was calculated using the linear programming model based on the unabated emissions and current control applications, as well as unit cost, potential application rate, and emission control efficiency of various control technologies (Sun et al., 2014), as follows:

Minimize

$$Cost_p^r = \sum_i Cost_{p,i}^r \tag{E5}$$

Subject to

$$Cost_{p,i}^r = UC_{p,i} \times \Delta Emis_{p,i}^r \tag{E6}$$

$$\Delta Emis_{p,i}^r = (1 - CE_{p,i}) \times (AppR_{p,i}^r - Cur\_AppR_{p,i}^r) \times Unabated\_Emis_p^{r,s} \tag{E7}$$

$$Unabated\_Emis_p^{r,s} = \frac{baseline\_Emis_p^{r,s}}{1 - \sum_i [(1 - CE_{p,i}) \times Cur\_AppR_{p,i}^r]} \tag{E8}$$

$$Cur\_AppR_{p,i}^r \le AppR_{p,i}^r \le \max\_AppR_{p,i} \tag{E9}$$

$$\frac{\sum_i \Delta Emis_{p,i}^r}{\sum_s baseline\_Emis_p^{r,s}} = CtrR_p^r \tag{E10}$$

Where $Cost_{p,i}^r$ is the cost of technology i for pollutant p (i.e., NO_x, SO_2, NH_3, VOCs, and primary PM) at region r (i.e., Beijing, Tianjin, HebeiE, HebeiN, and HebeiS); $UC_{p,i}$ is the unit cost of technology i for pollutant p; $\Delta Emis_{p,i}^r$ is the emission reduction by the technology i for pollutant p at region r; $CE_{p,i}$ is the control efficiency of technology i for pollutant p; $AppR_{p,i}^r$ is the control application rate of technology i for pollutant p at region r; $Cur\_AppR_{p,i}^r$ is the current control application rate of technology i for pollutant p at region r; $Unabated\_Emis_p^{r,s}$ is the unabated emissions of pollutant p at region r in sector s where control technology i is applied; $baseline\_Emis_p^{r,s}$ is the baseline emissions of pollutant p at region r in sector s where control technology i is applied; and $\max\_AppR_{p,i}$ is the maxima application rate of technology i.

In this study, the data of $baseline\_Emis_p^{r,s}$, $Cur\_AppR_{p,i}^r$, and $CE_{p,i}$ were derived from the study of the bottom-up emission inventory of the BTH region (Zhao et al., 2017a,b). The parameters of $UC_{p,i}$ and $\max\_AppR_{p,i}$ basically referred to the ICET and GAINS-Asia models with some updates for power plants and key industries from references, as summarized in a separated paper (Zhang et al., in preparation).

In Fig. 2, the marginal abatement cost curses represents the optimized combinations of control technologies for each pollutants individually. Clearly, the cost increases sharply with the growth of the pollutant reduction ratio because the most cost-efficient control technologies will be first selected (Zhang et al., in preparation). The SO_2 and primary PM emission controls cost significantly less compared with other pollutants, and thus were prioritized for selection of control choices. The cost of NH_3 emission controls is slightly lower than NO_x and VOCs. Although not receiving much attention in current policy, NH_3 emission controls have the potential to be selected under higher reduction requirements when the cost of reducing NO_x and VOCs become much higher than NH_3. The pollutants cannot be fully controlled because of the limitations of control technologies. The maxima reduction ratio of NO_x, SO_2, NH_3, VOCs and primary PM was set to be about 85%, 75%, 75%, 65% and 95% respectively after considering all potential controls.

The marginal abatement cost curves for all pollutants were further input into the LE-CO to optimize the combination of pollutants. One thing should be noted that the marginal abatement cost curves for each pollutants were calculated individually. Some control technologies can simultaneously reduce multiple pollutants; for instant, vehicles

