IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 23 December 2023, accepted 5 January 2024, date of publication 8 January 2024, date of current version 1 February 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3351468

RESEARCH ARTICLE

The Optimization of Carbon Emission Prediction in Low Carbon Energy Economy Under Big Data

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ABSTRACT With the intensification of global climate change, low-carbon energy has become a hot topic, and governments around the world are implementing corresponding policies to promote its use. This research first establishes a Multi-universe Quantum Harmony Search-Algorithm Dynamic Fuzzy System Ensemble (MUQHS-DMFSE) composite model for carbon emission prediction. This model combines the MUQHS algorithm with the DMFSE method by designing the workflow of the MUQHS algorithm, creating a DMFSE composite prediction model, introducing a sliding factor matrix, and using the MUQHS algorithm to search for the optimal sliding factors, thus obtaining optimized prediction values. In the research on low-carbon economic development, the research applies the Data Envelopment Analysis (DEA) method and establishes Charnes-Cooper-Rhodes (CCR) and Banker-Charnes-Cooper (BCC) models to assess the technical efficiency, pure technical efficiency, and scale efficiency of decision-making units. This research also uses the BCC model to project the production frontier and calculate input redundancy and output gap rates, and evaluate low-carbon economic development. Through the establishment and application of these two models, the research achieves carbon emission prediction and low-carbon economic analysis, validating the feasibility of the research methodology. The results show that the composite model can effectively predict carbon emissions, with a Mean Absolute Percentage Error (MAPE) below 3.5% and Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) below 200 tons, demonstrating the feasibility and accuracy of the model. The research on low-carbon economic development in S Province based on the DEA method reveals the need for energy structure adjustment, clean and renewable energy promotion, control of carbon emissions, and optimization of industrial structure with a focus on developing the tertiary industry. Therefore, the use of artificial intelligence and big data analysis can provide more precise insights into the trends and patterns of low-carbon economic development, as well as more effective predictions of future energy demand and resource supply, offering high practical value and scientific significance.

INDEX TERMS Low-carbon energy, MUQHS-DMFSE composite model, low-carbon economy, energy demand, resource supply.

I. INTRODUCTION

A. RESEARCH BACKGROUND AND MOTIVATIONS

As the global economy rapidly develops and the population continues to grow, energy demand is constantly rising. Additionally, environmental issues are becoming increasingly prominent, with challenges such as climate change and air pollution urgently needing to be addressed [1], [2]. In this context, low-carbon energy has gradually become the focus of attention for governments and businesses worldwide, including renewable energy sources (such as wind and solar power) and clean energy sources (such as natural gas and nuclear power) [3], [4]. Artificial intelligence (AI) technology can help formulate low-carbon energy policies and plans,

The associate editor coordinating the review of this manuscript and approving it for publication was Giacomo Fiumara.

optimize energy production and utilization methods, and improve energy efficiency and supply security through rapid and accurate prediction and analysis of various factors [5], [6]. Additionally, big data technology can assist in collecting, integrating, and analyzing energy-related data, thereby gaining a better understanding of the energy market and industry characteristics and supporting decision-making and practices for low-carbon energy development.

However, the exploation on the application of AI and big data in the context of the low-carbon energy economy is still in a continuous development phase. Current research focuses on how to fully harness the potential of AI and big data in energy system planning, intelligent energy management, and smart energy interactions to achieve more sustainable, efficient, and environmentally friendly energy development. Additionally, researchers are also facing challenges such as data privacy and security, for which innovative solutions need to be found. In the ongoing exploration, AI and big data will continue to provide crucial support for the sustainable development of the low-carbon energy economy, driving the energy sector towards a more intelligent and environmentally friendly future.

B. RESEARCH OBJECTIVES

The objective of this research is to establish a composite model named Multi-universe Quantum Harmony Search-Algorithm Dynamic Fuzzy System Ensemble (MUQHS-DMFSE) for predicting carbon emissions. Simultaneously, it employs the Data Envelopment Analysis (DEA) method to evaluate and analyze the level of development in the context of a low-carbon economy. Empirical research is conducted to validate the effectiveness and practicality of the established models. The research uses S Province and BP Company as examples to examine both models, determining their feasibility and applicability. This research aims to provide theoretical support and practical analysis to promote clean energy, sustainable development, enhanced energy efficiency and economic benefits, industrial transformation and upgrading, technological innovation, and the enhancement of national competitiveness and influence.

This research introduces an innovative MUQHS-DMFSE composite model to predict carbon emissions in the low-carbon economy, making important research innovations and contributions. Firstly, the model combines the MUQHS algorithm and DMFSE method, and improves the flexibility and efficiency of the prediction model through clever design and workflow optimization. In particular, the sliding factor matrix is introduced, and the model can be adaptively adjusted in the dynamic environment through the optimization of the MUQHS algorithm, which can more accurately capture the trend of carbon emissions. Secondly, the DEA method is applied in the research of low-carbon economy, and the Charnes-Cooper-Rhodes (CCR) and Banker-Charnes-Cooper (BCC) models are established to comprehensively evaluate the efficiency of decision units. This method provides a new perspective for understanding the efficiency of decision units in the low-carbon economy, and provides data support for developing more accurate policies. The most important innovation is the empirical study part. The prediction performance and the application potential of the model in the study of low-carbon economic development are verified through the application in S province of China. The results show that the model performs well in carbon emission prediction, and provides a scientific basis for the development of low-carbon economy. All these contributions will enrich the research methods in the field of low-carbon economy, provide practical tools and guidance for policy formulation and strategic planning, and promote the realization of environmental protection and sustainable development goals.

II. LITERATURE REVIEW

Liu et al. proposed that research on the optimized development of a low-carbon energy economy based on AI and big data analysis would contribute to the application and promotion of low-carbon energy technologies, facilitate the coordinated development of energy and the environment, and accelerate the achievement of a low-carbon economy and sustainable development goals [7], [8]. Xu et al. pointed out that significant progress had been made in the research on the optimized development of a low-carbon energy economy based on AI and big data analysis [9], [10]. Feng and Chen proposed an AI algorithm-based optimization approach for low-carbon energy dispatch, which utilized AI algorithms such as neural networks and particle swarm optimization to minimize carbon emissions and costs in the power system [11], [12]. Chen and Du participated in a research project named "Energy Plan" and achieved good results by utilizing AI algorithms to optimize the dispatch of power systems, aiming to minimize carbon emissions and costs [13], [14]. Jian et al. analyzed energy consumption patterns and market demand using big data techniques to assist companies in formulating rational energy planning and management strategies, thereby minimizing energy consumption [15], [16]. Wang et al. advocated the vigorous promotion of the "Smart Energy" strategy in the field of energy, leveraging technologies such as the Internet of Things (IoT) and cloud computing to achieve intelligent management of energy systems, optimize energy structure, reduce carbon emissions, and improve energy efficiency [17], [18]. Tama et al. utilized technologies such as the IoT and cloud computing to realize real-time monitoring and management of the power grid, enhance the security and stability of the grid, and reduce energy waste and carbon emissions [19], [20]. Yao et al. achieved intelligent management of urban energy, optimization of urban energy structure and supply modes, reduction of carbon emissions, and improvement of urban sustainability through the application of AI and big data technologies [21], [22]. Li et al. mentioned that Japan had also actively implemented the "Smart Energy" strategy in the field of energy, utilizing big data analysis of energy consumption patterns and market demand to formulate rational energy planning and management strategies, minimize energy consumption, and improve energy efficiency through measures such as constructing smart grids [23], [24]. Wang et al. participated in a research project called "Smart Cities and Sustainable Development," which utilizes AI and big data technology to achieve intelligent management of urban energy, optimize urban energy structure and supply methods, reduce carbon emissions, and improve the sustainable development level of cities [25], [26].

