

CASE STUDY

China's targets for reducing the intensity of CO₂ emissions by 2020



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ARTICLE INFO

Article history:

Received 7 November 2012

Received in revised form

7 May 2013

Accepted 18 June 2013

Available online 19 July 2013

Keywords:

CO₂ emissions

Scenario analysis

LMDI method

Emission reduction target

ABSTRACT

This paper estimated CO₂ emissions based on the IPCC reference approach under five scenarios that consider China's economic and energy development strategy. Based on the LDMI method, the contributions of per-capita production value, industrial structure, energy intensity, energy mix and coefficients of discharge to CO₂ emissions were analyzed in nine carbon-intensive industries. The emission reduction target for nine industries and five influencing factors were allocated, using scenarios in which China's emission reduction target is not realized. The results show that the reduction target can be realized completely if energy intensity and the share of non-fossil fuel use in primary energy consumption can reach the objectives of China's mid and long-term strategic. There will be uncertainly if the share of non-fossil fuel use does not increase to 15%. And the task of reducing emissions in the industry of Smelting and Pressing of Ferrous Metals is the most arduous among the nine industries considered.

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1. Introduction

As the world's largest carbon emitter, China faces the challenge of deep emission reductions. In late 2009, the Chinese government announced that by 2020, China's carbon dioxide emissions per unit of GDP will be reduced by 40–45% from the 2005 level. To meet this target, the government should allocate the reduction obligation to regions, provinces and industries. In the last several decades, studies have proposed various emission reduction allocation plans based on different principles. Aldy et al. [1] and Den Elzen and Hohne [2] discussed the problem of greenhouse gas emission reduction target allocation among both the Annex I countries listed in the UNFCCC (United Nations Framework Convention on Climate

Change) and among developed and developing countries. Persson et al. [3] discussed target allocation in developing countries. Chinese scholars also conducted related research regarding the issue and produced new plans. Cong and Wei [4] studied the potential impact of introducing CET (carbon emissions trading) on China's power sector and discussed the impact of different allocation allowance options. Cong and Wei determined that CET is an effective tool. He [5], Wu [6], and Yi et al. [7] discussed the problem of allocating the Chinese reduction target among regions. But little research has been performed on how to allocate the CO₂ emission reduction targets among industries. Industries, especially carbon-intensive industries, are the main sources of carbon emissions. To achieve China's CO₂ emission reduction target, every industry should bear a definite reduction task. Whatever allocation plans we adopt, an effective energy strategy

is essential because fossil fuel use is the primary source of CO₂. Therefore, this paper proposed several scenarios based on China's energy and social development strategy and used a combination of methods of energy demand forecasting, CO₂ emission forecasting and the Logarithmic Mean Divisia Index (LMDI) to allocate China's emission reduction target among industries.

The remainder of the article is organized as follows: Section 2 provides a description of the methodology, Section 3 introduces the data sources and scenarios involved in empirical study, Section 4 presents the empirical results, and Section 5 gives results and considers the wider implications of the findings.

2. Methodology

This paper analyzed how well the Chinese reduction target will be realized under different development scenarios. The main

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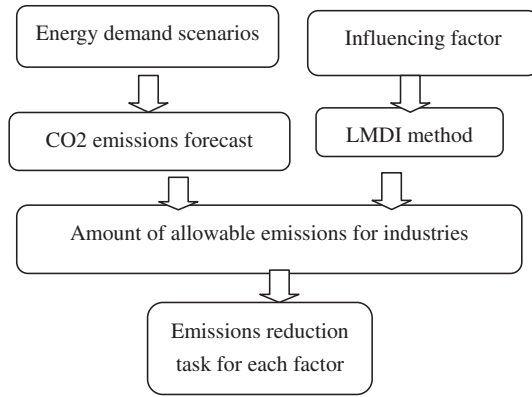


Fig. 1. Research methodology.

[11]. Ang compared different index decomposition methods, concluding that the LMDI method is the best [12]. Ang and Liu provided a method that can effectively process zero and negative values, which eliminated the only disadvantage of the LMDI and made the modified LMDI method more precise [13]. According to the LMDI method, we decomposed CO₂ emissions as follows:

$$C = \sum_{ij} c_{ij} = \sum_{ij} Q \frac{Q_i}{Q} \frac{E_i}{E_j} \frac{C_{ij}}{E_{ij}} = \sum_{ij} QS_i I_i M_{ij} U_{ij} \quad (5)$$

where C is CO₂ emissions; Q is total output, in terms of GDP; E is energy consumption; i is the i th industry; j is the j th type of energy, which includes coal, coke, crude oil, gasoline, kerosene, diesel oil, fuel oil, other petroleum products, natural gas and electricity; $S_i (=Q_i/Q)$ is the proportion of output value of the i th industry in GDP; $I_i (=E_i/Q_i)$ is the energy consumption of unit production value for the i th industry; $M_{ij} (=E_{ij}/E_i)$ is the proportion of the j th energy consumption in total energy consumption for the i th industry; and $U_{ij} (=C_{ij}/E_{ij})$ is the CO₂ emission factor for the j th type of energy consumption in the i th industry.

