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Retraction

Retracted: Low Carbon Economy Assessment in China Using the Super-SBM Model

Discrete Dynamics in Nature and Society

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

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[1] Y. Ding and Y. Han, "Low Carbon Economy Assessment in China Using the Super-SBM Model," *Discrete Dynamics in Nature and Society*, vol. 2022, Article ID 4690140, 9 pages, 2022.

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Research Article

Low Carbon Economy Assessment in China Using the Super-SBM Model

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This review proposes a performance evaluation system of low-carbon economic development based on multiobjective analysis in low-carbon environment. This is a modeling method combining super efficiency and relaxation-based measurement model (super-SBM model), which can effectively measure green innovation efficiency with unexpected outputs and traditional innovation efficiency without unexpected outputs. Using the Malmquist–Luenberger index method to dynamically analyze the efficiency of green innovation, a multiobjective model is obtained, including economic scheduling target considering wind power cost and low-carbon scheduling target considering carbon trading. The efficiency of green innovation considering unexpected output is obviously lower than that of traditional innovation without considering unexpected output. This phenomenon is more pronounced in some areas of central and western China. Technical efficiency improves the innovation level of environmental protection economy in China and the impact of technological progress is greater than that of technical efficiency. In this review, the output super SBM model is used to study the development of China's low-carbon industry, and the correlation between the prediction model and the performance change of low-carbon economic development is analyzed. The Malmquist–Luenberger (ML) index of environmental protection product development efficiency in China is not less than 1. Due to the improvement of the efficiency of scientific and technological development, the combination of the two will eventually lead to the improvement of the development of green products and environmental economic products in China. Combining with the empirical analysis, this paper puts forward some methods to promote the low-carbon economy in the economic zone.

1. Introduction

For the past few years, China has paid more attention to the adverse effects of industrial development on the ecological environment. The government reduces resource consumption and environmental pollution by developing renewable energy and establishing various emission reduction mechanisms [1]. At present, resources and environment problems associated with China's rapid economic development need to be solved urgently. In 2020, China's Global Environmental Performance Index (EPI) ranked 120th out of 180 countries and regions [2]. Therefore, the Chinese government plans to improve the overall coordination mechanism in the ecological field to achieve a comprehensive green transformation [3, 4]. Low-carbon products can bring benefits in different regions according to local conditions [5, 6]. This will help China achieve high-quality development and green transformation.

At present, we mainly discuss and distinguish the evaluation model of low-carbon economy from two aspects: (1) from the qualitative perspective, the evaluation model is discussed from different perspectives by establishing various theoretical models, among which the most important three perspectives are linear analysis, nonlinear analysis, and system construction [7, 8]. (2) From a quantitative perspective, specific evaluation numbers are obtained through empirical research on relevant theoretical frameworks [9, 10]. Beise [11] proposed that enterprises should adopt cleaner production methods, such as process and technology, to reduce environmental problems. Ghisetti and

Rennings [12]divided green innovation into energy resource efficiency type and external reduction type. Zhang et al. [13] divide green innovation into three types: resource-saving, environment-friendly, and hybrid green innovation based on the framework of "motivation-process-result." The evaluation methods of green innovation efficiency into two different types: the first type is data envelopment analysis (DEA). For example, Sueyoshi et al. first proposed the DEA-RAM model and through this model, the data of economic benefits are calculated [14]. The second type is random forward edge analysis (SFA). For example, Aigner et al. proposed the stochastic frontier model for the first time and analyzed the factors affecting the efficiency of technological innovation [15].

The data size of output indicators of environmental protection and economic development speed includes two categories: the first is a phase of input and output evaluation index system and does not include intermediate output. Yan et al. selected the human resources, capital, infrastructure investment, and scientific and technological achievements, such as economic, social, and environmental performance of nine indicators to measure regional innovation efficiency in China [16]. Guo et al. constructed an evaluation index system of total factor productivity of low-carbon economy consisting of three first-level indicators of input, expected and unexpected output, and five second-level indicators of labor, capital, energy, regional GDP, and "three wastes" emissions [17]. The second type is two-stage input–output index system, including intermediate output. Jiang et al. constructed an evaluation index system consisting of 5 first-level indicators of innovation input intermediate output, non-R&D input, expected, and nonexpected output and 15 second-level indicators to measure green technology [18]. Through the summary of existing literature, many scholars have conducted a lot of studies on the efficiency of low-carbon economic development, but there are some shortcomings in evaluation methods and index selection [19]. DEA is the main evaluation method, but the traditional DEA model seldom considers the "slack" variable and the unexpected output at the same time, which may cause the efficiency value to be overestimated [20].