Existing literature has extensively explored the research on optimizing low-carbon energy economies using AI and big data analytics technologies, achieving significant progress in various aspects. From a research perspective, studies have considered the application of low-carbon technologies and the coordinated development of energy and the environment from a macro level. They have also delved into the economic and low-carbon dispatch of specific systems from a micro level. In terms of research methods, common AI algorithms include neural networks, particle swarm optimization, etc., while big data technologies are represented by the IoT and cloud computing. In terms of research objects, studies have targeted power systems as well as urban or corporate levels. Although there are different research perspectives, they all emphasize the use of AI and big data technologies for intelligent analysis and optimization of complex energy systems, reducing carbon emissions, and improving economic, environmental, and societal benefits. However, there are still some shortcomings in the existing literature. Firstly, most studies are limited to specific systems and specific algorithms, lacking comparative analysis of various algorithms and models. Secondly, empirical research cases are relatively scarce, mostly staying in the theoretical analysis stage, and the actual application effects require further validation. Thirdly, the interpretability of algorithms and models is weak, making it difficult to delve into their underlying mechanisms of operation. Therefore, future research should strengthen the comparison of different models, expand the cases of empirical research, and enhance the interpretability of algorithms in order to obtain more scientific and interpretable research conclusions. This will provide more valuable theoretical support and practical guidance for the development of low-carbon energy economies.

III. RESEARCH METHOD

A. MUQHS-DMFSE COMBINATION MODEL FOR PREDICTING CARBON EMISSIONS

The MUQHS-DMFSE combination model is a predictive model that combines the Multi-universe Quantum Harmony Search Algorithm (MUQHS) and the Dynamic Fuzzy System Ensemble (DMFSE) method [27], [28]. MUQHS is a heuristic algorithm inspired by the multiverse theory of quantum physics [29]. It uses ideas similar to quantum computing, dividing the search space into multiple different universes and applying and updating search strategies in each universe [30], [31]. This algorithm is commonly used to solve optimization problems and classification and regression problems in machine learning [32], [33]. The DMFSE method is a DMFSE method that can combine the outputs of multiple models with weights to improve the accuracy and stability of predictions [34], [35].

The MUQHS is a heuristic intelligent optimization algorithm inspired by the multiverse theory in quantum physics. This algorithm divides the search space into multiple distinct subspaces or 'universes,' where each universe employs different search strategies for individuals and cooperatively optimizes the problem, thereby enhancing the diversity and efficiency of the search. Specifically, the MUQHS algorithm begins with problem initialization, including algorithm parameter settings and configuring the Harmony Memory. Then, within each universe, new Harmonies (harmony vectors) are generated through operations such as random selection and Pitch Adjustment. Subsequently, the algorithm employs quantum computational concepts like quantum rotation gates to propagate information between adjacent universes, facilitating collaborative searching across different universes. Finally, through operations like memory updates, it iteratively obtains the optimal solution. Compared to the traditional single-universe Quantum Harmony Search (QHS) algorithm, MUQHS introduces universe hierarchies and quantum mechanisms, significantly improving the algorithm's global search capabilities.

This algorithm has been successfully applied in various fields, such as combinatorial optimization, machine learning, and engineering design optimization. In this research, the authors integrate the MUQHS algorithm with the DMFSE method to construct a carbon emission prediction model. MUQHS is employed to search for optimal parameters of the dynamic fuzzy system, thereby enhancing prediction accuracy.

The DMFSE method is an approach that integrates outputs from multiple fuzzy systems. DMFSE employs various fuzzy systems to perform fuzzy classification on a sample data set, obtaining the probabilities of each sample belonging to different categories. It then calculates the weights of different fuzzy systems using the mean squared error method and combines the outputs of various systems. Compared to a single fuzzy system, DMFSE significantly improves prediction robustness.

In this study, the researchers establish multiple fuzzy logic systems, utilize the MUQHS algorithm to optimize sliding factors, construct a DMFSE ensemble model, and apply it to carbon emission prediction. This method fully leverages the optimization capabilities of MUQHS and the ensemble learning characteristics of DMFSE, leading to a significant improvement in the accuracy and robustness of carbon emission prediction. The organic integration of these two algorithms provides an effective new approach to carbon emission prediction and offers insights for modeling other complex systems. It demonstrates the promising application prospects of AI technology in sustainable development and the transition to a low-carbon economy.

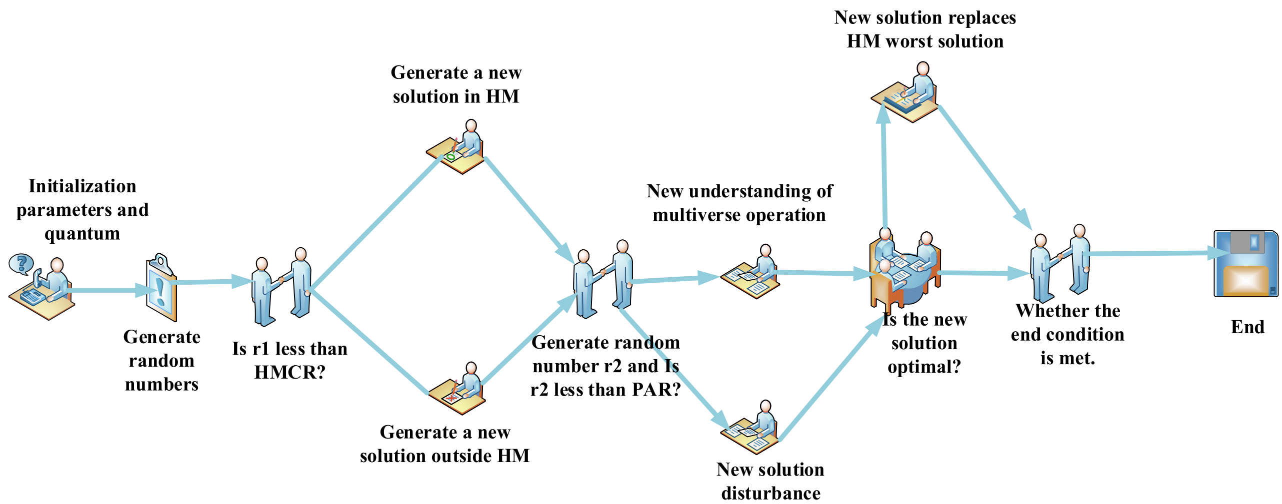

FIGURE 1. The process of the MUQHS algorithm.