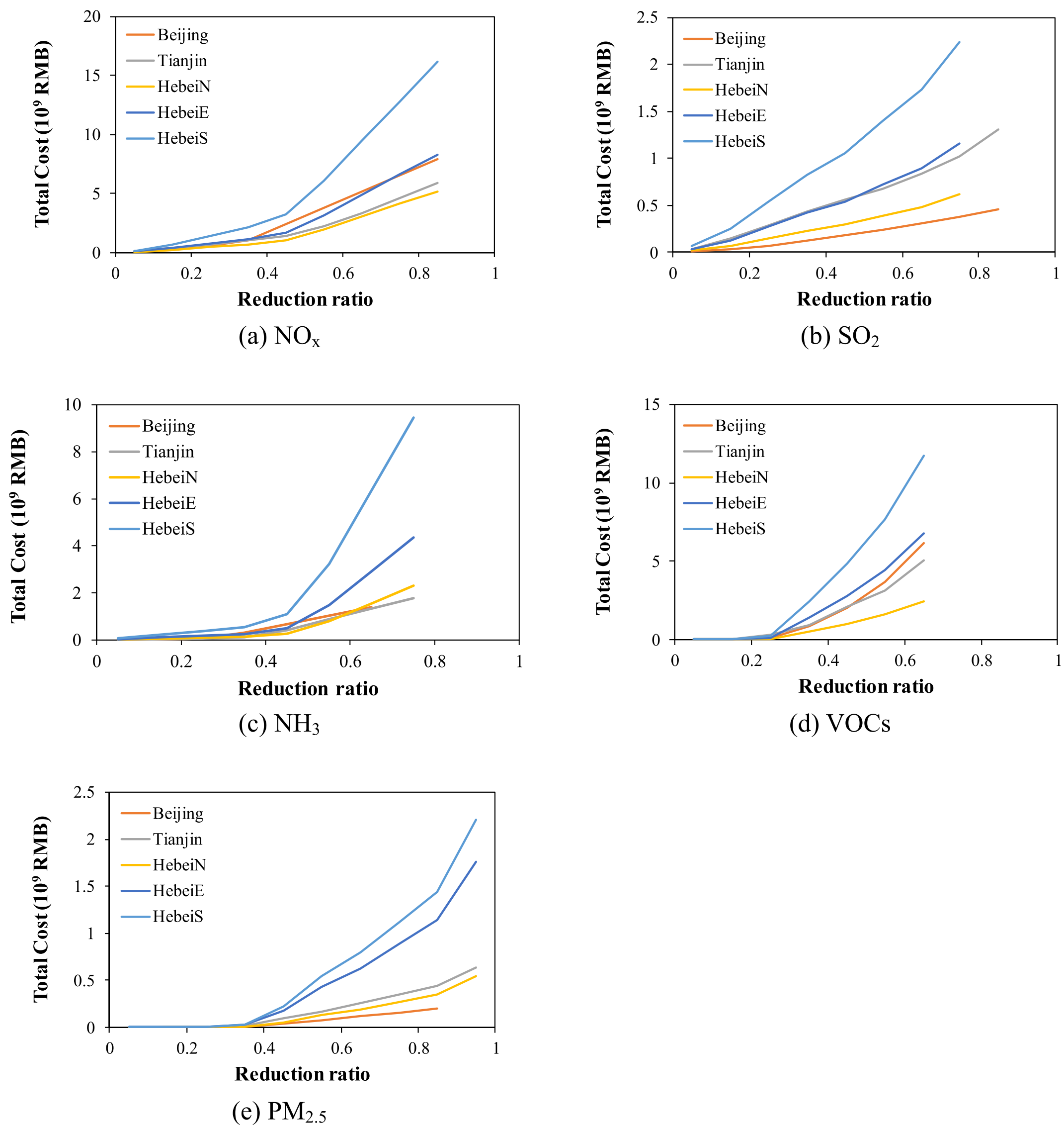

Fig. 2. Marginal abatement cost curves of five pollutants in Beijing-Tianjin-Hebei region.

technologies can reduce NO_x, VOCs, and primary PM. To avoid double counting issue, the cost for such multiple-pollutant control technology will be included only for the pollutant with the highest application rate (i.e., its cost for other pollutants will be set as zero) in the calculation of total cost with the combination of pollutant controls. To simplify the optimization process in this study, we assumed that the control technologies could be applied in each region independently. Such assumption might lead to an uncertainty when only applying strengthened local controls, since some technology applications need be ensured with corresponding agreement across provinces (e.g., improvement of fuel quality, vehicle standard). However, the uncertainty becomes negligible when regional joint control is applied.

2.3. Response of air quality to emission controls

This study adopted the pf-RSM method, which quantifies the responses of air quality to emission controls with a set of polynomial functions (Xing et al., 2018). The responses of $PM_{2.5}$ and O_3 concentrations to primary PM emissions exhibits linear behaviors that can be represented through linear regression (Zhao et al., 2017a,b). Thus, the following linear term was added into the pf-RSM to represent the response to primary PM emissions:

$$\Delta Conc = \left[\sum_{i=1}^{a} A_i\cdot(E_{P1})^i + \sum_{j=1}^{a'} A'_j\cdot(E_{P2})^j + \sum_{i=1}^{b} B_i\cdot(E_{P1})^{a_i^1}\cdot(E_{P2})^{a_i^2}\right] + C_i\cdot E_{PM} \tag{E11}$$

Where $\Delta Conc$ is the response of O_3 and $PM_{2.5}$ concentrations to changes in individual emissions; E_{P1} and E_{P2} are the change ratios of two precursor (*P1* and *P2* can represent any two of NO_x, SO_2, NH_3, VOCs, or POA) emission related to baseline; E_{PM} is the change ratio of PM emission related to baseline; A_i, A'_j, B_i, C_i are the coefficients of terms; the superscript *i, j* is the degree of precursor; a_i^1 and a_i^2 are the degrees of precursors *P1* and *P2*, respectively; and the superscript *b* is the total number of interaction terms between *P1* and *P2* (i.e., a_i^1 multiplied by a_i^2).

The term selections for pollutants in pf-RSM were determined in the previous paper (Xing et al., 2018), and the coefficients of A_i, A'_j, B_i, C_i were fitted for daily concentrations of $PM_{2.5}$ and O_3, as well as precursor concentrations of NO_x, SO_2, NH_3, VOCs, and POA required for the five regions of BTH (Beijing, Tianjin, HebeiN, HebeiE, and HebeiS). The selected terms in E11 for $PM_{2.5}$ and O_3 in single-regional RSM are the same as Xing et al. (2018), as summarized in Table 1. Then the single-regional RSMs in five regions was combined together based on

Table 1
The selected terms in the pf-RSM for $PM_{2.5}$ and O_3.