In 1978, Charness, Cooper, and Rhodes initiated DEA model to measure the degree to which the inputs (outputs) of decision-making units need equal proportion improvement when they reach the production frontier. The DEA model is a new advanced learning method, as one of the main research methods of efficiency evaluation [21]. The super-SBM model makes up for the weakness that the SBM model cannot distinguish effective decision units. First, the effective units are deleted from the production possible set and the distance from them to the production front is measured [22]. The super-SBM model is very efficient in evaluating the cross-sectional data of the development efficiency of the low-carbon economy. However, what we usually refer to as industrial development is often a dynamic process involving the improvement of production technology and the proficiency of worker skills [23]. Obviously, from the viewpoints of Dell, McDuffie, and Becker, it can be found that they are all in favor of a causal relationship model, and they propose a simple and intuitive model of the impact of organizational effectiveness, which effectively solves the process of human resource management practice. The problem is that the variable in this model is benefit, and the only influencing factor of this variable is the original variable. However, the specific situation is often more complex, and the general situation is much more complicated than the theoretical idea. In practice, the model needs to set more variables, and in these models, it is only an ideal situation, and there are a very few variables to consider. Therefore, these theoretical assumptions also lead to certain defects in the linear mode, which needs to be improved in practice [24]. The Malmquist index contains two methods, a component of the catch-up effect and a component of the frontier movement. The catch-up effect reflects the change effect of technical efficiency, while the frontier movement reflects the movement of all referenced production fronts in two periods [25]. The theory has carried out a detailed discussion on the antecedent part, and also added a lot of process influencing factors, so that the theory can more truly reflect and approach the actual situation. The paper considers that the SBM model with undesired output may have multiple decision units that are effective at the same time, so it is not convenient to distinguish and sort these decision units. The super-SBM model with unexpected output effectively solves the discrimination and ranking problems when multiple decision units are effective at the same time. It can reflect the essence of efficiency evaluation of regional low-carbon economy [26]. Based on some research background, this paper uses the super-SBM model and ML indicators to measure and analyze the different levels of low-carbon economy operating efficiency in most provinces and cities in China. Incorporate resource and environmental factors into the input and output indicators of innovation process. The low-carbon economic operation efficiency including undesired output is calculated and compared with the traditional innovation efficiency without undesired output. The static and dynamic levels of low-carbon economic operation efficiency in China are analyzed comprehensively [27]. Traditionally, we believe that due to pollution emissions, environmental quality in nonmodern urban areas may be better than in areas with a high level of modernization. This paper mainly studies and evaluates the development of low-carbon economy by using the super-SBM model. At the same time, it also conducts effective forecasting of production frontiers and dynamic monitoring and practical demonstration of changes in low-carbon economic development performance.

2. Advantages of Super-SBM Model and SOM Neural Networks

The method of super-SBM model belongs to packet envelope analysis model. This model measures efficiency from radial and angle, without considering the problem of input–output relaxation. Super-SBM model analyzes and calculates the growth efficiency of low-carbon economy. When input and output are nonzero slack, calculated efficiency value is not accurate. See the result in Figure 1, the spatial structure of the SOM neural network outputs the results of running the SOM neural network model.

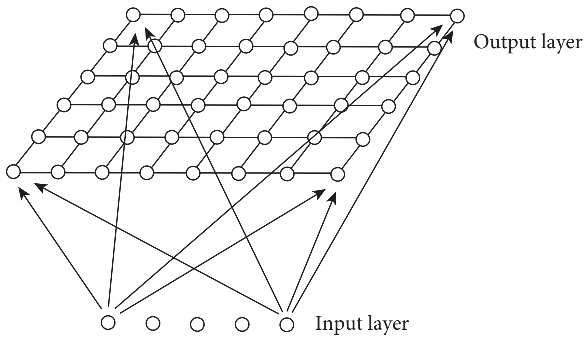

Figure 1: The spatial structure of neural networks.