The specific steps of the prediction are as follows:

Step 1: Design the MUQHS algorithm. The flowchart of the MUQHS algorithm is shown in Figure 1:

In Figure 1, the MUQHS algorithm consists of six steps. Firstly, the problem is initialized, and parameters and quantum are initialized. Then, a random search is conducted on quantum and harmony using the HMCR probability. Subsequently, local perturbations are applied to harmony using PAR. Next, multi-universe operations are performedon the new quantum and harmony, generating multiple sub-universes near the mother universe and increasing the number of new quantum and harmony. Then, the newly generated solutions are evaluated and judged. If the new solution is superior to the previous worst solution, the solution set is updated; otherwise, the new solution is abandoned. The uniqueness of the MUQHS algorithm lies in its incorporation of quantum and multi-universe operations, which enhances the diversity and breadth of the search, thus overcoming the limitations of traditional optimization algorithms. Through problem initialization and parameter settings, the algorithm can explore solutions with better fitness in the search space. By combining steps such as random search, local perturbations, and multi-universe operations, the algorithm continuously optimizes the solution set, enabling intelligent analysis and optimization of energy systems. This will contribute to improving the efficiency and reliability of energy systems, reducing energy costs, and promoting the development and application of low-carbon energy.

Step 2: Establish the DMFSE combination predictive model.

This method uses each fuzzy logic classifier to classify the dataset and generate a probability output. These probability outputs are combined to form an ensemble output. The expression for the DMFSE combination predictive model is given by Eq. (1):

$$\hat{a}_t = \sum\nolimits_{i=t}^{n} w_i \hat{a}_t^i \tag{1}$$

In (1), $\hat{a}_t^i$ represents the predicted value of the i-th predictive model for year t, w_i represents the weight coefficient of the i-th model, $\hat{a}_t$ represents the predicted value of the combined model for year t, and n represents the number of models. The DMFSE method uses mean square error to calculate the weights, as shown in Eq. (2), at the bottom of the next page.

γ represents the discount factor, and T represents the data length used for weight calculation. By substituting Eq. (2) into Eq. (1), the DMFSE model can be obtained as shown in Eq. (3), at the bottom of the next page.

Step 3: Complete the DMFSE combination predictive model optimized using the MUQHS algorithm.

In order to eliminate the error between actual values and predicted values at different time points, this research transforms the discount factor γ in the weight calculation process into a matrix $\gamma_{n\times T}$. The weight equation and the modified predictive model become Eqs. (4) and (5), as shown at the bottom of the next page, respectively.

Step 4: Select the optimal matrix of discount factors. In order to avoid blindly selecting P, which may lead to unsatisfactory predictive performance, the determination of the discount factor matrix $\gamma_{n\times T}$ is treated as an optimization problem of an objective function. The MUQHS algorithm searches for the optimal discount factors for different prediction time points and models [36], [37].

Step 5: Substitute the optimal discount factors into the model to obtain the optimal predicted values.

In the model, each predictor has a unique impact on performance. The sliding factor matrix is optimized by MUQHS algorithm, and the model is adjusted to adapt to data changes.

For example, the MUQHS algorithm is able to find the optimal combination of sliding factors at different points in time, making the model more sensitive to capture the changing trend of the system, thus improving the prediction accuracy of unknown data. The quantum harmonic search space enhances the global search ability and helps to find the global optimal solution. By simulating the search space of multiple universes, the algorithm is more likely to avoid falling into local optimality, improve the global search effect of the model, ensure the adaptability to diverse data, and thus improve the accuracy of the prediction. The input variables of dynamic fuzzy systems help the model adapt to the dynamic changes inside the system. For example, in economic development, input variables may include real-time economic indicators, environmental changes, etc., making the model more flexible, better coping with complex system dynamics, and improving the model's degree of fitting to the actual situation. The input and output indicators of low-carbon economic development reflect key economic, resource and environmental factors. By using these indicators, the model can more comprehensively understand the development of low-carbon economy, while taking into account many factors such as economic structure, resource utilization and environmental impact in the forecast, making the forecast more comprehensive and accurate.

B. LOW-CARBON ECONOMIC DEVELOPMENT BASED ON THE DEA METHOD

DEA is a commonly used non-parametric efficiency evaluation method used to assess the relative efficiency among different Decision-Making Units (DMUs). The fundamental models of DEA include the CCR model and the BCC model. The CCR model assumes uniform input and output proportions for all DMUs, while the BCC model allows for variations in input-output proportions among different DMUs. Through DEA analysis, it is possible to identify which DMUs are more efficient in resource utilization and provide improvement recommendations. DEA requires no predefined function forms or distribution assumptions, making it applicable across various industries and domains. This method holds wide-ranging value in efficiency assessment, performance management, and decision support. The specific steps of this method are as follows:

Step 1: Establish the CCR model.

In the CCR model, assuming there are n DMUs and each unit has m inputs and n outputs, the evaluation efficiency index f_j is represented by Eq. (6):

$$f_j = \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{n} v_i x_{ij}}, \quad (j = 1, 2, \cdots, n) \tag{6}$$

In Eq. (6), u_r and v_i denote the output and input weight coefficients, x_{ij} represents the input quantity of the j-th decision-making unit for the i-th input, and y_{rj} represents the output quantity of the j-th DMUs for the r-th output. This is illustrated in Eqs. (7), (8), and (9):

$$x_j = \left(x_{1j}, x_{2j}, \cdots, x_{mj}\right)^T > 0 \tag{7}$$

$$y_j = \left(y_{1j}, y_{2j}, \cdots, y_{sj}\right)^T > 0 \tag{8}$$

$$u = (u_1, u_2, \cdots u_s)^T, \quad v = (v_1, v_2, \cdots v_m)^T \tag{9}$$

By selecting suitable weight coefficients v and u, which are greater than or equal to 0, such that $f_i \leq 11$, the CCR model with the maximum efficiency index is obtained, as shown in Eq. (10):

$$h_0 = max \frac{u^T y_0}{v^T x_0} \tag{10}$$

$$w_i = \frac{1}{\left[\sum_{t=1}^{T} \gamma^{T-t+1}\left(a_t - \hat{a}_t^i\right)^2\right] \times \left\{\sum_{i=1}^{n} \mid \Sigma_{t=1}^{T} \gamma^{T-t+1}\left(a_t - \hat{a}_t^i\right)^2\right]^{-1}\right\}} \tag{2}$$

$$\hat{a}_t = \sum_{i=t}^{n} w_i \hat{a}_t^i = \sum_{i=t}^{n} \frac{\hat{a}_t^i}{\left[\sum_{t=1}^{T} \gamma^{T-t+1}\left(a_t - \hat{a}_t^i\right)^2\right] \times \left\{\sum_{i=1}^{n}\left[\sum_{t=1}^{T} \gamma^{T-t+1}\left(a_t - \hat{a}_t^i\right)^2\right]^{-1}\right\}} \tag{3}$$

