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Optimization of Clean Energy Investment and Power Generation under Carbon Reduction Targets: A Case Study of China

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Abstract: *In the context of the increasingly severe contradiction between energy supply and demand and the problem of environmental protection, the development and utilization of clean energy have become crucial. In this paper, the optimization problem of power generation is solved by analyzing it at both the macro and micro levels. At the macro level, the relationship between power generation and investment is analyzed by combining machine learning and statistical analysis models, and the consistency of conclusions is verified by building a random forest model. At the microscopic level, photovoltaic (PV) and wind power plants in Xinjiang were used as research subjects, exploring the factors influencing PV and wind power generation through the establishment of a stacked LSTM-LGB-XGB net model. Finally, an optimization strategy based on a linear programming algorithm is proposed, providing an effective method to maximize carbon emission reduction and achieve the optimal combination of investment share, PV power generation, and wind power generation.*

Keywords: *Clean Energy, Problem-Solving Optimization, Machine Learning, Stacked Model, Environmental Impact*

1. Introduction

In general, fossil fuels remain predominant in energy consumption matrices. Oil accounts for 39% of world energy consumption, and projections suggest that coal and natural gas will account for 45% and 23%, respectively, by 2030[1]. China's energy consumption has increased rapidly, with an annual growth rate exceeding 7% annually since 2000. In 2016, China's total primary energy consumption reached 3.1 billion tons of oil equivalent, accounting for 23% of global energy consumption[2]. This trend highlights the need to focus on clean energy development. At the same time, because the combustion of fossil energy produces significant pollutants, it leads to serious pollution problems. It has been found that the use of clean energy can achieve a substantial control effect[3]. Therefore, the global power industry and policymakers are focusing on the development of clean energy, which accelerates the global transition from fossil fuels to clean energy sources[4].

Therefore, the effective deployment of renewable resources for power generation has become the focus of current research. Present clean energy research mainly includes the transition of energy systems, policies on clean energy and carbon emissions, the impact of oil prices on alternative energy stocks, the relationship between clean energy and the economy, clean energy venture capital, etc[5]. Recently, there has been a growing interest in clean energy technologies and investing in areas including solar energy, wave energy, and other sectors that promote sustainable development[6]. At the individual investment level, many investors are realizing the accelerating consumption of clean energy and are beginning to include clean energy companies in their portfolios[7]. Furthermore, countries with more investment in clean energy are more likely to perform better in pursuing low carbon production[8].

Wind and solar power are the main sources of clean energy[9]. Among all clean energy sources, wind power and photovoltaic power generation play a critical role in addressing China's energy challenges[10]. Furthermore, based on the total installed capacity of photovoltaic and wind power, China has become the largest user of clean energy[11]. Therefore, research on China's investments in photovoltaic and wind power generation has significant practical significance. Building on previous studies, this paper analyzes the optimization of photovoltaic and wind power generation from an investment perspective at both macro and micro levels. At the macro level, using data from 2011 to 2021 in China, the Yule-Walker test confirms the relationship between investment ratios and clean energy generation. The study suggests that

ISSN 2616-5902 Vol. 6, Issue 7: 85-95, DOI: 10.25236/AJBM.2024.060712

increasing clean energy financing and capacity for photovoltaic and wind power can achieve energy and environmental efficiency goals. At the micro level, data from two Xinjiang power plants in 2019 were used to build a stack model.

The novelty of this paper lies in several aspects: (1) The analysis in this paper is more comprehensive, integrating both micro- and macro-perspectives to address the optimization of carbon emissions. (2) In the micro-level analysis, a stacking model named LSTM-LGB-XGB net is adopted for its superior predictive performance. (3) Environmental externalities are considered, elucidating the positive relationship between clean energy and total emissions. (4) From an investment point of view, optimal allocation ratios for investments in photovoltaic and wind power generation are determined through linear programming.

2. Data and Methodology

2.1 Data Analysis

This paper will integrate macro and microanalyses. At the macro level, our focus is on the volume of clean energy and electricity generation financing from clean sources, collecting data from 2011 to 2021 to capture the general trends in China. This includes 41 variables related to photovoltaic (PV) and wind power.