Main steps of establishing a neural network management efficiency evaluation model are as follows:

(1) In order to determine the risk factors, find out the appropriate evaluation criteria by analyzing the data.

The appropriate low-carbon economic index benefit factor can be selected as the evaluation standard, as shown in equation (1) [28].

$$N_{mn} = e^{-(m-n)^2/2\delta^2}, \tag{1}$$

where N_{mn} is standard evaluation function, and δ is the training speed of model, which is a constant.

(2) Input information points to the SOM neural network model.

The model is still in its infancy, it is especially important to choose the coefficients, which are related to the validity and accuracy of the model predictions. When using the low-carbon economic indicator benefit as the description object and through the set of elements determined during data processing, the selection range can be fixed between the closed interval of 0 and 1. At the same time, the use of the normalized calculation method can solve the problem of inaccurate settlement results. The normalized function is shown in equation (2):

$$q_{mn} = \frac{w_{mn} - w_m}{w_{mn} - w_n}, \tag{2}$$

where q_{mn} is the calculated weight $Wm = \mathrm{mix}\,(Wmn)$, $Wn = \max\,(Wmn)$, $Pmn \in [0, 1]$.

(3) Advantages of the SOM model. The correct selection of information points is related to the prediction results of the model, and there is a strong correlation between information points and prediction results. If the number of selected information points is small, the prediction accuracy of the output of the SOM model will be reduced. Equation (3) represents the appropriate information points selected in the model:

$$r_{mn} = \frac{\sqrt{\sum_{n=1}^{m}(w_m - w_n)}}{P-1}, \tag{3}$$

where r_{mn} is the optimal number of data points to hide.

(4) Select the output information points of SOM model

As mentioned above, the number of information points is related to the prediction result, and the model output value can directly reflect the quality of the evaluation result on this basis. The evaluation model results can be divided into five levels. From level one to level five. The lower the maximum safety factor of the number of levels, the level one is the safest level. It can be shown by formula (4) [29]:

$$H = \sum_{I=1}(J_I - J_P) \times \eta(J_I, J_P), \tag{4}$$

where H refers to the number of selected information points.

In addition, super-SBM model has three advantages: (1) effectively improve the inconsistency of input-output variables; (2) fully consider and solve the problem of poor output data; (3) propose solutions for the problem of different simultaneous ordering of multiple decision-making units. Compared to other data envelopment analysis (DEA) methods, the super-SBM model can more truly reflect the nature of the evaluation of low-carbon economic efficiency in different regions.

3. Construction of Low-Carbon Economic Operation Efficiency Evaluation Model

3.1. Traditional Evaluation Model. After determining the evaluation index set in traditional economic operation efficiency evaluation model, the dimensionless characteristic value and weight of each index can be determined by comprehensive fuzzy evaluation method. The model is used to determine the proportion of eigenvalues after considering the neutralization evaluation index. The weighted average method is generally used, and the next step is selected according to the evaluation indicators, then, the final evaluation result of super-SBM model was obtained [30].

Nevertheless, this method cannot be used for the efficiency evaluation of green economy. As the efficiency of green economy management is affected by various results, and there is a mutual relationship between various influencing factors. If only under a single functional condition, the relationship between each influencing factor and the result is not certain, so there is a typical nonlinear system. It truly reflects the efficiency of the evaluation model of human resources. In this process, the dynamic changes and nonlinear problems can be mainly checked and solved in the model shown in Figure 2.

If expert scoring method is used, the weights determined by this method are flawed to a certain extent. First, there is a large human factor, and there are great differences in the personal preferences of experts, which may cause the authenticity of the measurement to be disturbed. The second is poor flexibility [31]. The determined weight is difficult to be changed, which is inconsistent with the existence of uncertain factors in the actual situation.

