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Decomposition analysis of carbon dioxide emissions in China's regional thermal electricity generation, 2000–2020

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ABSTRACT

A major share of China's total carbon dioxide (CO_2) emissions is from the electric power sector. In 2010, almost 40% of all CO_2 emissions in China were from this sector. This is because the country predominantly depends on thermal electricity generation to meet its power requirement. This study analyses the CO_2 emissions from thermal electricity generation in China between 2000 and 2012 at the regional grid level. Logarithmic Mean Divisia Index methodology is employed to identify the factors that influence changes in CO_2 emissions over time. This study also predicts China's energy consumption and CO_2 emissions patterns between 2013 and 2020, forecasting rates of increase in energy consumption across six regional grids from 0.9% to 9.7%. CO_2 emissions related to thermal electricity generation increased from 981.33 million tons (Mt) in 2000 to 3342.79 Mt in 2012, which is an annual growth rate of 10.75%. These increases are not aligned with China's commitments on reducing emissions to the Asia-Pacific Economic Cooperation forum. China's CO_2 emissions are forecasted to increase to 5596 Mt by 2020 if the current increasing trends is not effectively curbed after 2012.

1. Introduction

Currently, CO_2 is considered the single most important cause of global warming and concerns about the effects of global climate change have prompted interest in capturing and sequestering CO_2. CO_2 emissions reduction is a major problem to be resolved for the sustainability of human life. Following China's ‘Reform and Opening Up’ program, which refers to the economic reforms being implemented in the country since the late 1970s, it has faced a gradual upward trend in CO_2 emissions. According to the International Energy Agency (2009), China overtook the US in 2007 as the world's largest producer of CO_2 emissions. In 2009, the Chinese government announced that the country would decrease its CO_2 emissions per unit of gross domestic product (GDP) by 40–45% between 2005 and 2020.

As the country's economic development progressed, China's electricity consumption increased from 77.63 million-tonne coal equivalent (Mtce) in 1991 to 427.37 Mtce in 2009, an average annual growth rate of about 9.93% [1]. In 2009, thermal power accounted for 80.29% of China's total supply of electricity, and 97.03% of that thermal power was coal-fired, resulting in massive quantities of CO_2 emissions along with great pressure to reduce it. During the 2014 Beijing meeting of the Asia-Pacific Economic Cooperation (APEC), China pledged to not increase its greenhouse gas (GHG) emissions and the US pledged to decrease its GHG emissions by 25%. For China, this pledge meant that the Chinese government promised a maximum level of CO_2 emissions, and it is important that the Chinese government adjust its national energy structure and improve its energy intensity to meet that pledge.

Index Decomposition Analysis (IDA) is a statistical methodology first used in the late 1970s to address problems related to the energy crisis. Since then, many new methods and index decomposition methods have been implemented and the IDA methodology has been increasingly used in energy-related environmental analyses. For example, IDA has been successfully used to quantify the influences of factors related to changes in energy consumption and CO_2 emissions [2–5]. In the past two decades, the Laspeyres IDA and the arithmetic mean Divisia IDA [6] have been the two most commonly used decomposition methods. However, these two methods have drawbacks. First, there is a problem related to residuals because the changes remain residual and unexplained and the residual itself cannot be predicted [7]. Second, the Divisia

Abbreviations: APEC, Asia-Pacific Economic Cooperation; CO_2, Carbon Dioxide; CESY, China Energy Statistical Yearbook; GDP, Gross Domestic Product; GHG, Greenhouse Gas; IDA, Index Decomposition Analysis; LMDI, Logarithmic Mean Divisia Index; Mt, Million tons; Mtce, Million-tonne coal equivalent.

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Nomenclature

i	the fuel type
j	the region
E_{ij}^t	energy type i used by region j at time t
F_i	the carbon emission factor of the ith fuel
O_i	the fraction of the carbon oxidized based on fuel type i
M	the molecular weight ratio of CO_2 to carbon equal to 44/12
E_j^t	energy used by region j at time t
C_{ij}^t	carbon emissions of energy type i used by region j at time t
Y_j^t	GDP of region j at time t
P_j^t	population of region j at time t
$S_{ij}^t = E_{ij}^t/E_j^t$	the proportion of energy type i used that accounts for total energy used by region j
$I_{ij}^t = C_{ij}^t/E_{ij}^t$	the regional CO_2 emissions intensity
$F_j^t = E_j^t/Y_j^t$	the regional energy used per unit of GDP
$R_j^t = Y_j^t/P_j^t$	the regional per capita GDP
ΔC_{total}	the change in CO_2 emissions
ΔC_S	the change in the energy structure effect
ΔC_I	the change in intensity effect
ΔC_F	the change in energy efficiency effect
ΔC_R	the change in economic development effect
ΔC_P	the change in the population effect

equations of the arithmetic mean have logarithmic terms that create problems in the calculations when zeros are present in the datasets.