At the micro-level, we selected data from two power plants in Xinjiang for the whole year of 2019, focusing on photovoltaic and wind power generation stations. Data were recorded at 15-minute intervals. For photovoltaic power research, we examined variables such as component temperature, ambient temperature, air pressure, humidity, total radiation, direct radiation, scattered radiation, and actual power generation. Wind power research focused on measurements including 10m, 30m, and 50m wind speeds, as well as wind directions at corresponding heights, along with temperature, air pressure, humidity, and actual power generation. These variables are based on actual data from the power plants in Xinjiang, China.

2.1.1 Macro-level

First, pre-processing is not only a technique used to transform raw data into a clean data set, but also to enhance the performance of machine learning models[12]. In this paper, the data is normalized to eliminate the difference in data dimensions, so that the data is comparable. The formula is as follows:

$$x_{new}=\frac{x-x_{min}}{x_{max}-x_{min}}$$

To avoid Type I errors (false positives), the Shapiro-Wilk test and the Bartlett test were performed on the data. The results of the Bartlett test, as shown in Table 1, rejected the null hypothesis. Based on this finding, and to ensure the accuracy and reliability of the results, we turned to nonparametric tests. Specifically, we used the Kruskal-Wallis test to verify significant differences between variables.

Table 1: The result of Bartlett test

Bartlett test	
Test statistic	523.87
P value	3.6×10^{-78}

Table 2: Results of the significance analysis (only significant variables are shown)

	Proportion of investment	Clean energy generation	TotalEmissions	Photovoltaic power generation	Annual installed capacity of wind power
The number of levels in the new group	4	4	4	4	4
N	11	11	11	11	11
Measured J-T statistics	38	7	9	7	7
Average J-T statistics	19	19	19	19	19
Standard deviation of J-T statistics	5.802298395	5.802298395	5.802298395	5.787394871	5.802298395
Standard J-T statistics	3.274564441	-2.068145963	-1.723454969	-2.07347179	-2.068145963
Asymptotic significance (two-tailed)	0.00105825	0.0386263	0.084806282	0.038128394	0.0386263

Table 2 presents the results of the significance analysis. The results indicate that at the 95% confidence level, four variables—investment proportion, clean energy generation capacity, photovoltaic generation capacity and annual increase in installed wind power capacity—reject the null hypothesis. In other words, this suggests that there exists a statistically significant ordered trend among these variables. Based on these results and in conjunction with our research theme, the following hypotheses were formulated for further investigation.

ISSN 2616-5902 Vol. 6, Issue 7: 85-95, DOI: 10.25236/AJBM.2024.060712

H1: The amount of financing for clean energy has a significant impact on the increase in photovoltaic generation and the annual growth of the installed wind power capacity.

2.1.2 Micro-level

The section begins with a correlation analysis of the variables used in this study. Correlation analysis is a statistical analysis method to study the relationship between two or more random variables with the same status. Correlation tests can reveal whether there is a linear relationship between two variables, as well as the direction (positive or negative) and strength of that relationship[13]. Using correlation analysis here can help to identify variables that may exhibit strong linear relationships with the target variable, aiding in the targeted selection of research variables and the construction of more effective prediction models.

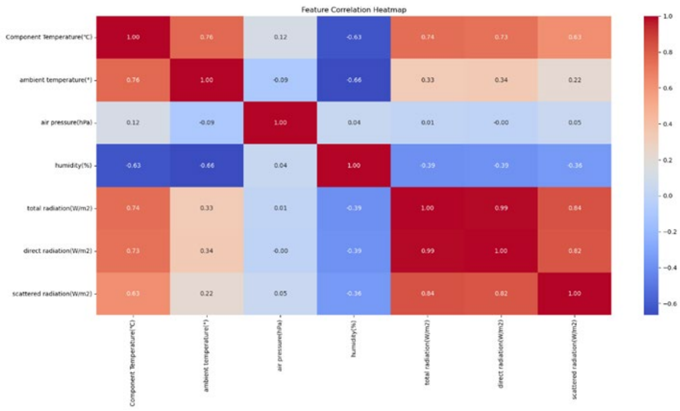

Figure 1: Results of the correlation analysis of the PV power generation variables

The results of the correlation analysis presented in Figure 1 indicate that the actual generated power of the target variable has a strong positive linear relationship with total radiation, direct radiation, and scattered radiation. Based on these results, the following hypotheses have been established for further investigation:

H2: There is a positive relationship between actual generated power and total radiation.

