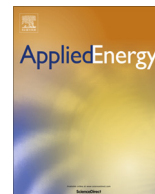




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Whole process decomposition of energy-related SO₂ in Jiangsu Province, China

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HIGHLIGHTS

- Factors driving air pollution changes are decomposed with a whole process treatment perspective.
- End-of-pipe treatment is the primary way to control air pollution in Jiangsu Province, China.
- 13 studied cities can be divided into four types of air pollution treatment.

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ABSTRACT

Effectively analyzing and then treating energy-related air pollution requires examining every factor, from the pollution source to the end of treatment. This paper applies index decomposition analysis and a whole process treatment perspective to identify the factors facilitating air pollution reduction across three stages: source prevention, process control, and end-of-pipe treatment. Empirical research using data from China's Jiangsu Province and its 13 cities reveals differences in local approaches to pollution prevention. At the provincial level, end-of-pipe treatment remains the primary approach to control air pollution emissions, indicating that the pattern of "pollute first, govern later" has not yet been fundamentally reversed. At the city level, 13 cities can be divided into four types, based on their approach to air pollution treatment: the leading type, process-dependent type, end-dependent type, and lagging type. Of these, 7 cities are using multiple control approaches, reflecting the comprehensive effect of whole process treatment. The Jiangsu Province should consider further strengthening effective whole process air pollution treatment models, by transitioning to pollution control, adjusting industrial structure, promoting technological progress, and consuming clean energy.

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1. Introduction

China's economy has developed significantly since initiating reforms and becoming more open; the country now has the world's second largest economy. However, this development has consumed extensive fossil-fuel based energy, leading to a series of environmental problems. According to the 2014 Environment Performance Index, China ranked only 118th of 178 countries in environmental quality. In 2012, seven of the world's ten most polluted cities were in China [1]. In recent years, haze produced by air pollution has gradually become the norm, spreading to most of China's provinces and cities. Alleviating the serious air pollution and building a resource-saving and environmentally-friendly soci-

ety have become important challenges for the Chinese government.

China's central government has developed a series of goals and has adopted many specific measures to improve environmental quality. For example, the government: has required an increase in clean energy consumption to 15% of total consumption by 2020; is promoting an industrial structure that will gradually become more low carbon and green; and is increasing investment and research into pollution-control technologies.

At the local government and enterprise level, however, these structural adjustments, technological changes, and production mode transformations take a long time. These governments and enterprises are generally using end-of-pipe treatments, which means "pollute first, govern later." This approach originated before the 1990s, when economic development was given the top priority; at the time, the environment was able to bear a large load and self-purify. As a result, end-of pipe treatment approaches became

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the main methods governments used to reduce pollution and improve the environment.

Starting in the 1980s, western countries began transitioning from an end-of-pipe treatment approach to more preventive pollution control methods [2,3]. This prevention approach involves transitioning to whole process control and treatment. This means reducing pollutant emissions through structural adjustments, technological progress, and terminal management [4,5]. Cleaner production approaches have revealed the limitations of end-of-pipe treatments, including their large investment requirements, high costs, incomplete control, insufficient resource utilization, and the short term nature of the pollution transformation. China's Environmental Protection Department has also proactively promoted the transition to the whole process treatment mode [6]. For example, the "Clean Production Promotion Law of the People's Republic of China" emphasizes the importance of controlling pollution at the source, improving resource utilization efficiency, and reducing terminal pollutant emissions.

Measuring pollution control effectiveness from the source to the end of each stage has become the new challenge. A tool called decomposition analysis is often used to identify driving factors behind pollutant and carbon dioxide emission changes, and can inform corresponding policies (see Section 2). Due to data availability constraints, these methods generally decompose the driving factors behind air pollution at the national and provincial level; few projects have focused on the effect of different emission reduction approaches at a more micro level.

This paper applies index decomposition analysis to decompose variations in air pollution treatments into source prevention, process control, and end-of-pipe treatment factors. This analysis is done from the perspective of whole process treatment. The study then empirically analyzes the effects of sulfur dioxide (SO₂) control at each stage from source to treatment, using 13 cities in Jiangsu Province, China as a case study. The paper closes with policy proposals for strengthening a whole process approach to treat air pollution at provincial and city levels.

