International Conference on Applied Energy 2019
Aug 12-15, 2019, Västerås, Sweden
Paper ID: 944

CONTRIBUTIONS TO INDUSTRIAL SO_2 EMISSIONS TREATMENT IN CHINA: A MULTI-REGION DECOMPOSITION AND ATTRIBUTION ANALYSIS

Ye Hang [1,2], Qunwei Wang [1,2*], Yizhong Wang [1,2]
1 College of Economics and Management, Nanjing University of Aeronautics and Astronautics,
29 Jiangjun Avenue, Nanjing 211106, China
2 Research Centre for Soft Energy Science, Nanjing University of Aeronautics and Astronautics,
29 Jiangjun Avenue, Nanjing 211106, China

ABSTRACT

Effectively treating industrial SO_2 emissions depends on the synergy of different factors from the industrial SO_2 generation source to the end of treatment. This study proposes a multi-region decomposition and attribution analysis approach to analyze the contributions of SO_2 emissions treatment. The approach can decompose industrial SO_2 emissions into six specific driving factors, including three whole process treatment (WPT) dimensions (i.e. source prevention, process control, and end-of-pipe treatment). This provides more detailed information about each factor's treatment effect from both temporal and spatial perspectives, and the contribution of each region to the key driving factors. The empirical study across 30 regions in China using data from 2005-2015 shows that the end-of-pipe treatment is the dominant dimension for decreasing industrial SO_2 emissions, of which Shandong, Inner Mongolia and Guangdong are the main contributors. The energy structure is the main factor promoting industrial SO_2 emissions reduction in the source prevention dimension. The treatment emphases are different among regions, and regions can be classified into four categories. Based on the empirical results, this paper identifies the policy implications of promoting China's industrial SO_2 emissions reduction.

Keywords: whole process treatment, industrial SO_2, index decomposition analysis, attribution analysis

1. INTRODUCTION

Reducing industrial SO_2 emissions is critical to solve the environmental pollution problem in China (Yang et al., 2016). To control SO_2 emissions, the Chinese government has adopted different emissions reduction measures, including updating facilities, optimizing structure, and strengthening supervision. In particular, there has been an emphasis on installing end-of-pipe treatment facilities. However, there are now fewer opportunities to reduce SO_2 emissions using end-of-pipe treatment measures. Under the stricter SO_2 emissions control target, maximizing SO_2 emissions reduction potential relies on WPT, including source prevention, process control, and end-of-pipe treatment. Therefore, it is important to estimate the effect of WPT on industrial SO_2 emissions.

Previous studies have focused on the effects different driving factors have on the aggregate pollutant emissions change; however, the contributions of different regions to each driving factor have not been quantified. Besides, previous studies have compared the SO_2 emissions between each region with their average level, and have analyzed the factors contributing to the corresponding differences. However, the differences in industrial SO_2 emissions between any two regions and their causes have not yet been explained.

This study investigated the treatment effects of China's industrial SO_2 emissions from the perspective of WPT. First, this study adopted the Temporal-IDA method to estimate the contributions of different WPT dimensions and their components to the changes in aggregate industrial SO_2 emissions. Second, this study used the AA method to conduct the regional attribution analysis of the decomposed driving factors. Third, Spatial-IDA method was applied to compare the industrial SO_2 emissions reduction performance across regions and their causes.

2. METHODOLOGY

2.1 Temporal decomposition analysis method

Assume that the industrial economy consists of N regions $n(n=1,...,N)$. The aggregate SO_2 emissions (P_i) generated across all regions from industrial sector (i) is expressed as Equation (1), based on an extended Kaya identity.