H3: There is a positive relationship between actual generated power and direct radiation.

H4: There is a positive relationship between actual generated power and scattered radiation.

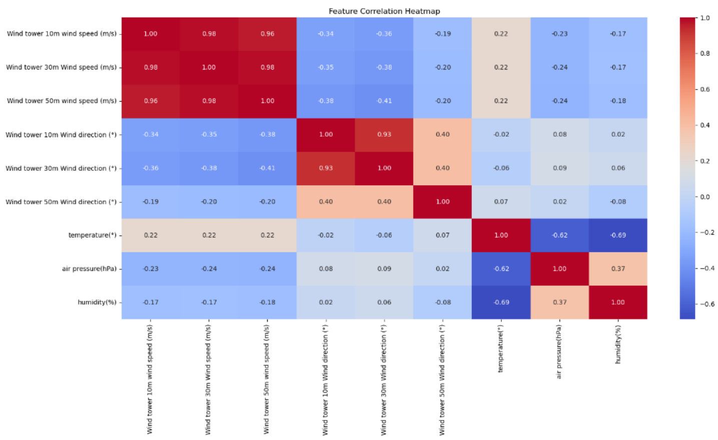

Figure 2: Results of the correlation analysis of the wind power variables

According to Figure 2, the results show that the actual power generation from wind energy has a strong linear correlation with the wind speeds measured at 10 meters, 20 meters, and 30 meters above ground level. Based on these findings, the following hypotheses have been formulated for further investigation. [14]

H5: There exists a positive correlation between the actual power output and the wind speed measured at 10 meters above ground level.

H6: There exists a positive correlation between the actual power output and the wind speed measured

ISSN 2616-5902 Vol. 6, Issue 7: 85-95, DOI: 10.25236/AJBM.2024.060712

at 30 meters above ground level.

H7: There exists a positive correlation between the actual power output and the wind speed measured at 50 meters above ground level.

2.2 Machine Learning Framework

2.2.1 Macro-level

2.2.1.1 Random Forest model

Based on the above knowledge, to better handle nonlinear and heteroskedastic macro-level data, we employed the Random Forest (RF) model. Random Forest (RF) is a machine learning method generally adapted to deal with problems of high dimensions and allows nonlinear relationships between predictor variables14. Random forests (RF) are an ensemble learning method that calculates an ensemble prediction value by aggregating a collection of randomly grown trees, with n tree <1 (BMC, research in progress, n.d.).

2.2.2 Micro-Level

At the micro-level, our aim is to predict the power generation of photovoltaic and wind power stations and to identify factors that influence actual power generation. To achieve this, we propose a stacking model of machine learning.[15]

Stacking is based on the concept of creating new classification models by combining classifiers. Regardless of the number of classifiers, learning is performed using the predictions of the classifiers and the data in the existing dataset to create a new model15.[16]

The significant advantage of the stacking algorithm lies in its ability to analyze the benefits of combining different models from multiple perspectives, thus enhancing the predictive performance of the model16. Subsequently, we elaborate on the stacking model employed during microlevel analysis, which comprises four layers:

In the first layer, LSTM processes feature combination F5, adding predictions to F1-F5. XGBoost trains on F1 and adds its predictions to F2 and F3. In the second layer, two XGBoost models train in parallel. The first model uses F2, integrating results into F4. The second LightGBM_2 model trains on F3, with results reserved for evaluation. In the third layer, XGBoost_2 trains on F4, and LSTM_2 trains on F5. Results are preserved for final fusion. In the fourth layer, results from XGBoost_2, LightGBM_2, and LSTM_2 are weighted and merged into the final prediction, Finla_model. Figure 3 shows the stacked model structure.