Term	O_3	$PM_{2.5}$
1	NO_x^5	VOC
2	NO_x^4	NH_3
3	NO_x^3	NH_3^2
4	NO_x^2	NH_3^3
5	NO_x	SO_2
6	VOC	VOC^2
7	VOC^2	NO_xVOC
8	VOC^3	NO_x^2VOC
9	NO_xVOC	NO_x^4VOC
10	NO_xVOC^3	NO_xNH_3
11	NO_x^5VOC	NO_x
12	NO_x^2VOC	NO_x^2
13	SO_2	NO_x^3
14	NH_3	NO_x^4
15	Primary PM	Primary PM

the latest extended RSM technique by which the multi-regional interactions are estimated as the sum of three components: 1) local chemistry formation of the pollutant associated with the change in its precursor levels at receptor region; 2) regional transport of the pollutant from source region to receptor region; 3) interregional effects among multiple regions (Xing et al., 2017a). January and July in 2014 were selected to represent winter and summer, respectively. The annual mean of $PM_{2.5}$ was roughly estimated through averaging these two months. The simulated $PM_{2.5}$ and O_3 concentrations in the pf-RSM were adjusted to be consistent with observations for the purpose of attainment analysis.

3. Results

3.1. Control pathway design to attain certain air quality goals

The ambient O_3 and $PM_{2.5}$ concentrations are contributed by multiple pollutants, therefore various combinations of pollutant controls can achieve the O_3 and $PM_{2.5}$ target, as list in Table 2. All of the scenarios can be one candidate to attain the air quality goals as $PM_{2.5}$ less than 35 μg m^{-3} and O_3 less than 100 ppb in Beijing. The emission reduction rate varies largely for all pollutants as NO_x, SO_2 and NH_3 from 5% to 95%, VOCs from 15% to 85%, primary PM from 55% to 95%, suggesting that there are multiple choices to attain certain air quality goals without consideration of control cost. For example, small reduction of NO_x (5%) can be compensated by large VOCs reduction (85%) for O_3 target as shown in Scenario 1, while part of VOCs reduction (70%) can also be replaced by substantial reduction of NO_x (95%) as shown in Scenario 16. Moderate primary PM controls (55%) requires large reductions in SO_2 (85%) and NH_3 (95%) in Scenario 2, while more aggressive controls of primary PM (95%) can loosen the controls on SO_2 (5%) and NH_3 (65%) as shown in Scenario 11. However, the control over 95% is unrealistic since it either exceeds the maxima reduction potentials or has extremely large cost. Optimization of the pollutant control combinations is necessary for maker more achievable policy.

Table 2
Potential candidates to meet the $PM_{2.5}$ and O_3 target achievement[a] in Beijing.

Scenario	NO_x	SO_2	NH_3	VOCs	Primary PM
1	5%	85%	95%	85%	55%
2	5%	65%	25%	75%	85%
3	65%	45%	65%	65%	85%
4	65%	25%	75%	65%	85%
5	65%	75%	95%	65%	65%
6	85%	95%	5%	25%	85%
7	75%	55%	65%	55%	85%
8	85%	65%	65%	35%	85%
9	85%	35%	65%	65%	85%
10	85%	15%	75%	65%	85%
11	85%	5%	65%	35%	95%
12	85%	75%	75%	65%	75%
13	85%	75%	5%	45%	85%
14	85%	75%	55%	35%	85%
15	85%	75%	65%	25%	85%
16	95%	55%	5%	15%	85%

[a] Based on LE-CO; $PM_{2.5}$ -target: monthly averaged concentration less than 35 μg m^{-3}; O_3-target: daily maxima hourly concentration less than 100 ppb.

Through the LE-CO, we defined and compared four types of optimized control combinations of pollutants to attain the ambient air quality targets. Beijing was selected as one example in Fig. 3. The four types are as follows: (1) To only meet the $PM_{2.5}$ target with no NH_3 control (Fig. 3a); (2) to only meet the $PM_{2.5}$ target but with NH_3 control (Fig. 3b); and (3) to meet both $PM_{2.5}$ and O_3 targets with NH_3 controls (Fig. 3c). Moderate to strengthened $PM_{2.5}$ targets were selected from 60 to 35 μg m^{-3}, whereas only one O_3 target was selected and set to 100 ppb. The controls were designed to be measured across the whole BTH region (i.e., the reduction in other regions of BTH was assumed to be the same as the target region).

In Fig. 3a – b, where only the $PM_{2.5}$ target was considered, the controls on primary PM and SO_2 emissions were the dominant selection (greater than 50% reduction) to achieve moderate $PM_{2.5}$ targets (i.e., greater than 40 μg m^{-3}) because of their lower control costs compared with other pollutants. Under strengthened targets (i.e., $PM_{2.5}$ lower than 40 μg m^{-3}), controls on other pollutants including VOCs, NO_x, and NH_3 could be partially considered. The difference between Fig. 3a and b is the choice on NH_3 controls; NH_3 can be observed to be a candidate for achieving $PM_{2.5}$ targets through replacing substantial reductions in NO_x and VOCs. Considering NH_3 controls might be a cost-efficient method of achieving $PM_{2.5}$ targets because the cost in Fig. 3a is lower than in Fig. 3b. However, they might not be helpful in reducing O_3, which is shown in the control on O_3 in Fig. 3b not being as effective as in Fig. 3a. In Fig. 3a, the O_3 and $PM_{2.5}$ are simultaneously reduced because of substantial controls on their common precursors (i.e., NO_x and VOCs). However, in Fig. 3b, the NH_3 control replaces NO_x and partial VOCs controls, leading to a comparatively lower reduction in O_3.