$$w_i = \frac{1}{\left[\sum_{t=1}^{T} \gamma_{it}^{T-t+1}\left(a_t - \hat{a}_t^i\right)^2\right] \times \left\{\sum_{i=1}^{n}\left[\sum_{t=1}^{T} \gamma_{it}^{T-t+1}\left(a_t - \hat{a}_t^i\right)^2\right]^{-1}\right\}} \tag{4}$$

$$\begin{aligned} \hat{a}_t &= \sum_{i=t}^{n} w_i \hat{a}_t^i \\ &= \sum_{i=t}^{n} \frac{\hat{a}_t^i}{\left[\sum_{t=1}^{T} \gamma_{it}^{T-t+1}\left(a_t - \hat{a}_t^i\right)^2\right] \times \left\{\sum_{i=1}^{n}\left[\sum_{t=1}^{T} \gamma_{it}^{T-t+1}\left(a_t - \hat{a}_t^i\right)^2\right]^{-1}\right\}} \end{aligned} \tag{5}$$

TABLE 1. Initial results of low-carbon energy economy indicators data based on DEA method in provinces.

Indicator		2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
T	A	3962	4387	4396	4457	5017	6006	6669	7139	7325	7896	8707	9570	9358
	B	867	938	1015	1427	1526	2244	3168	4534	5496	7067	8354	8640	9730
	C	3351	3463	3500	3545	3595	3670	3741	3818	3916	3988	4050	4120	4207
O	D	2952	3160	3464	3788	4292	4763	5360	6119	6894	7786	8922	9127	9353
	E	40	48	40	42	39	40	39	38	37	36	34	33	33
	F	2.4	2.3	2.2	2.0	1.9	1.8	1.7	1.5	1.3	1.2	1.1	1.0	0.9

In Eq. (10), $max \frac{u^T y_0}{v^T x_0} \leq 1$ $(j = 1,2, \cdots, n)$, $u > 0$, $v > 0$. Let $\frac{1}{v^T x_0} = t > 0$, $w = tv$, $\mu = tu$, the CCR linear model is shown in Eq. (11):

$$T_{ccR}\begin{cases} h_0 = max \mu^T y_0 \\ w^T x_j - \mu^T y_j \geq 0 \\ w^T x_0 = 1 \\ \omega \geq 0 \\ \mu \geq 0 \end{cases} \tag{11}$$

In practical applications, the dual form of the slack variable is introduced to evaluate the scale and technical efficiency of DMUs, as shown in Eq. (12):

$$Q_{CCR}\begin{cases} \min \varepsilon \\ \sum_{j=1}^{n} x_j \lambda_j + s^- = \varepsilon x_k \\ \sum_{j=1}^{n} y_j \lambda_j + s^+ = y_k \\ \lambda_j \geq 0; \varepsilon \in E \\ s^+ \geq 0; s^- \geq 0 \end{cases} \tag{12}$$

In Eq. (12), λ_j represents the combination proportion of the j-th DMUs, ε represents the radial optimization quantity, and s^+ and s^- are slack variables.

Step 2: The variable returns to scale BBC model is introduced based on this.

BBC model adds constraints to the CCR model, as shown in Eq. (13):

$$\sum_{j=1}^{n} \lambda_j = 1 \tag{13}$$

Step 3: Assessing DMUs Effectiveness

When $\varepsilon = 1, s^+ = 0, s^- = 0$, the DMU is effective. When $\varepsilon = 1$ and at least one of s^+ or s^- is greater than 0, the DMU is weakly effective. When $\varepsilon < 1$, the DMU is ineffective.

Step 4: Assessing DMU Scale Efficiency

If $\sum_{j=1}^{n} \lambda_j = 1$, he DMU has constant returns to scale. If $\sum_{j=1}^{n} \lambda_j > 1$, the DMU has increasing returns to scale, meaning that increasing inputs can enhance outputs. If $\sum_{j=1}^{n} \lambda_j < 1$, the DMU has decreasing returns to scale, indicating that increasing inputs does not improve outputs.

Step 5: Assessing Scale Efficiency $\frac{\sum_{j=1}^{n} \lambda_j}{\varepsilon} = 1$ indicates constant scale returns. $\frac{\sum_{j=1}^{n} \lambda_j}{\varepsilon} > 1$ implies decreasing scale returns. $\frac{\sum_{j=1}^{n} \lambda_j}{\varepsilon} < 1$ suggests increasing scale returns.

IV. MODEL PERFORMANCE EVALUATION

A. DATA COLLECTION

This research chose to test the performance of the carbon emission prediction model using data provided by BP. BP provides objective, high-quality, and globally consistent world energy data, including aspects such as oil, coal, natural gas, nuclear energy, and electricity generation. The data collection phase involved the application of big data technologies. Leveraging BP's globally sourced energy data, the experiment employed technologies like the IoT and cloud computing for extensive and in-depth production and emission data collection for various energy sources. This encompassed detailed analyses of multiple domains such as oil, coal, natural gas, and nuclear energy, ensuring the comprehensiveness and accuracy of the data. The data processing process included cleansing, integration, and transformation steps. Initially, this research performed data cleansing on the raw data, eliminating any potential anomalies or erroneous data. Subsequently, a comprehensive energy dataset was constructed by integrating data from different domains. Finally, the experiment transformed the data to meet the input requirements of the prediction model. BP and province S are used in this research as simulated data for case studies for the purpose of testing and validating the model. These entities do not represent existing companies or regions but demonstrate the model's applicability in different contexts. Through a detailed data collection and processing process, the experiment ensured the repeatability of the study and the credibility of the results. Additionally, the input and output indicator data of Province S in recent years are compiled and adjusted. The data obtained are presented in Table 1:

B. EXPERIMENTAL ENVIRONMENT

To better study the prediction of carbon emissions by the MUQHS-DMFSE combined model, this research selected data provided by BP Company to conduct performance testing on the model. BP Company offers objective, high-quality, and globally consistent world energy data, encompassing oil, coal, natural gas, nuclear energy, and electricity generation. China, India, and the United States are selected to test the robustness of the prediction model and forecast carbon emissions for these countries using different discount factors.