To overcome these problems, new and more precise methods have been proposed. Recently, Ang compared various IDA methods and concluded that the Logarithmic Mean Divisia Index (LMDI) method is preferred [8]. He provided a practical guide to the LMDI method that includes the general formulation process, summary tables for easy reference, and examples [9]. Ma and Stern used the LMDI to explore changes to China's energy intensity between 1980 and 2003. They concluded that technological change was a dominant contributor to decrease energy intensity, inter-fuel substitution contributed little to changes in energy intensity, and the contribution of structural changes depended on the level of sector disaggregation (industry sector versus industrial subsector) [10]. Wang et al. used energy data from 1985 through 2009 in a LMDI decomposition analysis of the factors influencing changes in China's transportation sector regarding CO_2 emissions [11]. The LMDI also was employed to identify the driving factors of change in GHG emissions in the cement industry from 2005 through 2009 [12].

Some scholars have analysed CO_2 emissions in the electricity power generation sector using the LMDI method. For example, Malla examined the roles of three factors (electricity production, electricity generation structure, and energy intensity of electricity generation) in seven countries between 1990 and 2005 [13]. In addition, He et al. decomposed of China's aggregate electricity intensity into the structure effect and the intensity effect, and analysed the decomposition results from 1995 through 2007 [14]. Wang et al. analysed the effect of sectoral energy intensity, fuel substitution, output structure, and total industrial output on the growth of electricity consumption in China's industrial sector between 1998 and 2007 [15]. Of note, the Zhang et al. study analysed the state of CO_2 emissions related to the generation of electricity in China between 1991 and 2009, finding that electricity generation efficiency played a dominant part in CO_2 emissions reduction [16].

To the best of our knowledge, only Zhou et al. systematically used the decomposition method to examine CO_2 emissions arising from regional thermal electricity generation in China [17]. However, that study did not examine the effects of regional economic development. In many developed countries, such as the US, UK, and in the European Union, CO_2 emissions from the power sector are projected to decrease through 2030 even as electricity demand increases by more than 40% because of investments in achieving the reduction goals. However, there is no study on the influence of economic development on CO_2 emissions in developing countries. Because China is a large country, marked variation in economic development is observable across its expanse. For example, industrially developed administrative regions, such as Beijing, Jiangsu, and Zhejiang, have remarkably high rates of economic growth with associated high rates of energy consumption to support economic development. Therefore, for a clear understanding, it is necessary to account for variation in regional economic development with the types of energy efficiency.

Unlike previous studies, the current study examines the influences of economic development and social factors in the creation of CO_2 emissions. Data covering 2000 through 2012 are employed and forecasts for 2013 through 2020 are estimated. Furthermore, the forecasted results provide useful suggestions for electricity generation reform in China. The balance of this paper is organized as follows. Section 2 presents the methods used to estimate CO_2 emissions arising from electricity generation and decomposes the components using the LMDI method. Section 3 presents data on CO_2 emissions across China's regional grids along with the LMDI analytical results. Section 4 discusses results and provides energy intensity forecasts for the regional grids under observation. Section 5 concludes the paper.

2. Methodology

2.1. Estimation of CO_2 emissions

Following the Intergovernmental Panel on Climate Change, total CO_2 emissions from electricity generation in a given year can be calculated as follows:

$$C^t = \sum E_{ij}^t \times F_i \times O_i \times M, \tag{1}$$

Because the 2000 through 2012 period analysed in this study is relatively short, we assume that the carbon emission sources of coal, gasoline, kerosene, diesel oil, fuel oil, and natural gas are constants across time. Indeed, these sources have changed over time only because of changes to fuel grades, which are so small as to be negligible when analysing macro-level changes in CO_2 emissions.

2.2. Decomposition of CO_2 emissions

The CO_2 emissions of thermal electricity generation in year t can be identified in terms of five contributing factors, as shown in Equation (2).

$$C^t = \sum_{i,j} C_{ij}^t = \sum_{i,j} \frac{E_{ij}^t}{E_j^t} \times \frac{C_{ij}^t}{E_{ij}^t} \times \frac{E_j^t}{Y_j^t} \times \frac{Y_j^t}{P_j^t} \times P_j^t = \sum S_{ij}^t I_{ij}^t F_j^t R_j^t P_j^t, \tag{2}$$