In Fig. 3c, where the O_3 target (< 100 ppb) is also considered, the NO_x and VOCs controls are critical even at a moderate level of $PM_{2.5}$ targets. The O_3 target can be achieved through reducing NO_x by 85% and VOCs by 55%, which also benefits $PM_{2.5}$ target attainment. The control on primary PM (approximately 55%) is smaller than in Fig. 3a – b because it was partially replaced with the controls on NO_x and VOCs, but also results significantly affect cost; the control cost of NO_x and VOCs is much higher than for primary PM and SO_2. Meanwhile, although NH_3 control is a cost-efficient method of achieving stricter $PM_{2.5}$ targets, the NH_3 control is not selected because of strengthened controls of NOx and VOC for O_3 attainment in Fig. 3c. Interesting finding is that, when $PM_{2.5}$ target becomes stricter from 40 μg m^{-3} to 35 μg m^{-3}, the least-cost optimization process leads to an enhanced reduction in SO_2 from 35% to 75% and VOCs from 25% to 55%, but a loosen reduction in NO_x control which is reduced from 85% to 75%. That indicates the control rate of certain pollutant may not be monotonously increasing along with the strengthening of air quality target due to the nonlinearities of the cost and air quality response.

3.2. Apportionment of control cost and effectiveness

Achieving $PM_{2.5}$ and O_3 targets in Beijing requires joint controls on multiple pollutants across the BTH region. To explore the control efficiency of certain pollutants and regional sources, we apportioned cost and control effectiveness. Fig. 4 estimates and displays the share of cost and effectiveness for the suggested control strategy for achieving both $PM_{2.5}$ and O_3 targets in Beijing. The reduced rates of NO_x, SO_2, NH_3, VOCs, and primary PM are 75%, 75%, 5%, 55%, and 85%, respectively in all regions. Combined with the marginal cost curves, the cost of reductions in individual sources are compared in Fig. 4a. The total cost is

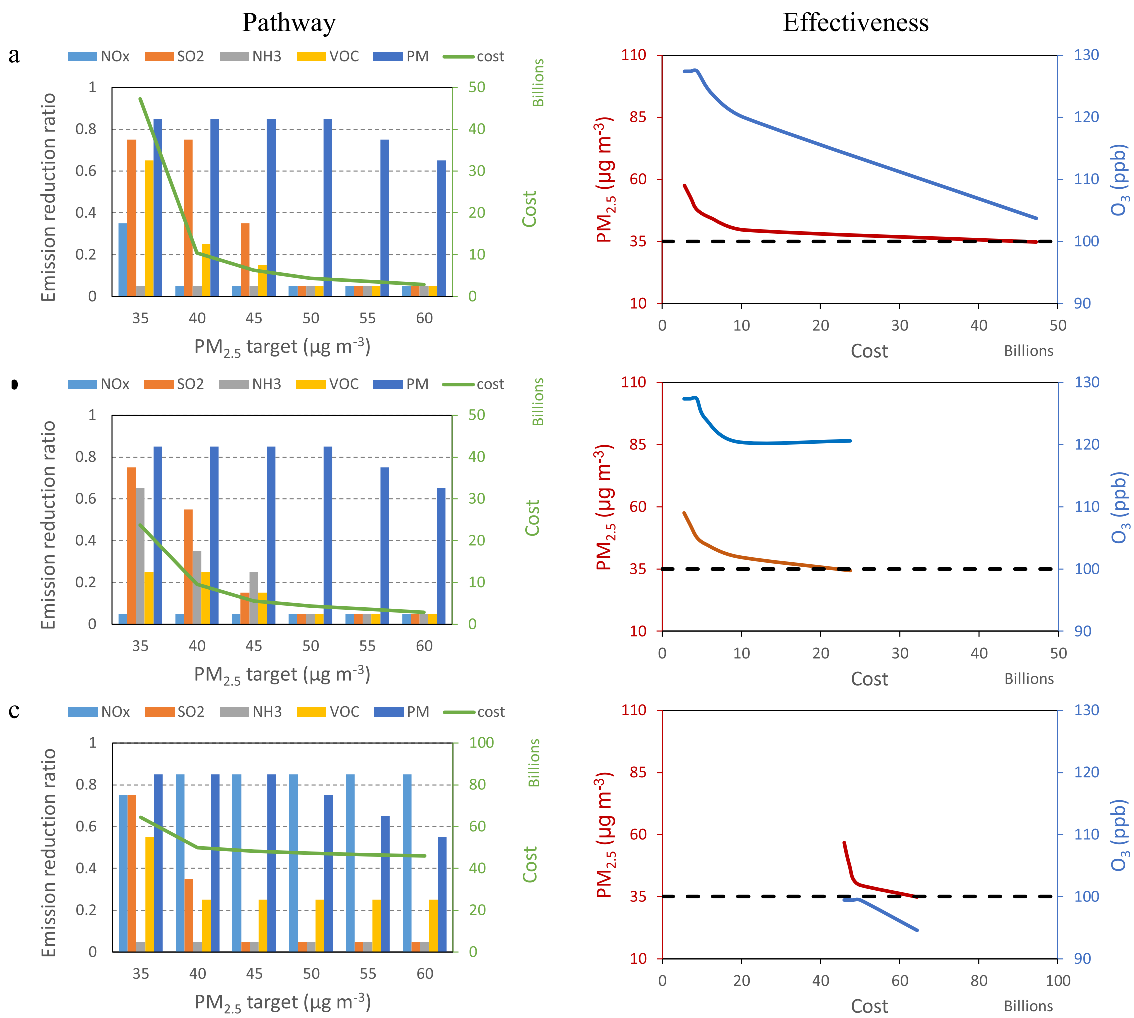

Fig. 3. Selected control pathways and their effectiveness to achieve certain $PM_{2.5}$ and O_3 targets in Beijing (a: only $PM_{2.5}$ target with no NH_3 control; b: only $PM_{2.5}$ target but with NH_3 control; c: both $PM_{2.5}$ and O_3 targets).

largely dominated by the NO_x and VOCs controls, even though their reduction rates are no greater than SO_2 and primary PM. The cost of reductions in HebeiS is the highest of all regions because HebeiS is responsible for the most emissions (Zhao et al., 2017a,b). Although the target region is Beijing, the shared costs in Beijing are lower than the shared costs outside.