3.2. Evaluation Method Based on SOM Neural Network. If only the original evaluation data are used as the output object, the intermediate parameters are not considered, the

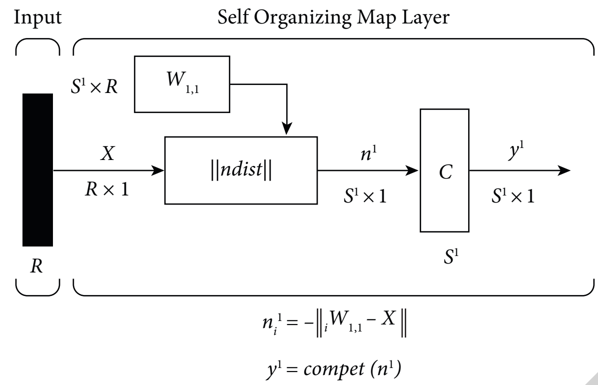

Figure 2: The low-carbon economic evaluation model based on SOM neural network.

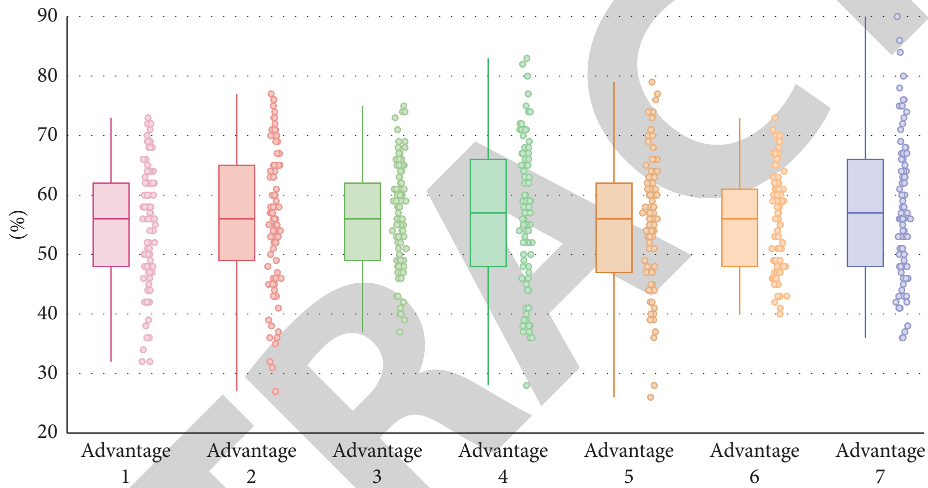

Figure 3: Clustering of input vector neurons with different benefits.

entire SOM model is equivalent to a closed interval, and only one benefit degree can be the output. If the whole evaluation system is regarded as a nonlinear function, the effectiveness of the evaluation index system can be realized, and the complex mechanism of the large system of human resource management can also be satisfied. Figure 3 shows a variety of input vector neurons that have different strengths and can exploit the strengths of the model from different angles. SOM model can well identify the elements, complex, high dimension, nonlinear relationship between its essence and is a kind of input and output layer of neural network, and they are all connected on the basis of the neurons (parameters) between the organization model for different types of intrinsic characteristics, thus mapping distribution and classification. It can effectively solve the problem of sample type recognition in which the parameters of each index are intermingled with each other and the category characteristics are not obvious.

There are various forms of neural network computing models, including SOM model. It consists of two layers: input and output, and there is a strong correlation between them. The only flaw is that cells at the same level are not linked. There are two forms of operation of the SOM network: forward propagation and backward propagation. When forward propagation does not meet the output requirements, it will turn to back propagation. At the same time, the input layer receives error information from the results fed back by the output layer. During this process, the connectivity of each cell in each layer of neurons and the error offset of each layer of neurons change, thereby continuously reducing the error.