$$P_i = \sum_{n=1}^{N} P_i^n = \sum_{n=1}^{N} \left(\frac{Y_i^n}{Y^n} \cdot \frac{C_i^n}{E_i^n} \cdot \frac{F_i^n}{C_i^n}\right) \cdot \left(\frac{E_i^n}{Y_i^n}\right) \cdot \left(\frac{P_i^n}{F_i^n}\right) \cdot \left(Y^n\right)$$
$$= \sum_{n=1}^{N} \left(IS^n \cdot CS_i^n \cdot FC_i^n\right)_{source} \cdot \left(EI_i^n\right)_{process} \cdot \left(PF_i^n\right)_{end} \cdot \left(Y^n\right)_{scale} \quad (1)$$

Equation (1) decomposes the industrial SO_2 emissions into four dimensions. The first dimension is source prevention, including the industrial structure factor (IS^n), energy structure factor (CS_i^n), and coal pollution intensity factor (FC_i^n). The second dimension is process control, represented by the energy intensity factor (EI_i^n). The third dimension is end-of-pipe treatment. The fourth dimension refers to a region's economic scale.

The aggregate SO_2 emissions change in the single-period ($[t,t+1]$) is denoted as $D_{P_i}^{t,t+1}$ and is expressed in Equation (2). The effects in Equation (2) can be calculated using the Sato-Vartia index formulas (LMDI-II).

$$D_{P_i}^{t,t+1} = \frac{P_i^{t+1}}{P_i^t} = \left(D_{IS}^{t,t+1} \cdot D_{CS_i}^{t,t+1} \cdot D_{FC_i}^{t,t+1}\right) \cdot \left(D_{EI_i}^{t,t+1}\right) \cdot \left(D_{PF_i}^{t,t+1}\right) \cdot \left(D_{Y}^{t,t+1}\right) \quad (2)$$
$$= D_{source}^{t,t+1} \cdot D_{process}^{t,t+1} \cdot D_{end}^{t,t+1} \cdot D_{scale}^{t,t+1}$$

2.2 Attribution analysis method

The attribution analysis method proposed by Choi and Ang (2012) is used to quantify the contributions of different regions to the effects calculated in Section 2.1. This method is presented using the case of energy intensity effect. Equations (3a) and (3b) expresses the contribution of the industrial sector in region n to the energy intensity effect during the $[t,t+1]$ period.

$$D_{EI_i}^{t,t+1} - 1 = \sum_{n=1}^{N} r_i^n \left(\left(EI_i^{n,t+1} / EI_i^{n,t}\right) - 1\right) \quad (3a)$$

$$r_i^n = \frac{w_i^{n,S-V} EI_i^{n,t}}{L\left(EI_i^{n,t+1}, EI_i^{n,t} D_{EI_i}^{n,t,t+1}\right)} \Bigg/ \sum_{n=1}^{N} \frac{w_i^{n,S-V} EI_i^{n,t}}{L\left(EI_i^{n,t+1}, EI_i^{n,t} D_{EI_i}^{n,t,t+1}\right)} \quad (3b)$$

where r_i^n is the weight of the industrial sector in region n, and $r_i^n\left(\left(EI_i^{n,t+1}/EI_i^{n,t}\right)-1\right)$ measures the impact of the industrial sector in region n on the energy intensity effect.

2.3 Spatial decomposition analysis method

The spatial-IDA method is applied to assess the industrial SO_2 emissions reduction performance between different regions. Equation (4a) shows the difference between a region's industrial SO_2 emissions (P_i^{Rn}) and that of the arithmetic average (P_i^{Rm}) (i.e. direct decomposition) (Ang et al., 2015; Liu et al., 2019).

$$D_{P_i}^{Rn-Rm} = \frac{P_i^{Rn}}{P_i^{Rm}} = \left(D_{IS}^{Rn-Rm} \cdot D_{CS_i}^{Rn-Rm} \cdot D_{FC_i}^{Rn-Rm}\right) \cdot \left(D_{EI_i}^{Rn-Rm}\right) \cdot \left(D_{PF_i}^{Rn-Rm}\right) \cdot \left(D_{Y}^{Rn-Rm}\right) \quad (4a)$$
$$= D_{source}^{Rn-Rm} \cdot D_{process}^{Rn-Rm} \cdot D_{end}^{Rn-Rm} \cdot D_{scale}^{Rn-Rm}$$