The primary PM control accounts for the largest share of reductions in $PM_{2.5}$, followed by SO_2, VOCs, and NO_x (see Fig. 4b). Considering its smaller share of cost, primary PM control is the most cost-efficient method of reducing $PM_{2.5}$. The primary PM controls are mostly through local reduction; whereas for gaseous pollutants (SO_2, NO_x, and VOCs), greater effectiveness is displayed in regional controls, particularly in Tianjin.

The reduction in O_3 was because of NO_x and VOCs controls (see Fig. 4c). The share of contributions from controls on regional sources (70%) is larger than the share from local controls (30%), which indicates the importance of joint controls on regional sources, particularly for NO_x. Moreover, controls on emission sources from Tianjin (25%) and HebeiE (20%) contribute considerable shares of effectiveness in O_3 reduction in Beijing.

3.3. Atmospheric environmental capacity and overloading rate

In this study, the atmospheric environmental capacity is defined as the maxima emission allowance reaching the ambient air quality standards of $PM_{2.5}$ and O_3, which corresponds to the 24-h mean $PM_{2.5}$ and 1-h maxima O_3 being 35 μg m^{-3} and 100 ppb, respectively. From our previous discussion, we estimated that the optimized control pathway to achieve the $PM_{2.5}$ and O_3 targets in Beijing is to reduce NO_x, SO_2, NH_3, VOCs, and primary PM by 75%, 75%, 5%, 55%, and 85%, respectively, across the whole BTH region (i.e., each region benefits from the joint controls). The emissions of NO_x, SO_2, NH_3, VOCs, and primary PM in Beijing are 197.0, 78.0, 52.2, 357.7, and 47.8 kt yr^{-1}. Thus, the emissions of NO_x, SO_2, NH_3, VOCs, and primary PM after reductions required to meet the $PM_{2.5}$ and O_3 targets (i.e., atmospheric environmental capacity) were calculated to be 49.3, 19.5, 49.6, 161.0 and 7.2 kt yr^{-1}, respectively, in Beijing. The current overloading rates of NOx, SO_2, NH_3, VOCs and primary PM are the ratios of atmospheric environmental capacity to current emissions, which are 4.0, 4.0, 1.1, 2.2, and 6.7, respectively.

The largest overloaded pollutant is primary PM considering its greater control effectiveness and lower cost, which suggests substantial potential in reducing primary PM emissions. NH_3 presents a small overloaded rate because its less effectiveness in reducing O_3; however, NH_3 controls could help to achieve stricter $PM_{2.5}$ targets when controls of NOx and VOC are limited and their costs become exteremly high.