3.3. Super-SBM Evaluation Model. At present, the research on low-carbon economy in China has made some advancements. In different research fields, the research design has a wider level, and scholars conduct research from the national to the city. From the perspective of research methods, data envelopment model (DEA) is commonly used to evaluate low-carbon economy, and different models will be selected according to the index system and research perspective of scholars. Some scholars use the traditional CCR model or BCC model for measurement. However, the traditional DEA model has certain limitations, so the improved super-efficiency DEA model (super-SBM) is more used at present. On this basis, we introduce nonexpected output, namely low-carbon cost input, as a variable, and use the nonexpected output super-efficiency SBM model to evaluate the efficiency of economic growth so that the measurement data can be more objective and guide the sustainable development level of low-carbon economy to a certain extent.

From the perspective of low-carbon economy, the primary issue in studying the efficiency of capital allocation is to measure the degree of low-carbon economics. According to the data, in the pursuit of low-energy consumption, low emissions, low pollution, and advocacy of green technological progress, we employ DEA-based green TFP indicators, including energy transition and accelerated CO_2 emissions, which measure the degree of change in low-carbon economic development.

Different from ordinary DEA, the green TFP index takes energy and carbon emission into account. Due to the lack of carbon emission price information and cost variables, environmental factors are often ignored by researchers in the analysis of their impact on economic growth. This is because the distance function obtained through linear programming is calculated based on seeking output maximization in the case of input or pursuing input minimization in the case of output input. Taking carbon dioxide emission as an input factor can make input-based distance function reflect the connotation of low-carbon economic better.

The super-SBM model considering the relaxation variable can be expressed as follows:

$$\rho = \min \frac{1/m \sum_{i=1}^{m} x_i/x_0}{1/s_1 + s_2\left(\sum_{r=1}^{s_1} y_r^g/y_{r0}^g + \sum_{r=1}^{s_2} y_r^g/y_{r0}^g\right)}, \quad (5)$$

$$\mathrm{s,t}, x_0 = X\lambda + S^-, y_0^g = Y^g\lambda - S^g.$$

where ρ is the target low carbon efficiency value.

In addition to measuring the technical efficiency level of green economy development performance, we also investigate the intertemporal dynamic changes of green economy development performance. The dynamic change of green economy development performance is not only related to technical efficiency but also closely related to technological progress. Therefore, based on the reference output-oriented Malmquist productivity index, on the basis of combining direction distance function, put forward considering the expected output of total factor productivity index, index and total factor productivity change further and are decomposed into two parts, namely, the change of the technical efficiency and technical progress, as shown in type (7):

$$\mathrm{TFP} = \left[\frac{D^t(x_{t+1}, y_{t+1})}{D^t(x_t, y_t)} \times \frac{D^{t+1}(x_{t+1}, y_{t+1})}{D^{t+1}(x_t, y_t)}\right]^{0.5}. \quad (6)$$

Equation (6) can also be decomposed into the product of three parts:

$$\mathrm{TFP} = \mathrm{PE} \times \mathrm{SE} \times \mathrm{TC}, \quad (7)$$

where TFP stands for low-carbon economic efficiency; TC stands for technological progress and change; PE represents pure technical efficiency change; and SE represents the change in scale efficiency.

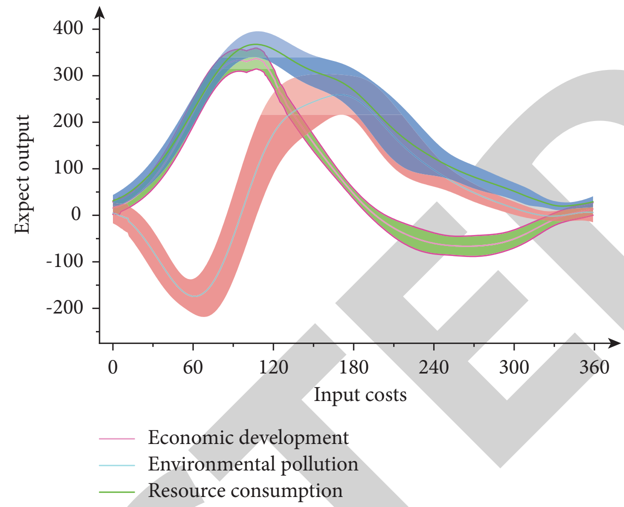

Figure 4: Eco-efficiency evaluation index system.

