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Intelligent Measurement of Total Factor Carbon Emission Efficiency of Logistics Industry in Hubei Province Under Low Carbon Constraints

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Abstract. Under the background of "dual carbon", Hubei Province has always attached great importance to the low-carbon-logistics transformation and has made green and efficient the focus of logistics industry development. The article takes energy and unexpected output into account and takes unit carbon emission added value and unit carbon emission conversion turnover as output factors. It constructs an SBM-DEA model to measure the carbon emission efficiency of the logistics industry in Hubei China. Finally, based on the research results, a carbon emission reduction path for the logistics industry in Hubei Province is proposed, including strengthen policy guidance and reasonably set freight rates; transfer of high carbon emission transportation methods; extend the logistics value chain and carry out logistics technology innovation.The research conclusion can provide theoretical support for the government.

Keywords. Low Carbon Constraints; Logistics; All Elements; Carbon Emission Efficiency.

1. Introduction

With the arrival of the new "retail revolution" era, Logistics industry becomes a significant guarantee for driving consumption and promoting economic development. Hubei Province, as the intersection of China's economic sectors, has favorable congenital conditions for developing the logistics industry. However, Logistics industry is also one of the most significant sources of carbon emissions, accounting for 18.9% of the total amount. It is the only sector among the five major industries of agriculture, industry, construction, and commerce where the proportion of carbon emissions continues to rise. Therefore, the government has paid much attention to the low-carbon transformation of logistics and has made the low-carbon development model a key focus of the logistics development.

At present, there is relatively little research on the carbon emission efficiency (CEE) of the logistics industry both domestically and internationally. More scholars are studying the CEE of the transportation industry, mainly focusing on traditional single factor CEE [1-5]. There is even less research on the comprehensive CEE of the logistics

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industry based on production function theory and considering energy input and carbon emission output [6-7]. In addition, DEA and its improved models are the main methods for measuring CEE, but there is almost no research on measuring the efficiency of all factor CEE using the SBM model based on relaxed variables and the improved DEA model based on the common frontier Meta Frontier production function [8-11]. The research of this project has high reference value for how to achieve higher logistics output and minimize environmental pollution with fewer resources, labor, and energy inputs. It has important theoretical significance for filling the research gaps and gaps in the field of CEE measurement.

2. Definition of Core Concepts

2.1. Single Factor/Total Factor CEE

The current definition of CEE in research is based on two perspectives: single factor and total factor.

Single factor CEE: refers to the ratio of carbon emissions to individual input variables, such as carbon emissions per unit energy consumption (i.e., carbon index). There are currently some studies that consider carbon emissions per GDP (i.e., carbon intensity) as CEE, but generally speaking, low carbon intensity does not necessarily indicate high CEE.

Total factor CEE: refers to the CEE that comprehensively considers input factors such as capital, manpower, energy, as well as output factors such as GDP and carbon emissions. Due to the unexpected output of carbon emissions, the smaller the value, the better. Therefore, the total factor CEE is defined as the maximum GDP and minimum carbon emissions that can be achieved by investing a fixed amount of capital, manpower, and energy elements at a certain technological level.

2.2. Total Factor CEE of Logistics Industry

The input factors of Logistics industry are similar to other industries, including capital, labor, energy, etc. Unlike other industries, the essence of logistics services is "providing displacement of people and things". Therefore, this article believes that the output indicators of Logistics industry should choose the physical form indicator - transportation turnover. In addition, since energy consumption data related to Logistics industry cannot be directly obtained, and Transportation, Warehousing, and Postal industries can approximately represent Logistics industry, and the data can be directly used from statistical yearbooks. This article uses data from Transportation, Warehousing, and Postal industries in Hubei Province to represent the logistics industry.

The total factor CEE of Logistics industry means: the maximum conversion turnover and minimum carbon emissions that can be achieved by investing a fixed amount of capital, manpower, and energy elements at a certain level of technology. The total factor CEE of Logistics industry is a relative efficiency, which ranges from 0 to 1.