3.4. Optimized combination between local and regional controls

To further investigate the combination of local and regional

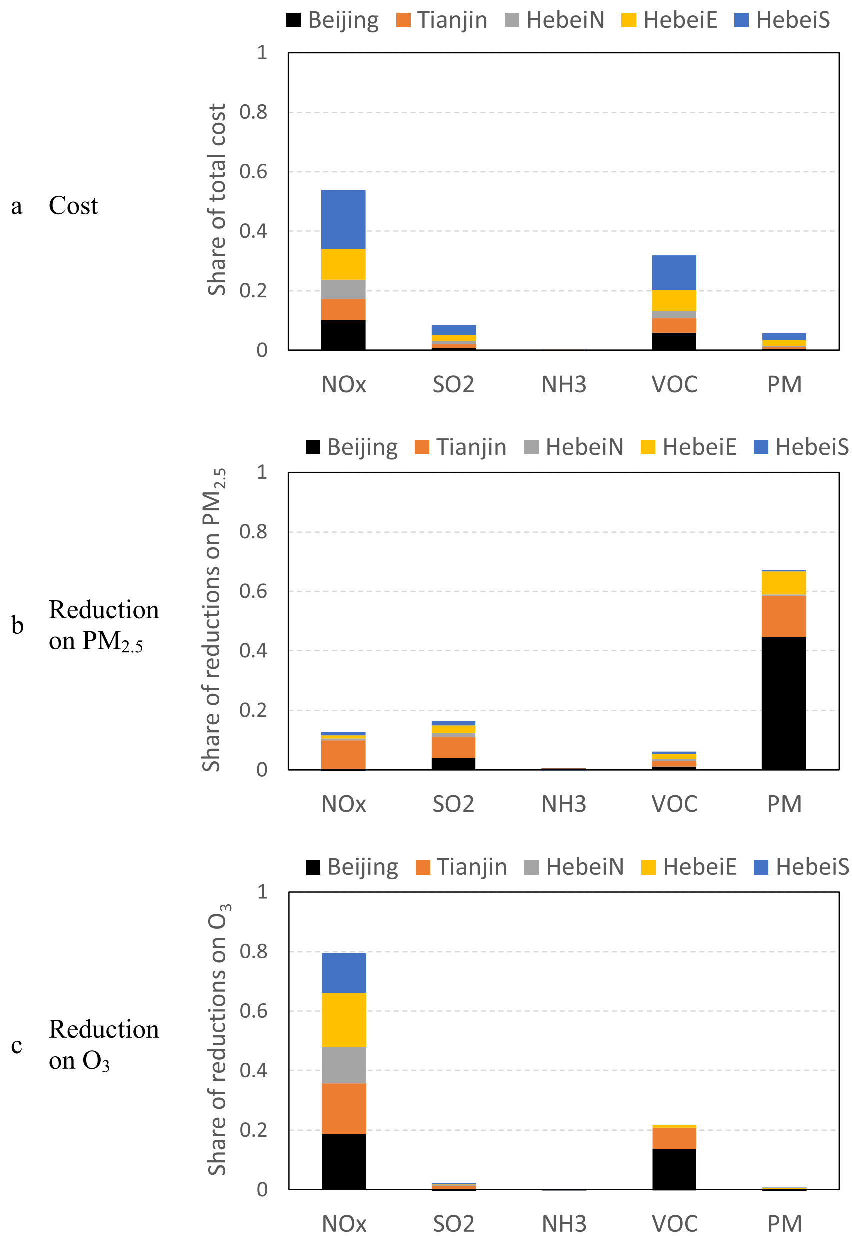

Fig. 4. Share of cost and effectiveness for the control strategy (the reduced rates of NO_x, SO_2, NH_3, VOCs, and PM are 75%, 75%, 5%, 55%, and 85%, respectively) to achieve both $PM_{2.5}$ (monthly averaged concentration less than 35 μg m^{-3}) and O_3 targets (daily maxima hourly concentration less than 100 ppb) in Beijing.

controls, the cost curves to achieve different $PM_{2.5}$ and O_3 targets were estimated from the LE-CO. In Beijing, as shown in Fig. 5, large variations in cost exist among five types of combined local and regional controls based on the ratios of local to regional reduction: (1) local to regional control is 1:1 (L:R = 1:1), representing that the same reduction rate is applied to local and regional sources; (2) local to regional control is 1:0.75 (L:R = 1:0.75), representing that the regional reduction rate is 75% of the local reduction rate; (3) local to regional control is 1:0.5 (L:R = 1:0.5), representing that the regional reduction rate is half of the local reduction rate; (4) local to regional control is 0.5:1 (L:R = 0.5:1), representing that the regional reduction rate is twice the local reduction rate; and (5) local to regional control is 1:0 (L:R = 1:0), representing that only local reductions are considered.

As the $PM_{2.5}$ target is strengthened, the cost increases in all cases (Fig. 5a). Under moderate $PM_{2.5}$ targets (i.e., 45–80 μg m^{-3}), the cases with higher ratio of local controls (i.e., L:R = 1:0.5 and 1:0.75) cost less than the case with a higher ratio of regional controls (i.e., L:R = 0.5:1). This is because local reduction is more effective at reducing local pollution than regional reduction, presenting a cost – efficient method of reducing certain amount of pollution. However, when the $PM_{2.5}$ target becomes stricter (i.e., < 45 μg m^{-3}), the case with an equal rate of local and regional controls (i.e., L:R = 1:1) costs less than the others. This is because the marginal cost of further reducing local pollution becomes equal or even higher than reducing regional sources. In addition, the cases with no or limited regional controls cannot achieve the most strengthened $PM_{2.5}$ target (i.e., L:R = 1:0).

Similar to $PM_{2.5}$, the local controls for O_3 (Fig. 5b) tend to be more cost – efficient under mild and moderate O_3 targets (i.e., > 104 ppb). When the O_3 target is strengthened (< 100 ppb), the cases with an equal rate of local and regional controls (i.e., L:R = 1:1) cost less than the others and also can achieve more strengthened O_3 target (i.e., < 95 ppb). The cost for reducing O_3 is much higher than reducing $PM_{2.5}$ due to the high cost associated with NO_x and VOC controls, and it will take more than 1% of the GDP in BTH to achieve strengthened O_3 target (i.e., < 90 ppb).