$$\begin{aligned} \Delta C_{act} &= \sum_{ij} \frac{C_{ij}^T - C_{ij}^0}{(\ln C_{ij}^T - \ln C_{ij}^0)} \ln \left(\frac{Q^T}{Q^0} \right); \\ \Delta C_{str} &= \sum_{ij} \frac{C_{ij}^T - C_{ij}^0}{(\ln C_{ij}^T - \ln C_{ij}^0)} \ln \left(\frac{S^T}{S^0} \right); \\ \Delta C_{int} &= \sum_{ij} \frac{C_{ij}^T - C_{ij}^0}{(\ln C_{ij}^T - \ln C_{ij}^0)} \ln \left(\frac{I^T}{I^0} \right); \\ \Delta C_{mix} &= \sum_{ij} \frac{C_{ij}^T - C_{ij}^0}{(\ln C_{ij}^T - \ln C_{ij}^0)} \ln \left(\frac{M^T}{M^0} \right); \\ \Delta C_{emf} &= \sum_{ij} \frac{C_{ij}^T - C_{ij}^0}{(\ln C_{ij}^T - \ln C_{ij}^0)} \ln \left(\frac{U^T}{U^0} \right) \end{aligned} \quad (6)$$

Then, the increment of CO₂ emissions is $\Delta C = \Delta C_{act} + \Delta C_{str} + \Delta C_{int} + \Delta C_{mix} + \Delta C_{emf}$, where ΔC_{pop} , ΔC_{act} , ΔC_{str} , ΔC_{int} , ΔC_{mix} , ΔC_{emf} stand for the emissions increment of CO₂ caused by changes in GDP, industrial structure, energy intensity, energy mix, and emissions factors, respectively.

2.2.3. CO₂ emissions increment of industries

The CO₂ emissions increment of the i th industry is:

$$\Delta C_i = \Delta C \cdot B_i \quad (7)$$

where B_i is the proportion of the emissions increment of the i th industry in the total emissions increment.

research methodology for this paper is shown in Fig. 1, including:

- (1) Forecasting the final energy demand, CO₂ emissions and the amount of allowable emissions under different scenarios in the year 2020.
- (2) Analyzing the historical contributions of GDP, industrial structure, energy intensity, energy mix, and carbon emission factors to CO₂ emissions in the nine largest carbon-intensive industries, based on data from 2001 to 2007.
- (3) Assuming the contributions remain unchanged until 2020 and then calculating the CO₂ emission reduction target and the amount of allowable emission for the nine largest carbon-intensive industries, where the contribution is a relative number. Due to the rapid development of industrialization in China, the relative effects of the five influencing factors on CO₂ emissions will not change greatly by 2020.
- (4) Analyzing the obligation that each factor should bear in each industry to reach China's 2020 emission reduction target.

2.1. Forecasting energy demand

2.1.1. Energy demand forecasting method for scenario 1

The commonly used methods in energy demand forecasting include the grey forecasting model, the regression analysis method, the experience model method, the time series method, and exponential smoothing [8]. This paper used the grey forecasting model to forecast the energy demand of scenario 1. Grey forecasting is less information required, easy optional, and highly precise. Observed time series are regarded as grey process changed with time, and the rule of ordered exponential series implicit in the system is developed via cumulative series. Most widely used in the literature is the GM(1,1) model, which is the grey model with one variable and one order. The validity of the GM(1,1) model should be checked via various tests [9].

2.1.2. Energy demand forecasting method for scenarios 2–5

The method of energy demand forecasting in scenarios 2–5 is based on the speed of economic development, the requirements regarding energy intensity objectives and the development of non-fossil fuel energy sources.

$$\text{The final energy demand: } E = IQ \quad (1)$$

where I is energy intensity, Q is total output;

$$\text{Energy demand of the } j\text{th type of sources } E_j = ES_j \quad (2)$$

where S_j is the share of the j th type of energy demand in the total energy demand. So

$$E_j = IQS_j \quad (3)$$

2.2. Estimating CO₂ emissions

2.2.1. CO₂ emissions

This paper estimated CO₂ emissions based on the emission factor approach of the IPCC [10], which is currently the most widely used method. The estimated value of the CO₂ emissions is the product of energy consumption and emission factors, as shown in formula (4).

$$\text{CO}_2 \text{ emissions } C = \sum E_j \times U_j \quad (4)$$

where E_j is the consumption of the j th type of energy and U_j is the emission factor of the j th type of energy.

2.2.2. LMDI method and increment of CO₂ emissions

The Index Decomposition Method is most popular for assessing the effects of CO₂ emissions influencing factors. This general analyzing framework includes specific methods, such as the laspeyres index method, Structure Decomposition Analysis (SDA), the Simple Average Decomposition Method, Adaptive Weighting Division (AWD), the Logarithmic Mean Divisia Index (LMDI) and so on. The Index Decomposition Method can avoid invalid results that stem from multicollinearity among factors

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