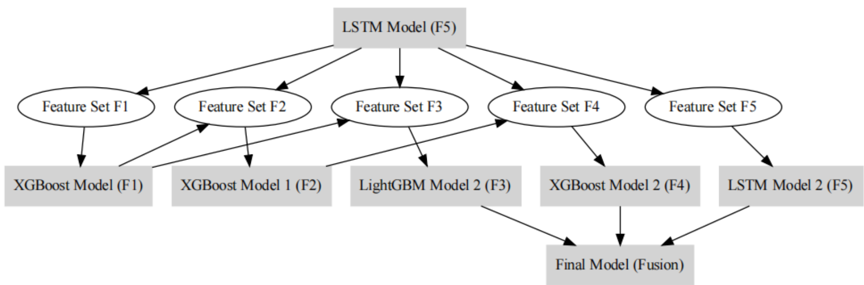

Figure 3: Stack model structure diagram

2.3 Evaluation metrics

To determine the predictive efficacy of different models, the mean absolute error (MAE), R2 (coefficient of determination) and Sharpe ratio are employed, which are commonly used in statistics16. These metrics serve as benchmarks to evaluate the performance of the models in this study.

ISSN 2616-5902 Vol. 6, Issue 7: 85-95, DOI: 10.25236/AJBM.2024.060712

3. Results and Discussion

3.1 Results of macro analysis

This section begins by testing the hypotheses established in this study. Importance measurement is a technique utilized to assess the relative significance of input variables (or characteristics) in a complex system or model, with the primary objective being the identification of the most crucial characteristics within the model[17]. The authors input macroscopic data, where the investment proportion is the target variable, into the Random Forest model for prediction, and visualize the feature importance analysis. The result is shown in Figure 4.

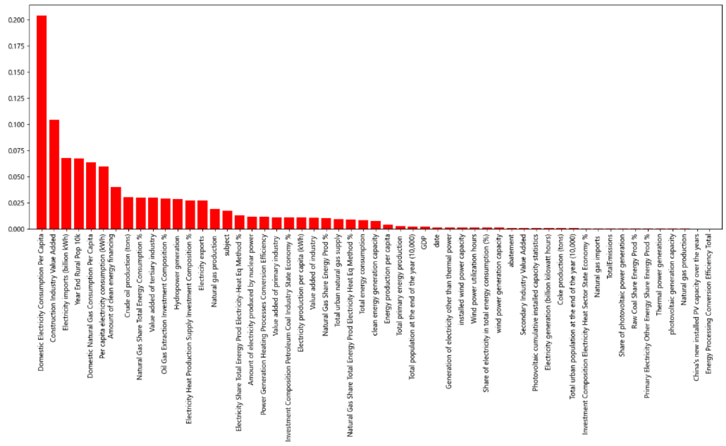

Figure 4: Visualization of importance analysis of macro variables

From the figure, it is evident that both photovoltaic (PV) electricity generation and installed wind power capacity significantly influence the predictive performance of the model, consistent with previous York-Haer-Tapastera tests. Through dual verification, it is reasonable to retain the null hypothesis that the amount of clean energy financing has a positive impact on the increase in photovoltaic power generation and wind power annual installed capacity. [18]

3.2 Microscopic analysis results and discussion

For power plants, accurate prediction is paramount, as electricity cannot be stored, necessitating precise anticipation of future demand18. Therefore, at the micro level, we use the LSTM-LGB-XGB net stacked model for PV and wind power plants to predict the data.