Equation (4b) shows the indirect decomposition between any two regions using two relevant direct decomposition effects.

$$D_{P_i}^{R1-R2} = \frac{D_{P_i}^{R1-Rm}}{D_{P_i}^{R2-Rm}} = \frac{D_{source}^{R1-Rm}}{D_{source}^{R2-Rm}} \cdot \frac{D_{process}^{R1-Rm}}{D_{process}^{R2-Rm}} \cdot \frac{D_{end}^{R1-Rm}}{D_{end}^{R2-Rm}} \cdot \frac{D_{scale}^{R1-Rm}}{D_{scale}^{R2-Rm}} \quad (4b)$$

3. DATA

This study analyzed the WPT effects of industrial SO_2 emissions across 30 regions in China. Based on data availability, the study period was set as 2005-2015, covering two Five-Year Plans (FYP) (i.e. 11th FYP and 12th FYP) in China. All data were derived from *China Annual Report of Environment Statistics*, *China Energy Statistical Yearbook*, and *China Statistical Yearbook.*

4. RESULTS AND DISCUSSION

4.1 Temporal decomposition analysis

Figure 1 shows the temporal decomposition results of China's industrial SO_2 emissions change across the full study period and during each of the two FYPs. China's industrial SO_2 emissions declined by 28.21% from 2005 to 2015. Both process control and end-of-pipe treatment decreased the industrial SO_2 emissions. In contrast, the source prevention inhibited decreases in industrial SO_2 emissions. This implies that China has not yet maximized the potential of source prevention and process control for promoting industrial SO_2 emissions reduction. Taking a temporal perspective, both end-of-pipe treatment and process control contributed to a reduction of industrial SO_2 emissions during the two FYPs. Source prevention transitioned from having a negative effect in the 11th FYP

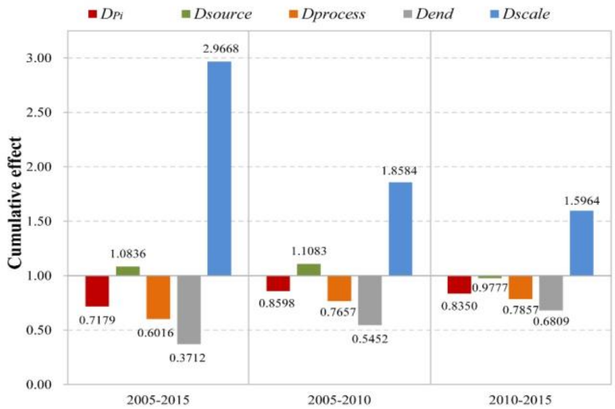

Fig. 1. Cumulative decomposition results of China's industrial SO_2 emissions change with respect to three WPT dimensions and economic scale, 2005-2015

to having a positive effect in the 12th FYP. This implies that source prevention measures were increasingly emphasized in the 12th FYP, helping to reduce SO_2 emissions.

Figure 2 shows the subdivision effects of the weak dimension (i.e. source prevention) in promoting the reduction of industrial SO_2 emissions. Across the full study period, coal pollution intensity was the main factor increasing industrial SO_2 emissions. Industrial structure was another important factor contributing to the increased industrial SO_2 emissions. In contrast, the energy structure was the main factor restraining the increase of SO_2 emissions in this dimension. In terms of two FYPs, the industrial structure transitioned from having a positive effect in the 11th FYP to a negative effect in the 12th FYP. The energy structure effect in the 12th FYP exceeded that in the 11th FYP. The inhibitive effect of coal pollution intensity on SO_2 emissions reduction was strengthened in the 12th FYP period. This indicates an urgent need to improve the industrial coal consumption, and to promote the clean and effective use of coal in the future.