We found similar results for the other four regions in BTH

(a) $PM_{2.5}$

(b) O_3

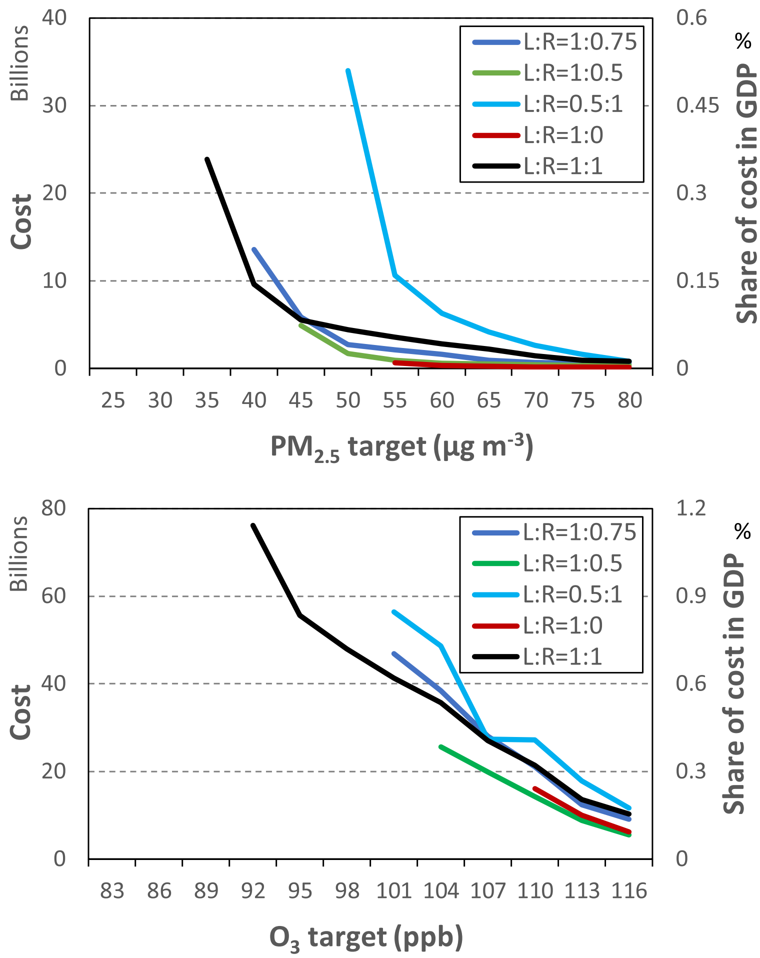

Fig. 5. Combination of multi-regional controls to achieve $PM_{2.5}$ and O_3 targets separately in Beijing (black line (L:R = 1:1) represents that the same reduction rate is applied in local and regional sources; dark blue line (L:R = 1:0.75) represents that the regional reduction rate is 75% of the local reduction rate; green line (L:R = 1:0.5) represents that the regional reduction rate is half of the local reduction rate; light blue line (L:R = 0.5:1) represents that the regional reduction rate is twice the local reduction rate; red line (L:R = 1:0) represents that only local reductions are considered, the secondary X-axis indicates the share of cost in GDP in 2014 GDP of Beijing – Tianjin – Hebei region). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

(Supplementary Information), except for the case with a higher ratio of regional controls (i.e., L:R = 0.5:1) in HeibeiE which tends to be slightly more effective in reducing O_3 due to greater effectiveness in regional controls than local controls. Our findings indicate that local reduction has priorities for attaining moderate $PM_{2.5}$ and O_3 targets. However, to achieve more aggressive targets, the same level of reductions must be conducted across the whole BTH region.

3.5. Sensitivities of optimization to the variation of control costs

The cost of controls largely determines the shares of reductions among the five pollutants. The sensitivity of optimization to control cost was analyzed to understand the robustness of the optimization to variations in control cost, which is likely to happen in the future because of the evolution of control technologies as well as the changes in the economic structure and air control policy. With LE-CO, we calculated the responses of the optimized control strategy to achieve both $PM_{2.5}$ (less than $35\,\mu g\,m^{-3}$) and O_3 (less than 100 ppb) targets in Beijing to a wide range of perturbations of cost from 10^{-10} to 10^{10} times as much as the current cost level. Optimization based on current cost estimation suggested that the reduced rates of NO_x, SO_2, NH_3, VOCs and PM should be 75%, 75%, 5%, 55%, and 85%, respectively. When the cost of certain pollutants changed from 10^{-10} to 10^{10} times the current level, its reduced rate increases or decreases, as displayed in Fig. 6.

For NO_x, when the perturbation of cost is within the range of 0.1–10 times the current level, it remains at the current optimized rate of 75%. The share of NO_x controls increases to the maxima reduction ratio of 85% when the cost becomes lower than 0.01 times the current level. In contrast, when the cost varies to larger than 100, it will be replaced by reducing other pollutants. The share of NO_x controls is at least 65% for O_3 target achievement.

VOCs exhibit similar result to NO_x. It remains at the current optimized rate of 55% when the perturbation of cost is within the range of 0.1–10 times the current level. When the cost varies to larger than 100, the share of VOCs controls reduced to the least as 25%.

For SO_2, the current optimized reduction rate remains at 75% when the cost becomes lower than the current level. If the cost of SO_2 increases in the future, the reduced rate of SO_2 will decrease to 35%.

The current cost of NH_3 seems too high for application, and thus its control is currently limited. However, if the cost of NH_3 control reduces to 0.1 time the current level, the reduction rate will increase to 65%.

The current cost level of $PM_{2.5}$ is low, and thus the current optimized reduced rate of $PM_{2.5}$ is 85%. Even though the cost of $PM_{2.5}$ increased by 10^{10}, it still maintains 85% reduction rate, indicating the importance of control on primary PM emissions.

Noteworthily, we only considered the variation in control cost for each pollutant individually. The simultaneous change of cost (i.e., the relative value of control cost of all pollutants kept the same) does not affect the order of priorities in the pollutant control selection.

4. Conclusion

This study developed a module for least-cost control strategy optimization and designed control pathways to attain certain air quality goals for $PM_{2.5}$ and O_3 in the BTH region. The optimization of combined controls is determined using the marginal abatement cost curves for each pollutant in each region and the response of air quality to certain emission control strategies. The results suggest that local primary PM control was the most cost-efficient method of reducing $PM_{2.5}$.NH_3

