Renewable and Sustainable Energy Reviews 94 (2018) 330–339

Contents lists available at ScienceDirect

Renewable and Sustainable Energy Reviews

journal homepage: www.elsevier.com/locate/rser

Total-factor carbon emission efficiency of China's provincial industrial sector and its dynamic evolution

Zhonghua Cheng[a,b,c,*], Lianshui Li[a,b], Jun Liu[a,b], Huiming Zhang[a,b]

[a] China Institute of Manufacturing Development, Nanjing University of Information Science & Technology, Nanjing 210044, China
[b] School of Management Science and Engineering, Nanjing University of Information Science & Technology, Nanjing 210044, China
[c] Reading Academy, Nanjing University of Information Science & Technology, Nanjing 210044, China

ARTICLE INFO

Keywords:
Carbon emission efficiency
Carbon emission performance
Technology gap
Meta-frontier
Non-radial directional distance function

ABSTRACT

An improvement in industrial carbon emission efficiency is crucial for achieving both reductions in carbon emissions and sustainable economic growth. In this paper, we use an improved non-radial directional distance function (NDDF) to construct a new meta-frontier total-factor carbon emission efficiency index (*TCEI*) with which we estimate the meta-frontier *TCEI* of China's 30 provincial industrial sectors in 2005–2015 and analyze their dynamic evolution. The results show that compared to traditional NDDF, the improved NDDF has more advantages in measuring both carbon emission efficiency and the technology gap ratio. For the study period, China's industrial meta-frontier *TCEI* is low, indicating that the industrial *TCEI* of many provinces still has much room for improvement. The meta-frontier *TCEI* has significant inter-group heterogeneity, with Eastern China having the largest carbon emission efficiency, followed by Central China, and Western China having the lowest. China's industrial meta-frontier *TCEI* increased significantly during the study period with technical progress playing a major role in promoting it. Over time, however, the meta-frontier *TCEI* growth rate decreased significantly as the deterioration in technological efficiency and the expansion of the technology gap have jointly inhibited the growth of carbon emissions efficiency. Carbon emission performance in various regions over different periods exhibit differing characteristics, that is, the carbon emission performance has significant spatial heterogeneity and period heterogeneity.

1. Introduction

Since the reform and opening up, China's economy has developed rapidly and has now become the world's second largest. This, however, has been accompanied by concomitant and increasingly serious environmental problems, with China, in 2007, surpassing the United States as the world's largest carbon emitter. In 2012, China's carbon emissions accounted for 28.8% of national totals. As a consequence, the international community has increasingly demanded that China take mandatory carbon emission reduction measures [54]. To this end, China has actively engaged in a framework of international climate cooperation and at the 2009 world climate conference held in Copenhagen, Denmark, China outlined its specific goals in the task to reduce carbon emissions, that is, China's carbon emissions per unit of GDP would be reduced by 40–45% by 2020 relative to 2009 levels. The "13th Five-Year" plan (2016–2020) also further proposed a specific target that the energy consumption per unit of GDP and the carbon emissions per unit of GDP would be reduced by 15% and 18% respectively by 2020 relative to 2015 levels. However, as the world's largest developing country, China still has a large number of issues to be resolved; the large poor population, the low levels of social welfare, and the challenge of changing economic development rapidly in a short time. How to effectively reduce CO_2 emissions under the premise of maintaining sustainable economic growth has become an important issue in China.

The industrial sector is not only the main source of China's economic growth, but is also the main factor in energy consumption and carbon emissions. The industrial sector contributes 40.1% to China's GDP, but its energy consumption and carbon emissions account for appropriately 67.9% and 84.2% of national total, respectively [50]. Therefore, in order to achieve the promised carbon emission reduction targets, industrial carbon reduction is key. Because industrial carbon emissions are mainly derived from the burning of fossil fuels in the process of industrial production, it follows that there are two ways for China to reduce industrial carbon emissions. The first way is to curb industrial energy consumption and reduce carbon emissions. The second way is to improve industrial carbon emission efficiency through structural adjustment and technical progress. The first way is at the expense of

* Corresponding author at: China Institute of Manufacturing Development, Nanjing University of Information Science & Technology, Nanjing 210044, China.
E-mail address: chengzhonghua0106@163.com (Z. Cheng).

https://doi.org/10.1016/j.rser.2018.06.015
Received 14 November 2017; Received in revised form 17 May 2018; Accepted 7 June 2018

sacrificing industrial development and is bound to inhibit China's overall economic growth. In view of this, the second way is the key to low-carbon development, that is, it is imperative to improve industrial carbon emission efficiency in order to achieve the win-win situation of both energy-saving and emissions reduction and economic growth, with further achievement of good and rapid economic development in the future. However, due to significant differences in technological levels, profitability, energy consumption and pollutant emissions between different regional industries, industrial carbon emission efficiency has obvious regional heterogeneity. This means that in order to improve industrial carbon emission efficiency, we must accurately measure the industrial carbon emission efficiency of different region and analyze the drivers of that growth of industrial carbon emission efficiency. Then we can put forward the corresponding policy recommendations.

Previous scholars have used a variety of methods to measure carbon emission efficiency and have achieved fruitful research results. The literature has laid a good foundation for the research of this paper. However, the literature exhibits deficiencies and defects in the measurements of carbon emission efficiency, so there might be certain bias and errors in their calculation results. In this paper we use an improved NDDF to construct a new meta-frontier *TCEI*. Compared to previous methods, the method of measurement in this paper is more advanced and advantageous, thus making the results more accurate and reliable. On this basis, we estimate the 2005–2015 meta-frontier *TCEI* for China's 30 provincial industrial sectors and then analyze their dynamic evolution. The structure of the paper is as follows: the second part is a literature review, the third part is the material and methods, the fourth part is the results and discussion, and the last part is the conclusion and policy recommendations.