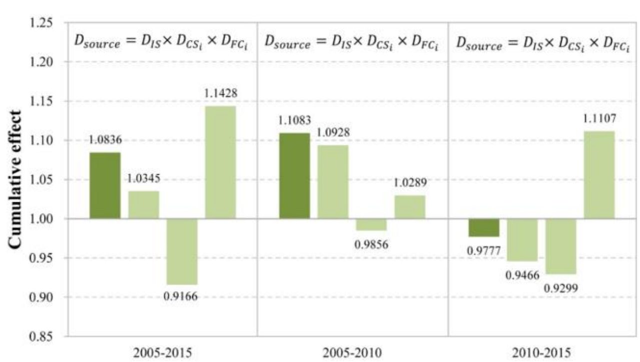

Fig. 2. Cumulative decomposition results of the source prevention effect and its three subdivision effects, 2005-2015

4.2 Attribution analysis

The end-of-pipe treatment is the major factor in decreasing industrial SO_2 emissions. Therefore, this section analyzed the regional attribution analysis for the end-of-pipe treatment effect using Equations (3a) and (3b). Figure 3 presents the percentage share of each region with respect to the attribution of this effect. Figure 3 shows that across the study period, all regions made a negative contribution (i.e. decreasing industrial SO_2 emissions) to the end-of-pipe treatment effect. The top five regions were R15-Shandong, R5-Inner Mongolia, R19-Guangdong, R16-Henan and R4-Shanxi. These regions accounted for over 40% of the total decrease in the end-of-pipe treatment effect during 2005-2015.

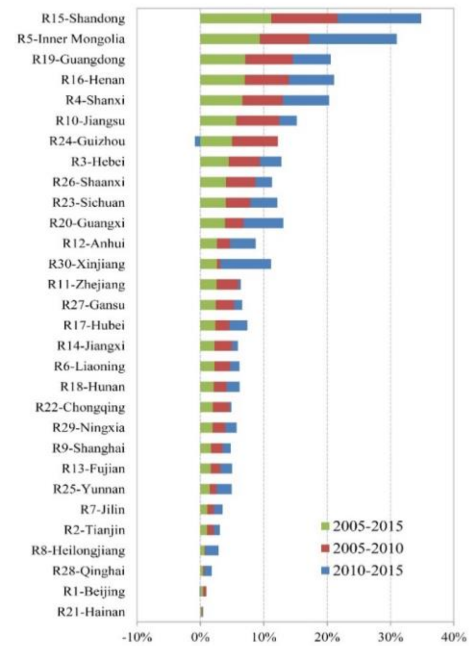

Fig. 3. Percentage share of each region in the attribution results of the end-of-pipe treatment effect, 2005-2015

4.3 Spatial decomposition analysis

Based on the direct decomposition results, all the regions were divided into four categories, shown in Figure 4 (a). Type A regions are defined as the *Leading type*, where integrated process treatment and end-of-pipe treatment performances are higher than average. These regions are benchmarks for other regions to emulate. Type B regions are defined as the *Process-dependent type*, where integrated process treatment performance is higher than average, and end-of-pipe treatment performance is lower than average. Type C regions are defined as the *End-dependent type*, where integrated process treatment performance is lower than average, and end of-pipe treatment was the main

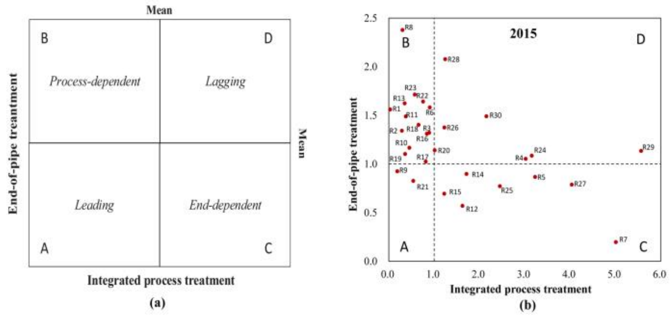

Fig. 4. Four categories of regions based on integrated process treatment and end-of-pipe treatment performances, and the classification results, 2015

method to control industrial SO_2 emissions. Type D regions are defined as the *Lagging type*, where both integrated process treatment and end-of-pipe treatment performances are lower than average. Figure 4 (b) presents the classification results in 2015. It is shown that only Shanghai and Hainan belonged to Type A. Most of the regions were Type B or Type C regions. Targeted WPT performance optimization measures should be informed based on the classification results.