3.2.1 Photovoltaic analysis results

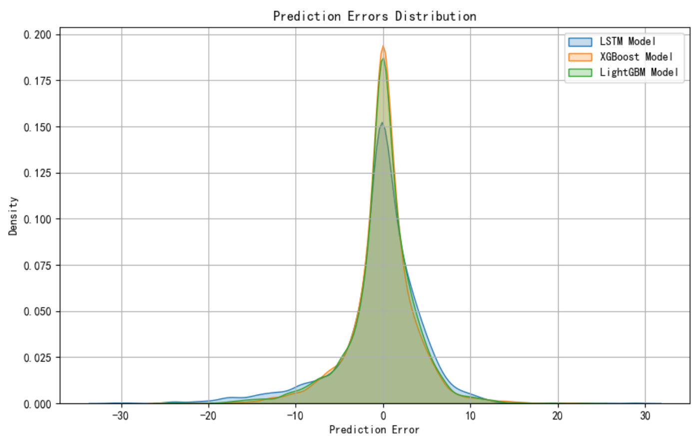

Figure 5: Distribution of prediction error.

The prediction of PV power generation entails two phases characterized by the presence or absence of daylight, with daytime demand being unavoidable19. Since the generation of PV power at night is 0,

ISSN 2616-5902 Vol. 6, Issue 7: 85-95, DOI: 10.25236/AJBM.2024.060712

the data is processed here with a new data set that includes all daytime data and 10% of nighttime data.

To gain a deeper understanding of the model's prediction effectiveness and error distribution, this paper adopts the density plot of prediction error as an important tool for assessing model performance and optimizing the model. The density plot of the error distribution in Figure 5 shows the favorable predictive and generalizability of the model.[19]

3.2.2 Model Evaluation

In this paper, MAE and R2 are used as the evaluation indices of the stacked model, and the evaluation results of the final model are shown in Table 3. MAE is 2.4453, and the coefficient of determination, R2, is 0.9320. The small values of MAE indicate that the model's prediction is highly accurate, and an R2 close to 1 indicates that the model has a good fitting effect. In this instance, the R2 value of 0.9320 indicates that the model can explain 93.20% of the variance in the target variable, indicating a relatively strong fit of the model.

Table 3: Evaluation of the performance of the photovoltaic stack model prediction.

Model	MAE	R
XGBoost_1	2.5512	0.9342
LightGBM _1	2.4783	0.9337
LightGBM _2	2.4783	0.9337
XGBoost_2	2.4799	0.9317
LSTM	3.1835	0.8901
Final_Model	2.5136	0.9338

3.2.3 Feature Importance Analysis and Visualization

To identify the influential factors driving the model predictions, this study conducted a feature importance analysis and visualization, where Shaple values were used as a measure of importance. Figure 6 illustrates the visualization results.

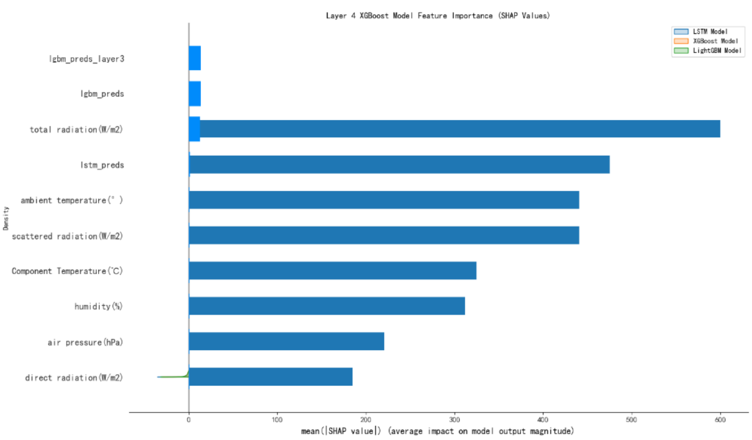

Figure 6: Visualization of the importance of the variable.

It becomes apparent that the results of the correlation analysis between the main influences predicted by the model and the correlation between them are largely consistent. Scattered radiation and total radiation are significant indicators affecting photovoltaic power generation. Therefore, we believe that the original hypotheses H2 and H4 are acceptable and that an increase in scattered radiation and total radiation will lead to an increase in the actual power generated by photovoltaic.[20]

3.2.4 Results of the analysis of wind power generation

The wind power generation data set is fed into the LSTM-LGB-XGB net stacking model for prediction. To facilitate a comprehensive assessment of the predictive performance of the model, the actual and predicted wind power generation data were subjected to random sampling for visualization. Examination of the visualizations indicates a favorable alignment between the model's predicted outcomes and the actual results.