Using this model to evaluate the ecological efficiency index, the results are shown in Figure 4. The development trend of low-carbon economy and environmental pollution is opposite.

4. Index Selection and Data Processing

Energy input is beneficial to the economic progress of a region, while scientific research input is essential to the development and progress of technology. In addition, the characteristics of industrial structure and urbanization level affect carbon emission level and energy consumption structure from different aspects. Therefore, on the basis of the previous studies, this paper selects corresponding indicators from the perspectives of energy, industrial structure, and urbanization level to measure the input of low-carbon economic development. In terms of the selection of output indicators for low-carbon economic development, these two indicators are favored by the majority of researchers due to the comprehensive and authoritative GDP indicators and the unique advantages of carbon productivity in measuring economic development. In Figure 5, we can see that with the increase of economic input, the comprehensive index of low carbon economy is significantly higher than that of medium carbon and high carbon. However, carbon productivity index has some defects because it cannot reflect the environmental cost in the process of economic development. In view of this, in this paper, GDP and unit carbon dioxide emissions of each region are selected to measure the expected output and unexpected output of low-carbon economic development. As can be seen from Figure 5, there are mainly three different forecast results of low-carbon economic development in China under low-carbon economy. The chart reflects the general development trend of low-carbon economy.

Figure 6 shows the DEA calculation method. This method can be used to evaluate the input and output prediction of multiple indexes. Its principle is to calculate and evaluate the computational efficiency of DMU by using

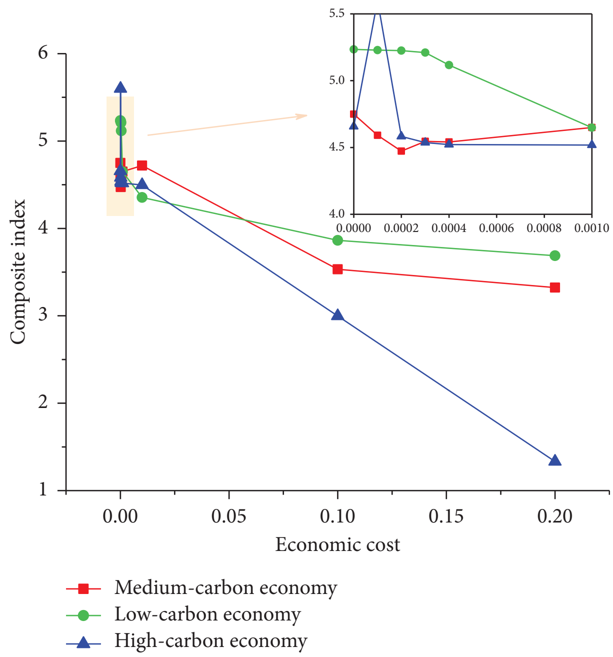

FIGURE 5: Various economic index models.

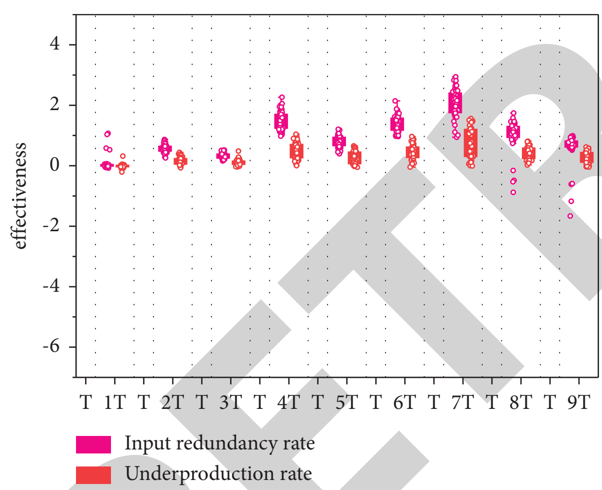

FIGURE 6: Input redundancy and output insufficient efficiency diagram.

mathematical programming model. From Figure 6, it can be seen that the ratio of research and development investment is higher than that of output, which also increases the difficulty of implementing. In the evaluation index model, the amount of research and development expenditure cannot be truly measured due to the flow index characteristic of "research and development expenditure of medium-sized and above industrial enterprises." At the same time, GDP is calculated according to current price without excluding price factors, so the data of these two indicators are processed accordingly, while the data of other indicators are based on original data.

$$K_{it} = (1 - \delta_{it})K_i + I_{it}, \tag{8}$$

where K_{it} is the *R&D* capital stock of region I in phase T; I_{it} is the actual *R&D* expenditure of Region I in Phase T.