C. INDICATOR SELECTION

For the research on low-carbon economic development based on the DEA method, this research selected the low-carbon economic development situation in Province S as the research object. In recent years, Province S has experienced rapid economic development, continuous expansion of the energy industry, and significant progress in the research and development of low-carbon technologies. The development momentum of a low-carbon economy is particularly strong in sectors such as agriculture and forestry. Based on this, two main categories of indicators are selected: input indicators (T) and output indicators (O) to assess the low-carbon economic development in Province S. The input indicators (T) include resource input (A), capital input (B), and labor input (C). The output indicators (O) include the gross domestic product (GDP) (D), the proportion of the added value of the tertiary industry to GDP (E), and carbon emissions (F). Resource input includes the input of resources such as energy and raw materials to support production and economic activities. This indicator reflects the extent to which the economic system uses natural resources and the consumption of environmental resources in the production process. Capital input, which involves investment in production assets and technical equipment, reflects the degree of utilization of capital facilities in the economic development of the province. The level of capital investment can affect productivity and economic growth. Labor input measures the input of labor in the production process. This includes factors such as the number of workers and the quality of the labor force, which is crucial for understanding the employment situation and the efficiency of human resource utilization in the province. The output indicator, GDP, is a measure of the overall size of a region or country's economy. The growth of GDP is usually related to the level of economic development and the increase of productive activities, and is a key economic indicator in a low-carbon economy. The ratio of value-added of the tertiary industry to GDP reflects the contribution of the service industry to the overall economy. In the development of low-carbon economy, the service industry is usually relatively low-carbon, so the increase of this proportion may indicate the optimization of the structure of low-carbon economy. Carbon emissions represent the amount of carbon dioxide emitted per unit of GDP output. This is a key environmental indicator used to assess the relationship between economic growth and carbon emissions. The development of low-carbon economy is usually accompanied by effective control and reduction of carbon emissions. The unique nature of these variables is their adaptability, which helps the model better cope with dynamic changes within the system. For example, real-time economic indicators and environmental change data help models make more accurate predictions in different stages of economic development and environmental contexts.

D. RESEARCH RESULTS

1) PERFORMANCE TESTING OF THE MUQHS-DMFSE COMBINED MODEL FOR CARBON EMISSION PREDICTION

The MUQHS-DMFSE composite model is introduced with the sliding factor matrix as one of the key predictors. The sliding factor matrix is used to describe the changing trend of each influencing factor in the system. By introducing a quantum harmonic search algorithm, the model looks for the optimal combination of sliding factors, so that it can adapt to the data changes at different time points. These optimized sliding factor matrices are used in the prediction process of the model to adjust and optimize the performance of the model. Specifically, the sliding factor matrix's role in capturing trends in carbon emissions is to balance past and current influences, ensuring that the model is adaptable to both historical data and the latest trends. The MUQHS algorithm generates multiple search Spaces in multiple universes, where each search space corresponds to a possible sliding factor matrix. These search Spaces constitute another important set of predictors in the model. By simulating these universes, the algorithm can find the optimal solution in different search Spaces, thus improving the global search ability of the model and enhancing the accuracy of the prediction. The unique nature of the space is that it provides a global search capability to help capture complex carbon emission patterns. The introduction of quantum harmonic search space enhances the global adaptability of the model and ensures that it can obtain reliable prediction results in different countries and regions. In DMFSE method, dynamic fuzzy system integration involves a series of input variables, which are used to construct a dynamic fuzzy system to deal with the dynamic changes within the system. These input variables may include economic, energy and environmental factors to capture more fully the complexity of the system and improve the ability to predict the development of a low-carbon economy. Finally, through the optimization of MUQHS algorithm and DMFSE method, the model generates a set of optimized predictor variables, which are adjusted and optimized to make the model predict carbon emissions more accurately. These optimized predictors are used in performance tests to verify the feasibility and accuracy of the model by comparing with actual values and evaluating using metrics such as MAE, RMSE and MAPE. In this research, the model's performance is evaluated by comparing predicted values and actual values in China, the United States, and India, as well as comparing predictions with different discount factor values and three numerical indicators. Figure 2 illustrates the actual and predicted carbon emissions in China, India, and the United States from 2012 to 2022.

In Figure 2, China and India show a growth trend, while the United States exhibits fluctuations. The predicted values closely align with the actual values for all years in the three countries. The sudden decline in carbon emissions is attributed to the impact of the COVID-19 pandemic, which led to reduced energy consumption. Despite this deviation, the overall prediction performance remains satisfactory. These results indicate the robustness of the proposed DMFSE combination prediction method based on the optimized MUQHS algorithm. Figure 3 presents the actual and predicted carbon emissions in China, India, and the United States for different discount factor values from 2012 to 2022.

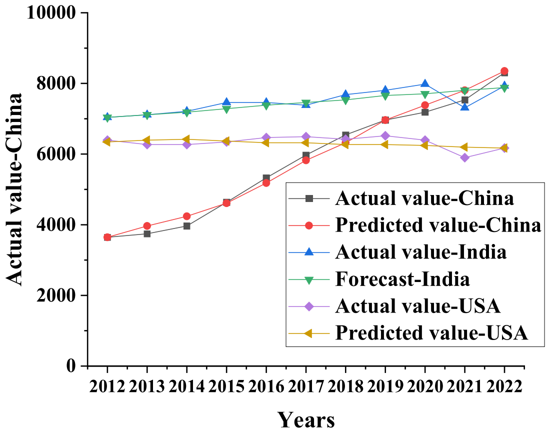

FIGURE 2. Actual and predicted carbon emissions in China, India, and the united states from 2012 to 2022.

In Figure 3, the discount factors are set as 0.1, 0.5, 1.0, and 1.5, with $\gamma^\wedge*$ representing the optimal discount factor for each country. The optimal discount factor for China is 1.0, for India is 0.00002759, and for the United States is 0.00002219. The predicted models align well with the actual situation.

In Figure 3, the national carbon emission statistics for China, India, and the United States are sourced from the China Association of Automobile Manufacturers (CAAM, http://www.caam.org.cn/), the Central Statistics Office (CSO, https://mospi.gov.in/central-statistical-office-cso), and the Environmental Protection Agency (EPA, https://www.epa.gov/), respectively. Due to recent overall environmental instability, the actual carbon emissions in the United States may be subject to some fluctuations. This is because carbon emissions are influenced by various factors, including economic development, energy policies, technological innovations, and more. Changes in the global economic and policy landscape and fluctuations in the energy market can all lead to differences between the actual and predicted carbon emissions in the United States. Furthermore, the significant fluctuations in actual carbon emissions shown in Figure 3(c) may also be related to adjustments in the domestic energy structure. In recent years, the United States has been increasing its investment and promotion of clean energy while gradually reducing its reliance on traditional energy sources such as coal and oil. This shift in the energy structure may result in more complex and uncertain changes in carbon emissions, leading to significant fluctuations in actual values. Therefore, the substantial fluctuations in actual carbon emissions in the United States are primarily attributed to the overall environmental instability and adjustments in the domestic energy structure. Consequently, this research needs to consider the combined effects of multiple factors when making carbon emission predictions to forecast future carbon emission trends. However, the predictions still remain largely consistent. Figure 4 displays the MAPE values for the three countries under different discount factors.