ISSN 2616-5902 Vol. 6, Issue 7: 85-95, DOI: 10.25236/AJBM.2024.060712

3.2.5 Model Evaluation

In this paper, MAE and R2 are used as the evaluation metrics of the stacked model, and Table 4 shows the evaluation results of the sub models and the final model of the stacked model. In this case, an R2 value of 0.8852 indicates that the model can explain 88.52% of the variance in the target variable, so it can be considered that the model is better suited.

Table 4: Evaluation of the performance of the wind energy stack model prediction.

Model	MAE	R
XGBoost_1	13.0273	0.8807
LightGBM _1	12.5279	0.8822
LightGBM _2	12.5279	0.8822
XGBoost_2	12.4351	0.8808
LSTM	15.1688	0.8441
Final_Model	12.6596	0.8852

3.2.6 Feature importance analysis and visualization

To identify the key factors affecting model predictions, this paper performs a feature importance visualization, ranking the main influencing factors in the prediction process of the XGBoost and LightGBM models. The F value is used here as a measure of importance, and the results of the visualization are shown in the figure below. [21]

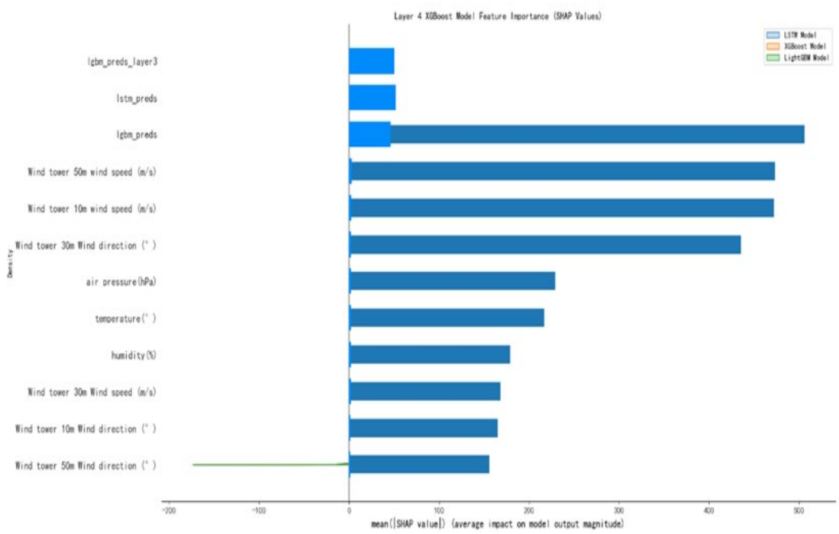

Figure 7: Visualization of the importance analysis of the wind power stack model.

From the graph, it can be inferred that the wind speed at a height of 50 meters on the wind tower is a significant factor that affects the actual power output of wind power generation. This conclusion is consistent with the results of the previous correlation analysis. Therefore, we can confidently infer that the null hypothesis of H7 is acceptable. The higher the wind speed at a height of 50 meters from the wind tower, the higher the actual power generated by the wind power,as shown in Figure 7.

4. Discussion Section

4.1 Considering Carbon-Neutral Targets

Considering the objectives of "peak carbon emissions" and "carbon neutrality," we have incorporated the environment as an externality in our analysis. Here, we have utilized total emissions as the primary measure of environmental impact.

ISSN 2616-5902 Vol. 6, Issue 7: 85-95, DOI: 10.25236/AJBM.2024.060712

4.2 Establishing an Equation for the Relationship between Emissions and Power Generation

4.2.1 Correlation analysis

Table 5: Results of the correlation analysis.