3. Calculation of Logistics Carbon Emission in Hubei Province

There are significant distinctions when calculating carbon emissions and carbon dioxide emissions. This study focuses on the carbon dioxide emissions, and the descriptions of carbon emissions in the study all represent carbon dioxide emissions. According to the IPCC (2006), greenhouse gases mainly composed of carbon dioxide, in addition to those generated by nature itself, mainly come from fossil fuels combustion. The calculation methods are divided into two types: the "top-down" and the "bottom-up" method. This article uses the "top-down" method. The calculation formula is as follows:

$$C = \sum_i C_i = \sum_i E_i F_i \tag{1}$$

In Formula (1), i represents form of energy; C represents carbon emissions; Ci is emission of the i-th energy form; Ei is consumption amount of the i-th energy form; Fi is carbon emission factor. The carbon emission factors of different fossil fuels are shown in Table 1.

Table 1 Carbon Emission Factors for Each Energy Type Unit: kgCO2/kg or m3

Energy type	Raw Coal	Crude Oil	Gasoline	Kerosene	Diesel Oil	Fuel Oil	Natural Gas
Emission factors	1.9003	3.0202	2.9251	3.0179	3.0959	3.1705	2.1622

According to Formula (1) and Table 1, the carbon emissions of Hubei's logistics industry from 2012 to 2022 can be calculated as shown in Figure 1.

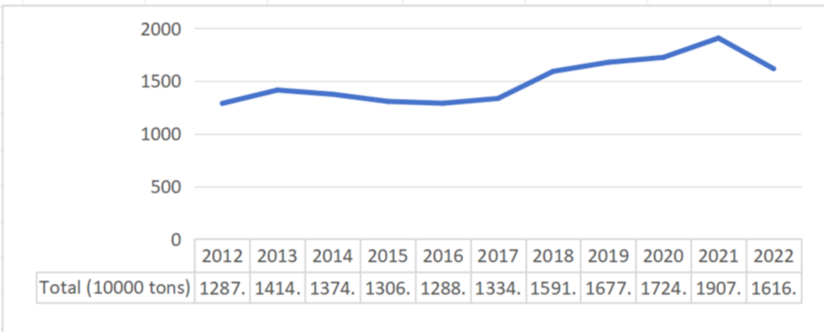

Figure 1 Logistics industry carbon emissions in Hubei Province

4. Measurement of Total Factor CEE of Logistics Industry in Hubei Province

4.1. Production Technology Collection

Assuming that Logistics industry is a DMU (denoted as O), each DMU has M input elements, and the element set is denoted as $x = (x_{1,}x_{2,}x_{3,} \dots x_{a,}) \in R_+^M$; N expected output elements, with the element set denoted as $y = (y_{1,}y_{2,}y_{3,} \dots y_{b,}) \in R_+^N$; Type I non expected output elements, with the element set denoted as $z = (z_{1,}z_{2,}z_{3,} \dots z_{c,}) \in R_+^I$; The production technology set for the t-th :

$$P^t(x^t) = \begin{cases} (y^t, b^t) \mid \sum_{q=1}^{O} \lambda_q^t y_{qn}^t, n = 1, \ldots, N \\ \sum_{q=1}^{O} \lambda_q^t x_{qm}^t \leq x_m^t, m = 1, \ldots, M \\ \sum_{q=1}^{O} \lambda_q^t b_{qi}^t = b_i^t, i = 1, \ldots, I \\ \sum_{q=1}^{O} \lambda_q^t = 1, \lambda_q^t \geq 0, q = 1, \ldots, Q \end{cases} \tag{2}$$

In equation (2), λ_q^t represents the weight of the input and output values of the qth DMU in the t-th period. When the Constant Returns to Scale (CRS) of production technology remains unchanged,$\lambda_q^t \geq 0$; When the variable returns to scale (VRS) of production technology is variable, $\sum_{q}^{O} \lambda_q^t = 1, \lambda_q^t \geq 0$.