5. Model Results Analysis

This part first evaluates the relative efficiency of China's economic zone development in order to understand the realistic level of different economies. Then, based on the relative efficiency evaluation, the paper makes a projection analysis on the production front of the ineffective cities to determine the degree of improvement of the ineffective cities' attribute value and the ideal value of input–output. Finally, the evolution of economic development performance from a dynamic perspective is investigated to reveal the deep-seated reasons for low-carbon economic. Based on the above analysis, this model is used to measure the speed of economic zone development in China.

From the input-oriented perspective, in terms of pure technical efficiency, DEA is effective when the efficiency values are all greater than 1, indicating that technological innovation, especially energy technology and emission reduction technology innovation, has been fully utilized in the low-carbon economic development of these cities. When the efficiency values are all 1, the weak DEA is effective, indicating that technological innovation effects such as energy technology and emission reduction technology are more effectively played in these cities. When the efficiency values are all less than 1, DEA is invalid, indicating that technological innovations such as energy technology and emission reduction technology have not played their due role in these cities. For cities with ineffective DEA, by projecting the production front of ineffective cities, we can not only understand the use status of their factor inputs but also analyze the reasons for their ineffectiveness and determine the extent to which their attribute values should be improved and the ideal value of input–output.

The total factor productivity (TFP) change index (Malmquist) and technological progress change (TC) index were introduced to evaluate the relationship between low-carbon technologies and the performance of low-carbon economic development more directly. The dynamic evolution of the performance of low-carbon economic development in China's economic zones presents the following states:

(1) Technical changes and TFP changes are stable
(2) Technological changes and TFP changes show an increasing trend year by year
(3) Technological change and TFP change showed a decreasing trend year by year
(4) Technological changes and TFP changes present a state of fluctuation
(5) Technological change and TFP change direction are inconsistent

The predicted results of these five models are all possible. In the super-SBM model, we can better judge the implementation of low-carbon economy and YI by simulating these change curves.

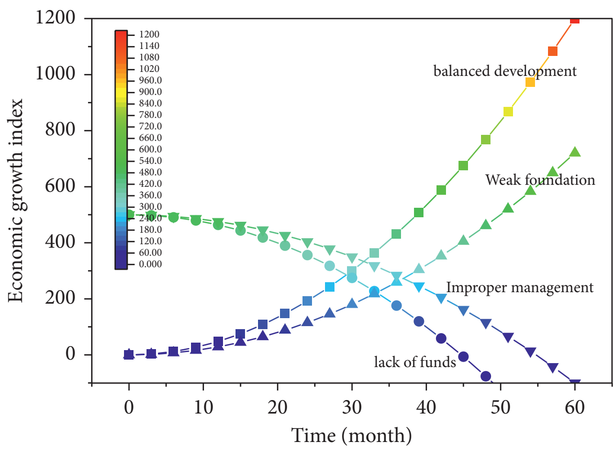

Figure 7: The development rate of low-carbon economy of four types of enterprises.

6. Regional Difference Analysis of Low-Carbon Economic Level

The ML index under technical conditions in period t can be expressed as follows:

$$\theta = \frac{1 + D\left(x^t, y^t, b^t, y^t, +b^t\right)}{1 + D\left(x^{t+1}, y^{t+1}, b^{t+1}, y^{t+1}, +b^{t+1}\right)} = \alpha \times \beta. \tag{9}$$

Where $\theta > 1$ indicates that the total increases, and vice versa represents a decrease, that is, the frontier shift effect. If $\alpha > 1$, it proves that the frontier of efficiency has expanded, and economic progress or technological innovation has occurred, and vice versa. Economic decline hinders efficiency improvements. The economic efficiency index reflects the change degree of the distance between the decision-making unit and the efficiency frontier between the t period and the $t+1$ period, that is, the catch-up effect. $\beta > 1$ proves that the relative efficiency of the decision-making unit is improved compared with the previous period, and the green resources are well utilized. If it is close to the frontier, on the contrary, the relative efficiency will regress, and the resource utilization will be poor, which is gradually far away from the efficiency frontier. Use this formula to analyze the development rate of low-carbon economy through enterprises. From Figure 7, we can see that balanced growth enterprises develop the fastest low-carbon economy and enterprises that are short of funds and improperly managed all show negative growth.