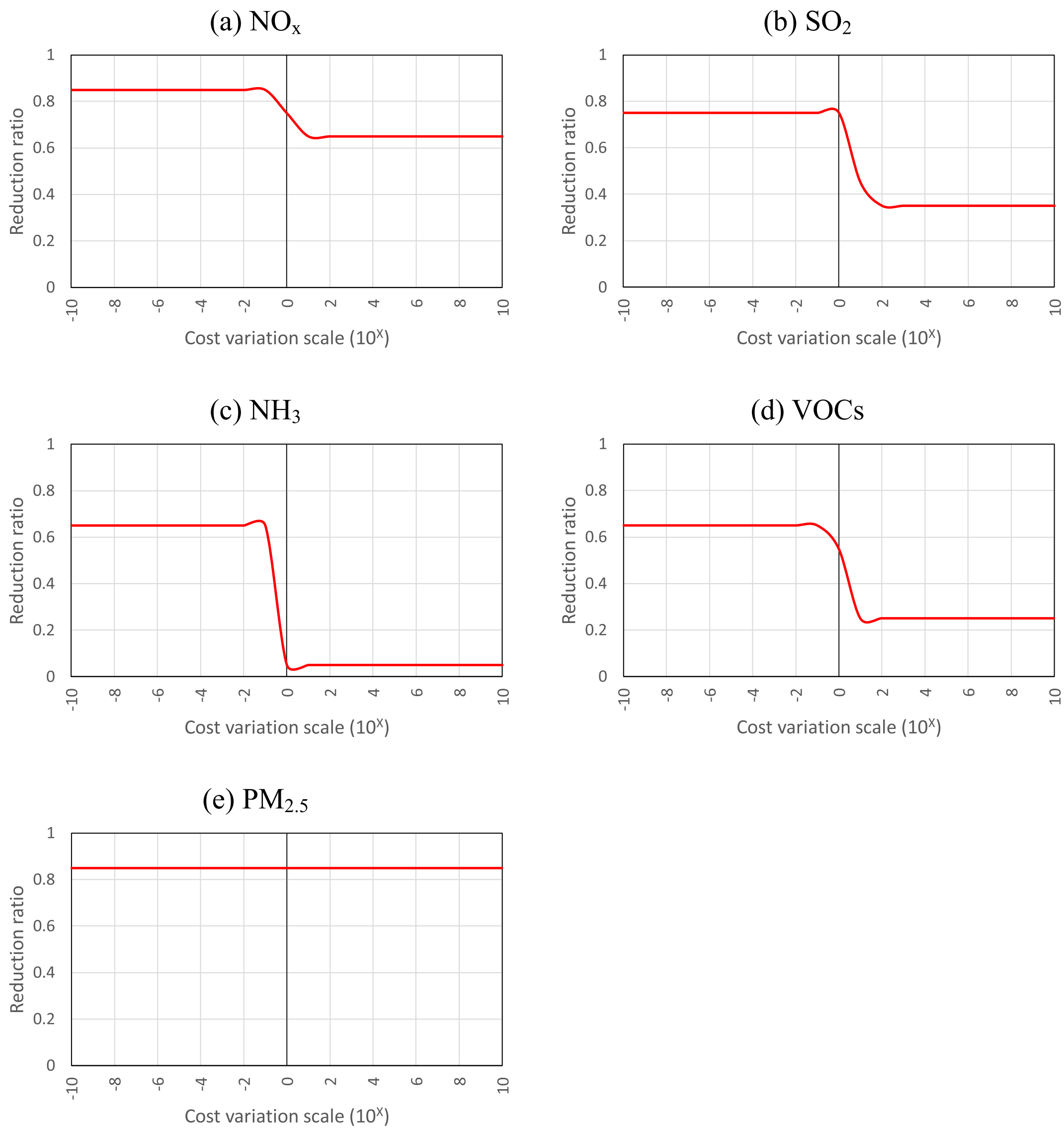

Fig. 6. Sensitivities of reduction ratios of five pollutants to the variation of control costs to attain air quality targets of both $PM_{2.5}$ (less than 35 μg m^{-3}) and O_3 (less than 100 ppb) in Beijing.

controls may be cost-efficient in achieving strengthened $PM_{2.5}$ target but may not be helpful in reducing O_3. In addition, the NH_3 controls require targeting completely different sectors (i.e., agriculture and livestock) from other pollutants that mostly related to energy consumptions, thus increasing the complexity in control actions or stakeholder engagement in implementing the regulation. Regional controls exhibit greater effectiveness for O_3 attainment, while same level of reductions in local and regional sources are recommended to achieve more aggressive air quality goals. Besides, the regional joint control becomes more important in the consideration of some control technologies that can only be implemented nationwide.

Uncertainties associated with the cost and air quality response to emissions will influence on the results of optimization. For cost estimations, uncertainties exist in this study because of the lack of local information about control cost and efficiency. Future investigation into the detailed costs are necessary to obtain an accurate estimation of control costs. The response of air quality to emission controls in this study was developed based on the Community Multi-scale Air Quality (CMAQ) Modeling System (version 5.0.1). To improve the simulation of SOA, we replaced the treatment of organic aerosols in the AERO6 aerosol module with the two-dimensional volatility basis set framework. This significantly increased the transition rate of VOCs to SOA, resulting in an increased contribution to $PM_{2.5}$ from VOCs emissions, which tends to be underestimated in the basic version of CMAQ v5.0.1. However, uncertainties in modeling $PM_{2.5}$ remain substantial enough to effect the response of air quality to emission reduction, and thus influence the optimization of control strategy. For example, recent studies have suggested that NO_2 and NH_3 plays a critical role in sulfate aerosol formation (He et al., 2014; Cheng et al., 2016; Wang et al., 2016), which has not been addressed well in current modeling work. Further improvements in the atmospheric modeling of secondary aerosols are crucial for improving the accuracy of control policy design.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2019.05.022.

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