Table 1 shows the source prevention performance index (SoPI) matrix between any two regions in 2015 (i.e. indirect decomposition results). Taking the comparison of R1-Beijing and R2-Tianjin as an example, their SoPI was 0.13. This indicates that R1-Beijing had a higher source prevention performance than R2-Tianjin. Besides, their process control performance index (PrPI) was 0.82, and their end-of-pipe treatment performance index (EnPI) was 1.16. This implies that the lower industrial SO_2 emissions level in R1 when compared to R2 was primarily due to a higher source prevention level and a more efficient process control performance. Based on the pairwise comparison results, all regions can identify the root of their emission differences between themselves and the reference regions; that is, clarifying their advantages and weaknesses with respect tom WPT.

Tab. 1. Source prevention performance matrix for pairwise comparisons among 30 regions in China, 2015

Region	R1	R2	R3	R4	……	R30
R1	1.00	0.13	0.33	0.11	……	0.22
R2	7.72	1.00	2.54	0.83	……	1.69
R3	3.04	0.39	1.00	0.33	……	0.67
R4	9.25	1.20	3.04	1.00	……	2.03
……	……	……	……	……	……	……
R30	4.56	0.59	1.50	0.49	……	1.00

5. CONCLUSIONS

In general, China's approach to industrial pollution prevention and control has not moved beyond the "pollute first, clean up later" approach. End-of-pipe treatment has remained the main way to reduce industrial SO_2 emissions. During the 12th FYP period, the source prevention effect on SO_2 emissions reduction began to appear; however, there remains room for further improvement. The energy structure was the main factor promoting industrial SO_2 emissions reduction in the source prevention dimension. Shandong, Inner Mongolia, Guangdong, Henan, and Shanxi were the main contributors to the end-of-pipe treatment effect. To reduce total industrial SO_2 emissions over time, China should pay special attention to the regions that contribute the most to the key driving forces.

Based on the decomposition results of integrated process treatment and end-of-pipe treatment, all regions were classified into four categories: *Leading type*, *Process-dependent type*, *End-dependent type,* and *Lagging type*. Different categories of regions should adopt targeted WPT improvement measures. The pairwise comparison results between any two regions can highlight improvement measures oriented toward catching up with specific benchmark regions.

ACKNOWLEDGEMENT

Authors are grateful to the financial support from the National Natural Science Foundation of China (nos. 71573186 and 71834003), the Fundamental Research Funds for the Central Universities (nos. NE2017005 and NW2018002), and Six Talents Peak Project of Jiangsu Province (no. JY-032).

REFERENCE

[1] Ang B W, Xu X Y, Su B. Multi-country comparisons of energy performance: the index decomposition analysis approach. Energy Economics 2015; 47: 68-76.
[2] Choi K H, Ang B W. Attribution of changes in Divisia real energy intensity index—An extension to index decomposition analysis. Energy Economics 2012; 34(1): 171-176.
[3] Liu N, Ma Z, Kang J, et al. A multi-region multi-sector decomposition and attribution analysis of aggregate carbon intensity in China from 2000 to 2015. Energy Policy 2019; 129: 410-421.
[4] Yang X, Wang S, Zhang W, et al. Impacts of energy consumption, energy structure, and treatment technology on SO_2 emissions: A multi-scale LMDI decomposition analysis in China. Applied Energy 2016; 184: 714-726.