The super-SBM model is used to analyze and calculate the efficiency of China's low-carbon economic development. In order to compare the regional differences of the impact of low-carbon environment on economic efficiency in different regions of China. The ML index can evaluate the factor input according to the results of the frontier function and can also effectively deal with the data fluctuation of economic output and environmental output. The model budget of eastern China remains at an efficient level of 0.8, while that of Central China is only around 0.5 and that of western China is only around 0.35. Traditionally, we believe that less-developed regions are likely to have better pollution emissions, environmental quality, and low-carbon approaches than economically developed provinces due to industrial underdevelopment. The results contradict the judgment that developed eastern China is economically superior to central and western China, but central China is the best in terms of controlling environmental pollution and maintaining less pollution. This can also be confirmed by Figure 8, which shows that the index is more comprehensive in the central region, followed by the western and eastern regions.

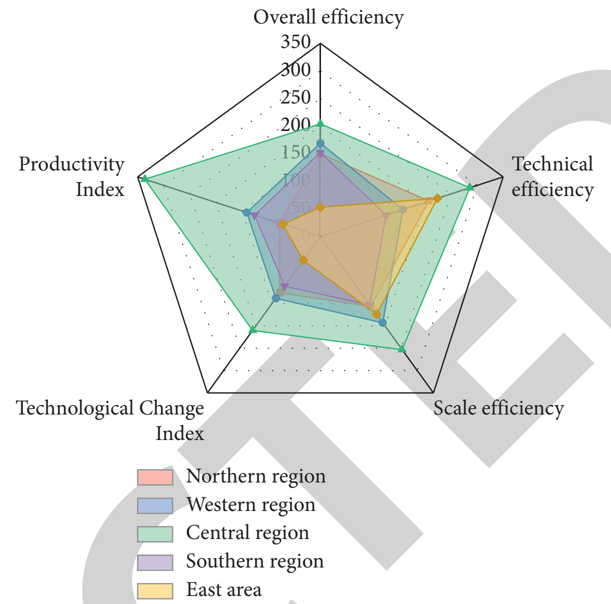

Figure 8: Distribution map of low carbon index in various regions.

7. Conclusion

The super-SBM model is used to analyze relative evaluation efficiency of low-carbon economic, projection performance of production frontier, and the dynamic evolution characteristics of the relative evaluation efficiency of low-carbon economic development in China. From the perspective of the dynamic evolution of low-carbon economic performance, technological change and TFP change have strong similarities. Different from other research methods, the SOM model can effectively deal with the analysis of China's economic situation because of its applicability, accuracy, and validity. This study establishes a research model of economic development efficiency from the perspective of low-carbon development. The following conclusions can be drawn: (1) the efficiency of green innovation considering undesired output is lower than that of traditional innovation without considering undesired output. (2) China's overall low-carbon economy development level is low, but the overall efficiency of green innovation in China is increasing, but the average efficiency is relatively low, showing inefficiency, and there is a large room for progress. (3) The average ML index of China's green innovation efficiency is greater than 1, in which technical efficiency and technological progress jointly lead to the improvement of China's green innovation level.

The impact of technological progress is greater than that of technical efficiency, and its convergence with the ML index is higher. (4) There is a big difference in the development level of low-carbon economy among the three major regions of China, east, middle, and west. The eastern region is characterized by relatively low-carbon development, and the western region is the most backward, with the highest carbon emissions, but the weakest development capacity, with obvious high-carbon characteristics; the central region is located between the two. (5) The super-SBM model can be effectively used to analyze the evaluation of low-carbon economy.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

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