	TotalEmissions	Clean energy generation capacity	Photovoltaic generation capacity
TotalEmissions	1		
Clean energy generation capacity	0.951929868	1	
Photovoltaic generation capacity	0.903619131	0.988045089	1
Wind power generation capacity	0.917002071	0.818866261	0.720588388

From the figure, it can be inferred that there is a positive correlation between photovoltaic power generation and wind power generation. With the increase in clean energy, total emissions also increased. This observation contradicts common expectations. Which is not in line with common sense. Next, this anomaly is explained through a deeper analysis,as shown in Table 5.

4.2.2 Emission Reduction Equation

The production processes of wind and photovoltaic power generation inherently emit no pollutants or greenhouse gases to the external environment20. The emission reduction of such clean energy sources broadly refers to the quantity of the mass of all pollutants and greenhouse gases emitted to the outside world (atmospheric environment, water environment, soil environment, etc.) when their power generation is equivalently replaced by thermal power generation. Typically, this calculation focuses on the reduction of carbon dioxide (CO2) emissions when replacing emissions from fossil fuel combustion.

$$Y = x_1$$

Y: Annual emission reduction (wind or photovoltaic)

X1: Annual grid-connected electricity generation

D: Greenhouse Gas Emission Intensity

According to the 2018 Annual Development Report of China's Power Industry released by the China Electricity Council in 2019, the annual intensity of CO2 emissions for the year 2018 was reported as 841 grams per kilowatt hour21. Therefore, the value of D is 8.41 × metric tons per kilowatt hour. Figure 8-9 shows the annual reductions in emissions from photovoltaic power generation and shows the annual reductions in emissions from wind power generation (Unit: million tons).

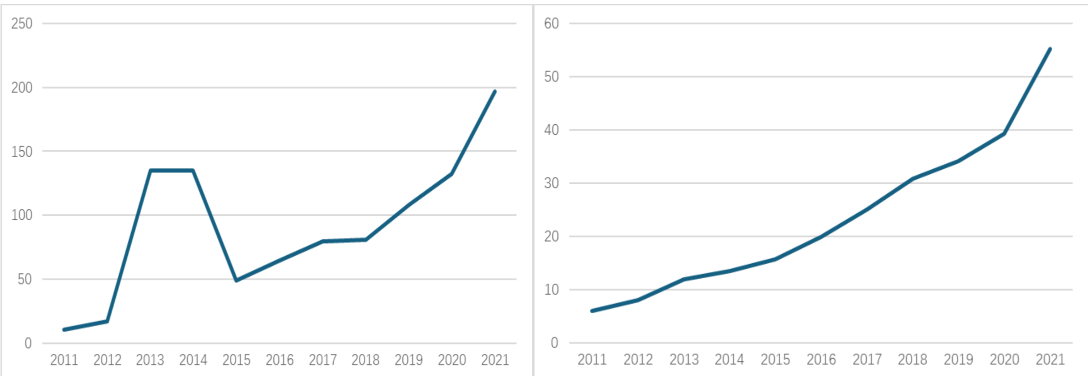

Figure 8-9: Annual emissions reductions from photovoltaic and wind power.

From the figure, it can be inferred that the emission reductions from photovoltaics and wind power are gradually increasing over time. However, because the rate of increase in CO2 emissions from other sources is greater than the rate of increase in emission reductions from clean energy. As a result, an anomalous phenomenon arises where total carbon dioxide emissions increase despite an increase in clean energy generation. To achieve the goal of curbing the increase in carbon dioxide emissions, it is still necessary to further increase clean energy generation until optimal emissions reduction effects are attained.

ISSN 2616-5902 Vol. 6, Issue 7: 85-95, DOI: 10.25236/AJBM.2024.060712

5. Optimization Problem

5.1 Overview of Optimization Problem Solving

In this section, we explore the problem of finding optimal future investments and quotas for photovoltaic (PV) and wind power generation to maximize emissions reductions. This study adopts the methodology proposed by Sanyal, which has envisioned the elimination of fossil fuel emissions in an idealized midcentury scenario22. Using linear programming, we forecast the emission reduction potential of future clean energy scenarios.