The above production technology concentration data is the observed values under the production technology level of the t period, without considering the non-synchronicity of the reference technology, and there is a certain deviation in the measured efficiency results. To ensure the synchronization of reference technologies, some scholars have proposed a global production technology set:

$$P^G(x) = \begin{cases} (y^t, b^t) \mid \sum_{t=1}^{T} \sum_{q=1}^{O} \lambda_q^t y_{qn}^t \geq y_n^t, n = 1, \ldots, N \\ \sum_{t=1}^{T} \sum_{q=1}^{O} \lambda_q^t x_{qm}^t \leq x_m^t, m = 1, \ldots, M \\ \sum_{t=1}^{T} \sum_{q=1}^{O} \lambda_q^t b_{qi}^t = b_i^t, i = 1, \ldots, I \\ \sum_{q=1}^{O} \lambda_q^t = 1, \lambda_q^t \geq 0, q = 1, \ldots, Q \end{cases} \tag{3}$$

In equation (3),$P^G(x) = P^1(x^1) \cup \ldots \cup P^t(x^t)$, the global production technology set is the union of the production technology sets for each period, that is, the sample data for periods 1 to t use the same production frontier, making the measured efficiency comparable.

4.2. Construction of Directional SBM-GML Index Measurement Model

In traditional radial DEA models, one of the basic requirements is to minimize input while maximizing corresponding output. In this regard, some scholars have expanded and generalized the non-radial and non-angular directional distance function based on the previous work [12-14]. This article draws inspiration from this processing method and obtains the global directional SBM model as follows:

$$S_v^G(x_o^t, y_o^t, b_o^t; g^x, g^y, g^b) = \max_{s^x, s^y, s^b} \frac{\frac{1}{M}\sum_{m=1}^{M}\frac{S_m^x}{g_m^x} + \frac{1}{N+I}\left(\sum_{n=1}^{N}\frac{S_n^y}{g_n^x} + \sum_{i=1}^{I}\frac{S_i^b}{g_i^b}\right)}{2}$$

$$s.t.\begin{cases} \sum_{t=1}^{T}\sum_{q=1}^{O}\lambda_q^t x_{qm}^t + S_m^x = x_{mO}^t, m = 1,\dots,M \\ \sum_{t=1}^{T}\sum_{q=1}^{O}\lambda_q^t y_{qn}^t - S_n^y = y_{nO}^t, n = 1,\dots,N \\ \sum_{t=1}^{T}\sum_{q=1}^{O}\lambda_q^t b_{qi}^t + S_i^b = b_{iO}^t, i = 1,\dots,I \\ \sum_{q=1}^{O}\lambda_q^t = 1, \lambda_q^t \geq 0, q = 1,\dots,O \\ S_m^x \geq 0, S_n^y \geq 0, S_i^b \geq 0 \end{cases} \tag{4}$$

In the formula, x_O^t are the vectors of the input elements, y_O^t are the expected output elements, and b_O^t are the unexpected output elements ; g^x、g^y、g^b are the corresponding direction vector; S_m^x、S_n^y、S_i^b are the corresponding relaxation vector.

4.3. GML index model

The M index is an indicator that measures the fluctuate of CEE. To study the changing efficiency including unexpected outputs, this article draws on the research methods of other scholars and further decomposes the GML index into pure efficiency change (GPEC), technological progress rate (GPTC), and scale efficiency change (GSEC) based on the global directional SBM. The relevant calculation formulas are as follows:

$$\begin{aligned}
GML_t^{t+1} &= \frac{1+\vec{S}_v^G(x^t, y^t, b^t; g^t)}{1+\vec{S}_v^G(x^{t+1}, y^{t+1}, b^{t+1}; g^{t+1})} = GPEC_t^{t+1} \times GPTC_t^{t+1} \times GSEC_t^{t+1} \\
GPEC_t^{t+1} &= \frac{1+\vec{S}_v^t(x^t, y^t, b^t; g^t)}{1+\vec{S}_v^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; g^{t+1})} \\
GPTC_t^{t+1} &= \frac{\left[1+\vec{S}_c^G(x^t, y^t, b^t; g^t)\right] / \left[1+\vec{S}_v^t(x^t, y^t, b^t; g^t)\right]}{\left[1+\vec{S}_v^G(x^{t+1}, y^{t+!}, b^{t+1}; g^{t+1})\right] / \left[1+\vec{S}_v^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; g^{t+1})\right]} \\
GSEC_t^{t+1} &= \frac{\left[1+\vec{S}_v^G(x^t, y^t, b^t; g^t)\right] / \left[1+\vec{S}_c^G(x^t, y^t, b^t; g^t)\right]}{\left[1+\vec{S}_v^G(x^{t+1}, y^{t+!}, b^{t+1}; g^{t+1})\right] / \left[1+\vec{S}_c^G(x^{t+1}, y^{t+!}, b^{t+1}; g^{t+1})\right]}
\end{aligned} \tag{5}$$