2. Literature review

Increasingly serious air pollution is leading to more attention on controlling and reducing pollutant emissions. Decomposition analysis identifies the driving factors underlying air pollutant emissions; the analysis method is widely used in energy and environment fields [7–11]. Decomposition analysis splits the variation in research objects, such as energy consumption and carbon emissions, into a number of related factors. This method identifies both positive and negative factors, and analyzes the degree of influence of the different factors, thereby providing a basis for targeted policy proposals.

The two main decomposition analysis methods include structure decomposition analysis (SDA) and index decomposition analysis (IDA). Rose and Casle [12] and Su and Ang [13] studied the theoretical basis and characteristics of SDA. They noted that SDA requires an input–output model as a foundation; this generates more precise results, but requires large amounts of data, limiting its application. IDA has the advantage of requiring relatively few data, and can further analyze structural effects [14]. More energy and environment journal papers have applied IDA than SDA [15]. Additional methods within the IDA method include the Laspeyre Index methods and the Divisia Index methods [16]. Within those methods, the Laspeyre Index methods include the basic Laspeyres index, the Paasche index, and the Fisher ideal index. The Divisia Index methods include the arithmetic mean Divisia method (AMD), the Logarithmic Mean Divisia Index method (LMDI) and other parametric Divisia methods [17]. Each method have its

own benefits and drawbacks; however, based on an analysis of the residual term, zero processing, and overall consistency, the LMDI is considered the best method [16].

The LMDI refines the conventional index analysis method using the logarithmic mean weight function. This method is symmetric and additive, instead of using the arithmetic mean weight function [18]. Ang and Choi [19] first introduced the logarithmic mean Divisia method II (LMDI II). Ang et al. [20] later presented the logarithmic mean Divisia method I (LMDI I). Compared to the LMDI II, the LMDI I is consistent in aggregation and its weighting scheme has more advantages for calculations [21].

In recent years, LMDI I has been widely used in the energy and environment field to determine the key factors affecting total energy consumption and carbon emission changes [17,22,23]. At the national level, Gonzalez et al. [24] used the method to study changes in overall energy consumption of 27 European Union Member States. The study showed that industrial structural changes and economic scale effects led to continuous increases in energy consumption from 2001 to 2008, despite increases in overall energy efficiency. Chung et al. [25] analyzed the factors influencing household energy consumption in Hong Kong from 1990 to 2007, finding that increases in resident count was the main factor increasing energy consumption; changing resident behaviors was ineffective in reducing energy consumption. Xu et al. [26] found the primary driving factors in carbon emissions were population size and energy structure. Other scholars have conducted similar research on energy consumption and carbon dioxide (CO₂) emission changes, using data from Lithuania, Ireland, South Korea, the Philippines, and Latvia [27–31].

In addition to nation-level studies, scholars have used LMDI I to analyze energy savings and emission reductions at the industry-specific and province level. Sorrell et al. [32] found that declining manufacturing output was an important factor driving carbon intensity decreases in the United Kingdom's road transport sector from 1989 to 2004. Zhang et al. [33] decomposed the drivers of the Chinese power sector's carbon emissions from 1991 to 2009, finding that economic activity greatly influences increases in carbon emissions. Akbostancı et al. [34] decomposed the CO₂ emissions of Turkish manufacturing industry during 1995–2001. They found that total industrial activity and energy intensity are key factors driving CO₂ emission changes.

Xu et al. [35] studied Chinese sectoral greenhouse gas (GHG) emissions from 1996 to 2011, and found economic growth and energy intensity declines were primarily responsible for emission changes in economic sectors, including agriculture, industry, transportation, and the commercial and service sectors. Zhang et al. [36] studied intercity transportation energy consumption in China from 1980 to 2006, finding that energy intensity played a leading role in reducing energy consumption. Also in China, Zhao et al. [37], Yue et al. [38] and Tan et al. [39] analyzed energy consumption and carbon emissions in Shanghai, Jiangsu, and Chongqing, respectively. The influence of each factor differed, but the resulting conclusion was the same: energy intensity reductions and industrial structural adjustments are needed to address serious energy and environmental problems.

Decomposition elements indicate significant variation in the number of decomposed factors, due to IDA's strong flexibility. Table 1 shows the factors decomposed in selected studies targeting different objects. Many studies analyzing CO₂ and SO₂ emissions focus on source prevention factors (such as energy structure) and process control factors (such as energy intensity) [40,43]. This involves decomposing emission variations into structural effects, intensity effects, and scale effects.

A few studies have taken a whole process treatment approach [6], however, many studies have not addressed the driving effect of end-of-pipe treatments on reducing pollutant emissions. As

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