In Figure 4, the Mean Absolute Percentage Error (MAPE) for the three countries remains below 3.5 under different discount factors. The model exhibits the smallest MAPE value for carbon emission predictions in India, particularly when the optimal discount factor is selected. China has the highest MAPE value, exceeding 2.5, followed by the United States, which surpasses 2.0. India, on the other hand, shows

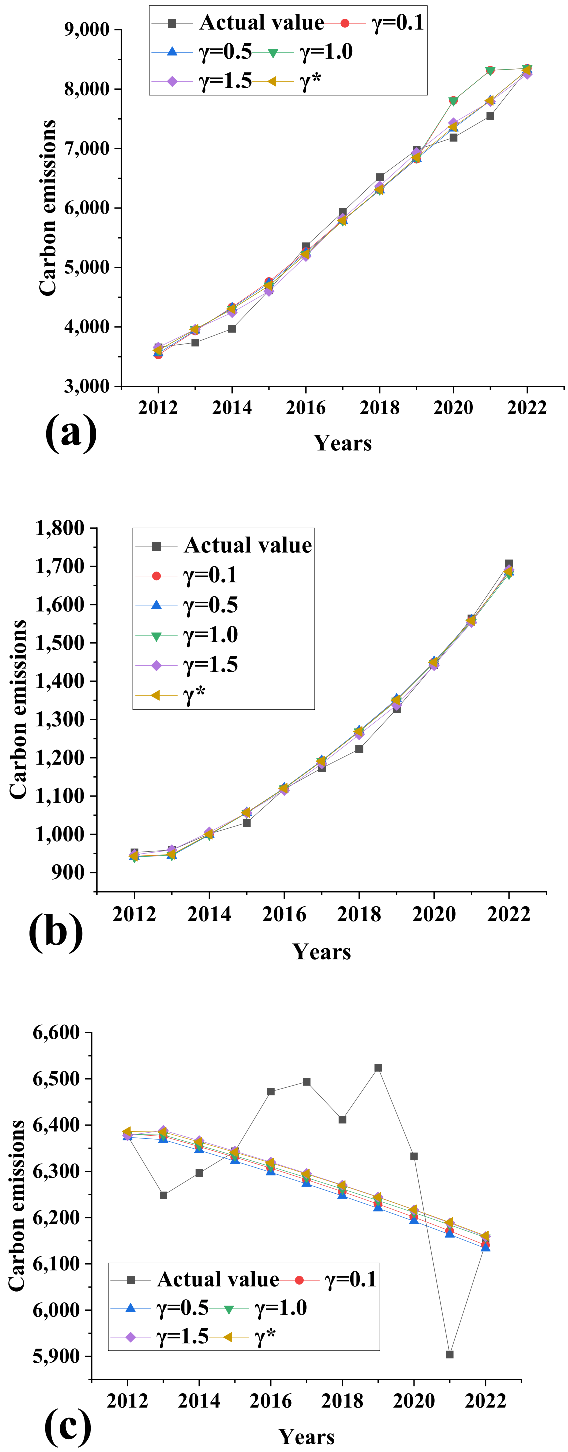

FIGURE 3. Carbon emission predictions under different discount factors from 2012 to 2022 ((a) China's carbon emission prediction; (b) India's carbon emission prediction; (c) United states' carbon emission prediction).

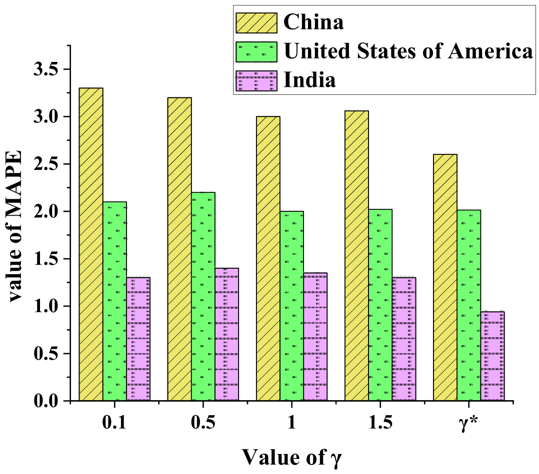

FIGURE 4. MAPE values for the three countries under different discount factors.

the lowest MAPE value, around 1.0. Figure 5 displays the MAE and RMSE values for the three countries under different discount factors.

In Figure 5, the Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) for the three countries under different discount factors remain within a manageable range, staying below 200 tons. Among them, India exhibits the smallest error, consistently below 30. The data demonstrates the model's stability and indicates a lack of technological innovation in resource utilization in India, reflecting the current state of its economic development. Figure 6 illustrates the carbon emission predictions for the three countries in 2022.

In Figure 6, it is evident that in terms of carbon emission predictions, the United States has the smallest deviation compared to the actual values. In terms of relative error, China exhibits the smallest relative error of only 0.34. The relative errors for the other two countries are also controlled below 3.2, further affirming the accuracy of the MUQHS-DMFSE combined model in predicting carbon emissions.

2) RESEARCH ON LOW-CARBON ECONOMIC DEVELOPMENT BASED ON THE DEA METHOD

This research analyzes the technical efficiency, pure technical efficiency, and scale efficiency through the CCR model and BCC model. The results are presented in Figure 7.

Inefficient DEA mainly results from ineffective utilization of input resources, leading to resource wastage. The suboptimal allocation of input factors contributes to the inefficiency in technical efficiency. Overall, Province S achieves high technical efficiency, reaching 0.9854. The pure technical efficiency is slightly lower than the scale efficiency, suggesting that in the process of developing a low-carbon economy in Province S, improving industrial structure, controlling the scale of labor-intensive and capital-intensive industries, and expanding the scale of high-tech industries can enhance the level of technical efficiency in economic development. For the DEA analysis, this research employs the BBC model

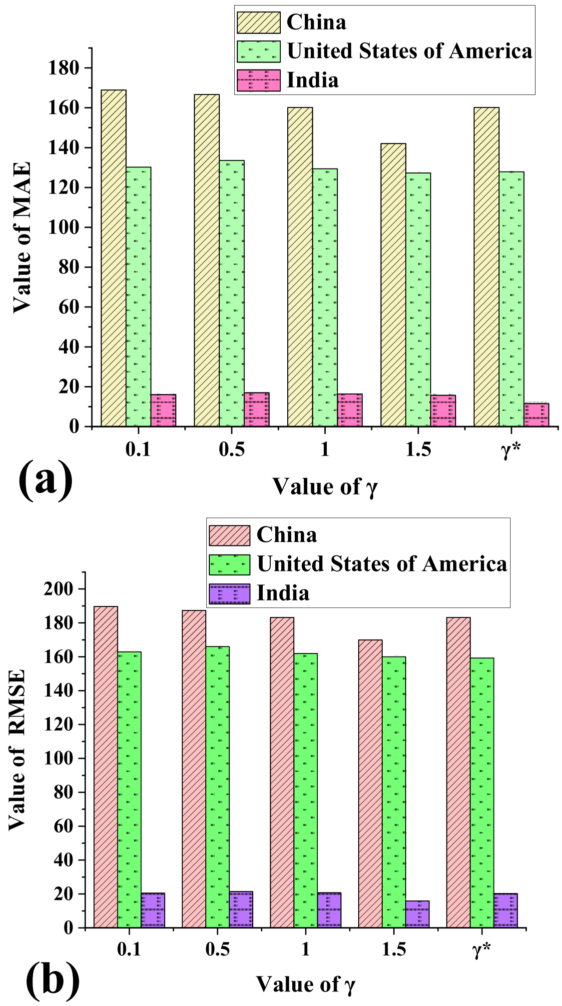

FIGURE 5. MAE and RMSE values for the three countries under different discount factors ((a) MAE values; (b) RMSE values).

to project the production frontier and calculate input redundancy rates and output shortfall rates. Figure 8 illustrates the DEA 2020 frontier projection analysis and the input redundancy rates and output shortfall rates for the period from 2015 to 2020.