5.2 Linear Programming Model

According to the IEA report, power and heat generation are responsible for 46% of global emissions increase due to the increased use of fossil fuels to meet the growth in electricity demand23. Therefore, this study establishes a corresponding constraint that the reduction of carbon emissions must not exceed 46% of China's total emissions data in 2021.

Below is the set objective function:

Max (EmissionReduce)=$ax_1 + bx_2 + cx_3$

EmissionReduce: Emission<C1

x_1: Amount of clean energy financing (millions of dollars), 0<x_1<C2

x_2: Photovoltaic cumulative installed capacity statistics,x_2>0

x_3: Installed wind power capacity,x_3>0

C1: 46% of China's total emissions data in 2021

C2: Maximum amount of clean energy financing in the last decade

5.2.1 Coefficient Determination

According to Weng, CF et al., every 1% increase in domestic clean energy investment reduces domestic carbon emissions by about 0.05% on average24. Using the investment amount data and carbon emission data for the year 2021 as a reference point, the coefficient "a" is derived as 1.764. This coefficient represents the reduction in domestic carbon emissions per million dollars of increased investment in clean energy.

Based on data from the ESG Rating Center, the average reductions in carbon emissions per unit of net feed-in electricity for photovoltaic and wind power are approximately 0.74 tCO2e/MWh and 0.75 tCO2e/MWh, respectively (11). Combined with data from the Bureau of Energy Statistics (BES), the average annual hours of use of wind power and photovoltaic power in Xinjiang are 1976.8 and 1579 hours, respectively. According to the formula:

Annual carbon reduction per MW of installed capacity = reduction in carbon emissions ×Annual utilization hours

We have determined the annual carbon emission reductions per MW of installed capacity for photovoltaic and wind power to be 116,846 and 148,260 tons, respectively. Considering emissions in millions of tons, the coefficient b is 0.116846 for PV and c = 0.14826 for wind power.

5.3 Optimized Solutions

As shown in Table 6, through the application of linear programming techniques, we obtain a set of optimal combinations of investment allocations, photovoltaic power generation capacity, and wind power generation capacity to achieve the goal of maximizing emissions reduction.

Table 6: Optimal allocation combination.

Clean energy financing (million dollars)	44180000
PV generation (MWh)	20611.19
Wind power generation (MWh)	10631.4

ISSN 2616-5902 Vol. 6, Issue 7: 85-95, DOI: 10.25236/AJBM.2024.060712

6. Conclusions

The results of this study not only enhance the understanding of the impact of clean energy investment, but also provide strong strategic support for the reduction of carbon emissions, demonstrating the potential of data-driven modeling to be applied in energy policy and environmental management.

Increase Support and Investment in Photovoltaic (PV) and Wind Energy: Our research indicates that wind power and photovoltaic (PV) power generation are significantly influenced by investment, while both have tangible impacts on carbon emissions. Therefore, governments should increase investment and support for photovoltaic and wind power, with a particular focus on the annual growth of installed wind power capacity, to achieve better results in clean energy generation.

Optimize Funding Allocation Strategies: In the face of the increasing urgency of the Peak Carbon Goal, governments should consider adjusting and optimizing funding allocation strategies for PV and wind power projects and develop specific investment guidelines. Given that wind power generation produces more effective annual reductions in carbon emissions compared to photovoltaic, the government can appropriately increase investment in wind power to achieve greater carbon reduction.

Substantial Investment Potential in Photovoltaic and Wind Energy: To reduce carbon emissions, investors must thoroughly assess the economic viability and environmental benefits of projects before making investments in clean energy. Based on this study, current photovoltaic and wind power generation still requires significant investment to reach the optimal power generation threshold. When the generation capacity reaches the near-optimal threshold, the government and investors can appropriately reduce the investment in clean energy.

Although this study provides extensive research evidence based on the case of China, it has certain shortcomings that can be addressed in subsequent studies. The lack of data from power plants in other regions restricts the scope of the analysis, as the study relies solely on data from power plants in Xinjiang, leading to a relatively narrow data source. This study only considered the relationship between one process, electricity production and carbon emissions in China, and future studies could examine the entire life cycle of photovoltaic and wind power generation.

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