2. Literature review

Many scholars have started to study the carbon emission efficiency in recent years. The measurement of carbon emission efficiency can be divided into two categories: single-factor carbon emission efficiency and total-factor carbon emission efficiency [4,46,50]. Some scholars use carbon intensity [48,5,57] and carbon productivity (CO2 emissions per unit of output) [20,30] to create a single-factor carbon emission efficiency index. Their calculations are simple and operational. Under the framework of the single-factor analysis, an improvement in carbon emission efficiency is not only dependent on the carbon emission reduction potential, but also dependent on the output capacity enhancement potential [19]. The main drawback of a single-factor carbon emission efficiency, though, is that it only considers the outputs, ignoring the effects of input factors such as capital, labor, energy etc, and their effects on carbon emission efficiency [31,47]. Based on the theory of total-factor productivity, total-factor carbon emission efficiency not only takes the CO_2 production process into account, but also considers the effects of different input factors and their substitution on carbon emission efficiency [4,58]. Because the *TCEI* effectively overcomes the drawbacks of single-factor carbon emission efficiency, it provides both a new way of thinking and a method for measuring carbon emission efficiency.

As a relative efficiency analysis, the calculation of the *TCEI* requires the construction of a production frontier. The commonly used methods include data envelopment analysis (DEA) and stochastic frontier analysis (SFA) [25,47] although, because SFA needs to set a specific function form and its assumptions are too strict, it has some limitations in practical application [45,50]. DEA, on the other hand, has been widely used in environmental performance evaluation because it does not need either model setting or parameter estimation, allows the existence of inefficient items, has less data constraints and can further decompose carbon emission performance [19,21,28]. When using DEA to measure environmental performance, we first construct a production frontier using linear programming and convex analysis after which we then project different decision units onto the production frontier, and evaluate the relative efficiency by comparing the distance from which the decision units deviate from the production frontier [29,42,59]. Many scholars thus use the traditional DEA to evaluate environmental performance [10,17,40,41,43,49].

One problem is that traditional DEA does not consider undesirable output, which can deviate greatly from the actual production process. In order to incorporate the undesirable output into the traditional DEA model, Färe et al. [14] first proposed a weak disposability of pollution variable and postulated the DEA model for environmental efficiency evaluation under a total-factor framework. The solution process of this DEA model, however, is too complicated and so has certain limitations in practical application. Reinhard et al. [37] and Hailu and Veeman [18] treated the pollutants as input factors so as to meet the environmental performance evaluation requirements for pollutant reduction and output expansion. But this method does not accord with the actual production process, so there are some errors in its measurement results. Scheel [38] took the reciprocal of undesirable output in the measurement process and treated it as desirable output, but it inevitably deviated greatly from the actual production process. Färe et al. [15] adopted the Shepherd directional distance function and the Malmquist index to estimate technical efficiency, but the measurement process did not consider undesirable output. On this basis, Chung et al. [8] proposed a new radial directional distance function (DDF) to better resolve problems in environmental efficiency evaluation when considering undesirable outputs. [13] and Zhou et al. [60] also used this DDF to measure the environmental efficiency. Based on these evaluation ideas, Zhou et al. [58] regarded CO_2 as an undesirable output and proposed a total-factor carbon emission efficiency index. Many scholars have subsequently used this radial DDF to measure *TCEI* [27,4,47,56,9].

In the process of measuring the *TCEI*, the above studies have all adopted the traditional radial DDF but, because this function causes both undesirable output and desirable output to change by the same proportion, and is thus unable to describe situations in which undesirable output and desirable output change by different proportions, it deviates greatly from the actual production process [46,61]. In fact, in the actual production process, enterprises often encounter situations where the proportion of increases in desirable output is greater than that of decreases in undesirable output. This is often due to technological innovation and technical progress [55]. Because the radial DDF cannot eliminate any inefficient components caused by the input-output slack, it may overestimate carbon emission efficiency [16,53]. Färe and Grosskop [12] proposed a generalized NDDF to measure the total-factor energy productivity. Based on this NDDF, Zhou et al. [61] adopted carbon intensity to define a new total-factor carbon emission efficiency index. The index is defined as the ratio of carbon emission intensity under frontier technology to actual carbon emission intensity, where the carbon emission intensity under frontier technology can be calculated from both the desirable output and the carbon emissions under frontier technology. Because this NDDF relaxes the requirements that both the desirable output and undesirable output change by the same proportion, it makes the model more realistic and the results more accurate and reliable [44,53]. Many scholars have subsequently used this NDDF to measure *TCEI* [11,22,25,26,39].

The above models, however, all regard the decision units as homogeneous, that is, they assume that all decision units have the same production frontier. In reality, because the growth modes and the production technology sets of different decision units are not exactly the same, environmental efficiency, calculated by the same production frontier constructed by all decision units, is unable to accurately reflect the technological differences of decision units [28,32,52]. Moreover, if the relative efficiency and productivity are calculated according to respective production technology sets of each decision unit, it will be difficult to compare the results because their referenced benchmark production frontiers are not unified [50]. Oh [35] and Oh and Lee [36] integrated the group production heterogeneity into the traditional Malmquist-Luenberger index model and effectively resolved this problems. According to the research on meta-frontier function of Battese and Rao [1], Battese et al. [2] and O'Donnell et al. [34], the decision units can be divided into several groups with inter-group heterogeneity, and each group has the same production frontier. We can then measure the group-frontier *TCEI* and meta-frontier