In Figure 8, the 2020 frontier projection analysis indicates that there is no need to adjust total energy consumption, as it remains unchanged. However, other indicators require certain adjustments. The adjustment magnitude for the proportion of the tertiary industry is the smallest, requiring only a 119 adjustment. Based on the DEA method, the research on the low-carbon economic development in Province S identifies energy utilization as the main factor contributing to DEA inefficiency. While the GDP grows, the excessive carbon emissions resulting from a low proportion of the tertiary industry indicate the future development direction for Province S.

E. DISCUSSION

Optimizing the development of a low-carbon energy economy has always been a hot topic, and the emergence of AI and

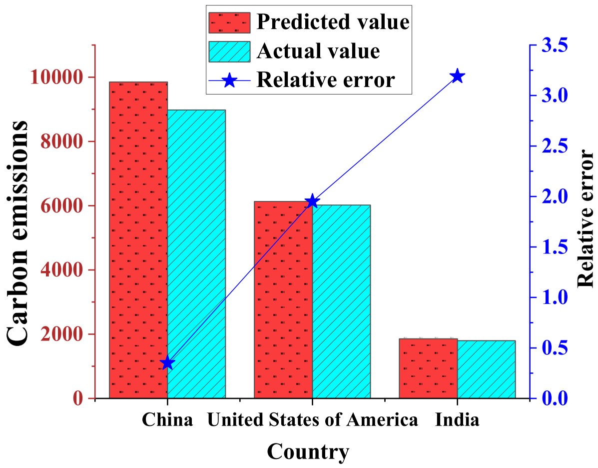

FIGURE 6. Carbon emission predictions for China, India, and the united states in 2022.

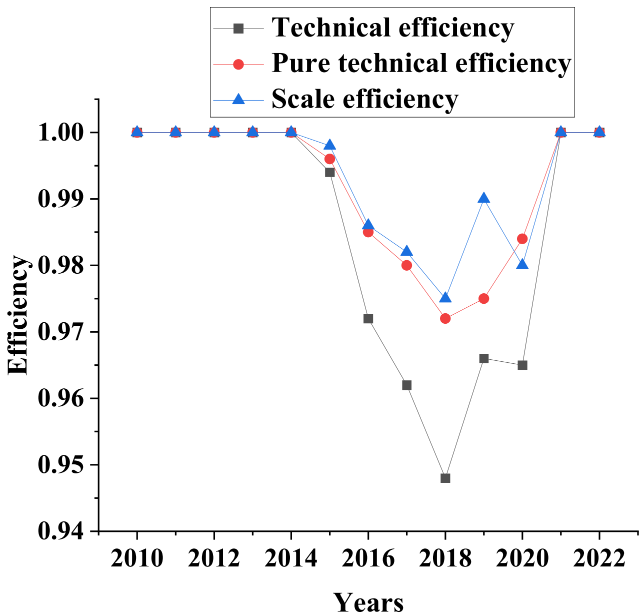

FIGURE 7. Analysis of low-carbon economic efficiency in province s from 2010 to 2022.

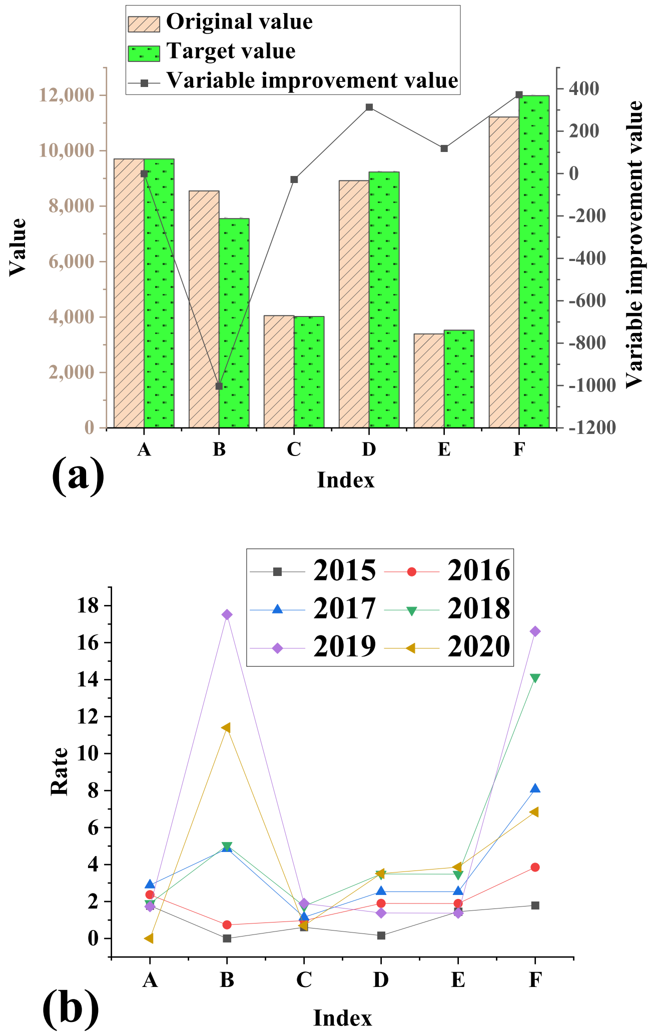

FIGURE 8. Projection analysis of the 2020 frontier of S Province and input redundancy rate and output deficit rate of each index from 2015 to 2020 ((a) 2020 Frontier Projection Analysis; (b) Input Redundancy Rates and Output Shortfall Rates from 2015 to 2020).

big data analytics technologies has brought new opportunities and challenges to this field. According to Krishna et al., AI algorithms and big data models are used to predict energy demand and price trends by analyzing historical data, current trends, and market factors. This can help companies make more accurate decisions for better production and operational planning [38], [39]. Furthermore, Wang et al. argued that utilizing AI algorithms and big data models enables intelligent analysis and optimization of various complex factors in energy systems, thereby improving the efficiency and reliability of the energy systems [40], [41].