In the formula, GML_{t+1}、$GPEC_{t+1}$、$GPTC_{t+1}$、$GSEC_{t+1}$ are greater than 1 (less than 1), respectively, indicating an increase (decrease) in total factor carbon emission efficiency, an increase (decrease) in pure technical efficiency, a reversal of technological progress, and an increase (decrease) in scale efficiency; GML_{t+1} =1, it means that the total factor CEE level remains unchanged.

4.4. Input output variable selection

The basic principle of DEA is to establish a production frontier by the input and output variable data of each DMU and calculate the relative efficiency value by measuring the degree of deviation between each DMU and the production frontier. Therefore, the selection of variables directly determines the size of efficiency.

Based on the above considerations and the availability of variable data, combined with the concept of the total factor CEE of the logistics industry, this paper selects three resources, namely labor, capital, and energy, as input factors. When these three elements are input into the transportation production process, in addition to obtaining expected output (converted turnover), they will also bring unexpected output (carbon emissions).

Table 2 Explanation of input-output variables

Classification	Variables	Method of calculation
Input variables	Manpower	The average of employees in the previous and the current year
	Capital stock	Perpetual inventory method
	Energy	Conversion of terminal energy consumption into standard coal
Output variables	Converted turnover	Passenger turnover is converted into freight turnover
	Carbon emissions	The top-down method

4.5. Measurement of Total Factor CEE

Before applying DEA model, it is necessary to test whether each input and output variable has "Isotonicity", that is, whether the input and output variables are correlated. This article uses Pearson correlation analysis for validation, and the results are shown in Table 6. The correlation coefficients of each input and output variable are greater than 0.5 at the 5% significance level. Therefore, the selection of variables is relatively reasonable and suitable for DEA analysis.

Table 3 Correlation Test of Input and Output Variables

	Conversion turnover	Carbon emissions
Practitioners	0.589**(0.000)	0.744**(0.000)
Capital stock	0.846**(0.000)	0.730**(0.000)
Energy input	0.832**(0.000)	0.999**(0.000)

Based on the variable data of the logistics industry in Hubei Province from 2012 to 2022 and the directional SBM-GML index model, this section uses MaxDEA6.8pro software to calculate the total factor CEE of the logistics industry. The results are presented in Figure 2.

	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Efficiency	0.513	0.517	0.543	0.563	0.544	0.488	0.54	0.598	0.634	0.651	0.639

Figure 2 Carbon Emission Efficiency of Logistics Industry in Hubei Province from 2012 to 2022

From the results, we can notice that the overall CEE of the logistics industry in Hubei Province from 2012 to 2017 was relatively low, due to the rapid development of society and economy in Hubei, with a large amount of capital investment and relatively complete transportation infrastructure. However, the large, expected output generated by these investments is not enough to cover up the lack of producing massive, unexpected outputs, resulting in a low level of overall factor CEE. From 2018 to 2022, CEE steadily increased. The increase from 0.54 to 0.64 reflects that after transportation infrastructure construction, the CEE of logistics has also improved. However, the average CEE over the years is only 0.56, which is at a moderate level. This indicates that there is ample room for Logistics industry carbon emission reduction in Hubei Province.

5. Research on path of logistics industry carbon emission reduction in Hubei Province

Against the backdrop of the country's vigorous promotion of carbon emission reduction, Hubei Province can scientifically and effectively guide prices in combination with carbon tax policies; Focusing on railway and waterway transportation with lower carbon emissions, enhancing the optimization level of transportation routes and improving the efficiency of multi-modal transportation networks; Seize the important opportunity of industrial digitization, develop smart logistics, and extend the logistics value chain; Strengthen the information construction, improve technological content, and accelerate high-quality development.

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