Furthermore, the results of this research are compared with recent research literature on low-carbon energy economics that utilizes modern technologies. Jiang et al. [42] proposed an IoT energy efficiency framework applicable to heterogeneous small-cell networks. The research employed mathematical models and algorithms to optimize energy distribution and management within cells, aiming for efficient energy utilization and carbon emission reduction. By optimizing aspects like data transmission, energy supply, and distribution, the efficiency of cell networks was improved. Chen [43], based on digital twin technology, explored collaborative innovation research on key common technologies in the new energy vehicle industry. The research involved data modeling, analysis, and optimization of various aspects of new energy vehicles, proposing an innovation model based on digital twins. The results demonstrated the significant role of digital twin technology in the new energy vehicle industry. Lin et al. [44] achieved a non-intrusive decomposition of residential electricity loads through the low-resource model transfer method. The research employed constrained resource model transfer techniques to extract the main components of electricity load through data analysis and processing. The results indicated the excellent performance of this non-intrusive decomposition method in the precise analysis and assessment of residential electricity loads. Chen et al. [45] proposed an integrated energy system low-carbon economic dispatch method for short-term wind power output prediction. The research utilized predictive modeling of wind power output and optimized electrohydrogen production and distribution within the energy system to enhance energy efficiency and reduce carbon emissions. The results showed favorable performance of this method in the dispatch of integrated energy systems. Xiao et al. [46] conducted a comprehensive review of electric vehicle routing problems and introduced a new comprehensive model with nonlinear energy charging and discharging characteristics. By considering factors such as electric vehicle charging and discharging characteristics, energy consumption, and route planning, the research optimized electric vehicle charging routes, improving energy utilization. The results demonstrated the effectiveness of this comprehensive model in electric vehicle route planning. Cai et al. [47] explored methods for renewable energy systems to participate in electricity spot market bidding and settlement. The research involved modeling and optimization of energy output, costs, and market trading rules for renewable energy systems, proposing a method for energy systems to participate in the electricity spot market. The results indicated that this method effectively enhanced renewable energy systems' economic benefits and market participation capabilities.

In summary, the primary focus of the aforementioned literature research is that AI and big data analysis technologies play a crucial role in optimizing the development of a low-carbon energy economy. These technologies, through analyzing and predicting historical data, market trends, and relevant factors, can assist companies in making more accurate decisions, thereby improving production and operational planning. The research also demonstrates that the application of AI algorithms and big data models in energy systems can intelligently analyze and optimize various complex factors, enhancing the efficiency and reliability of energy systems.

This model has a wide range of potential applications in the real world, especially in the low-carbon energy economy. Firstly, the model can be applied at the government decision-making level to help formulate and optimize low-carbon policies. By predicting carbon emission trends, the government can more accurately adjust policies, promote industrial structure optimization, promote clean energy development, and effectively control carbon emissions. Secondly, the model also has important application value at the enterprise level. Enterprises can use this model to predict carbon emissions, develop environmental protection strategies, improve the efficiency of production processes, and consider carbon emissions in product design to achieve a balance between economic growth and environmental sustainable development. In addition, the model has potential applications for financial institutions. Financial institutions can use this model to evaluate the low-carbon economic development of enterprises, reduce investment risks, promote more capital flow to low-carbon and sustainable development fields, and promote the development of green finance. In practical application, the model can also provide a more comprehensive assessment of low-carbon economic development for the society, and guide the public to participate in and support low-carbon environmental protection activities more rationally. In general, the model, with its highly accurate forecasting performance and comprehensive consideration of multiple factors, provides strong decision support for decision-makers at different levels and promotes the sustainable development of low-carbon economy.

V. CONCLUSION

A. RESEARCH CONTRIBUTION

This research first establishes the MUQHS-DMFSE combination model for carbon emissions prediction. This model combines the MUQHS algorithm with the DMFSE method. By designing the workflow of the MUQHS algorithm and establishing the DMFSE combination prediction model, a sliding factor matrix is introduced. The MUQHS algorithm is used to search for the optimal sliding factor, thus obtaining optimized prediction values. In the research on low-carbon economic development, the DEA method is applied to establish CCR and BCC models to evaluate the technical efficiency, pure technical efficiency, and scale efficiency of decision units. The carbon emission prediction performance of the MUQHS-DMFSE combination model was tested, and the results showed that in the predictions for China, India, and the United States, the MAPE values were all below 3.5%, and the MAE and RMSE values were below 200 tons, verifying the feasibility and accuracy of the model. Additionally, this research conducted a DEA analysis of the low-carbon economic development situation in province S, calculated various efficiency values, and carried out a projection analysis. Recommendations for efficiency improvement were proposed. The research results showed that the MUQHS-DMFSE combination model could effectively predict carbon emissions with a MAPE below 3.5%, MAE below 200 tons, and RMSE below 200 tons, confirming the accuracy of the model. The technical efficiency in province S was found to be 0.9854, with pure technical efficiency slightly lower than scale efficiency. Adjusting the industrial structure and developing the tertiary industry were recommended. The province should also adjust its energy structure, promote clean energy, control carbon emissions, optimize industrial structure, and develop the tertiary industry to foster low-carbon economic development. Overall, this research, through the establishment of a carbon emission prediction model and a low-carbon economic evaluation method, along with empirical verification, has confirmed the effectiveness of the proposed methods. It provides important theoretical support and practical guidance for the development of a low-carbon economy.

The practical innovation contributions of this research can be summarized as follows: Firstly, employing the DEA method provides a comprehensive evaluation of the efficiency levels of different decision units, offering a scientific basis for formulating strategies for low-carbon economic development. Secondly, the comprehensive model demonstrates excellent performance in carbon emission prediction, with the accuracy of prediction results fully validated, thus providing an effective tool for controlling and reducing carbon emissions. Additionally, the research emphasizes the necessity of measures such as adjusting the energy structure and optimizing the industrial structure for achieving a low-carbon economy. This has important reference value for government and corporate policy-making and development strategies.

B. RESEARCH LIMITATIONS AND FUTURE WORK

The optimization and development of a low-carbon energy economy based on AI and big data analysis require the research and development of complex algorithms to consider multiple variables and factors comprehensively. This will require more computing resources and time. In the future, the research framework can be extended to introduce Network DEA model to better capture the complex relationships and interactions within the system. Network DEA takes into account the interactions between decision making units, which helps to evaluate its efficiency more comprehensively. The result can help people to effectively determine and model the connection structure between the various decision units in the system. This includes determining the relationships between inputs and outputs, as well as the interdependencies between individual decision units. Such analysis will help measure the efficiency of the system more accurately. The application of Network DEA can explain the efficiency score of each decision making unit more deeply. This research will not only focus on the overall efficiency, but also in-depth understanding of local efficiency issues in the system, so as to provide more specific and professional recommendations for system improvement. Sensitivity analysis can be performed to consider the effect of different weight assignments and parameter settings on efficiency assessment. The result can help this research determine the robustness of the system and provides more reliable recommendations for improving the system. Practical cases can be selected for study to verify the applicability of Network DEA model in low-carbon economy. This case study will further confirm the effectiveness and feasibility of the proposed method in practical application. Further research can be conducted on machine learning, deep learning, and other big data analysis algorithms to develop more efficient and accurate algorithms to support the optimization and development of a low-carbon energy economy.

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