Optimization of Regional CO_2 Emission Prediction Model and Discussion on Management Response Strategies

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Abstract: Against the backdrop of global climate change and CO_2 emissions, the formulation and path planning of regional dual CO_2 targets have become important issues in today's society. This article first establishes a comprehensive analysis model that includes multiple indicators such as economy, population, and energy consumption to evaluate the current status of CO_2 emissions. A CO_2 emission prediction model was designed for different scenarios using ARIMA time series and polynomial regression analysis. The BP neural network model was used to modify and tune the model parameters, and strategies and measures were proposed to achieve CO_2 peak and CO_2 neutrality goals. The advantages and disadvantages of the above measures were evaluated. The results of this study can provide important references for regional planners and decision-makers on emission reduction pathways and management to achieve sustainable CO_2 reduction goals.

Keywords: Autoregressive Integrated Moving Average Model Time Series; Multiple regression Modelling; Neural Networks; CO_2 Neutrality; CO_2 Emission Reduction

1. Introduction

Climate change is an urgent global challenge with far-reaching implications for ecological security, economic development and social stability. As one of the main drivers of climate change, regional CO_2 emissions have become a focus of attention for governments, enterprises and research institutions. As the international community's commitment to emission reduction continues to strengthen, accurate prediction of regional CO_2 emissions is crucial for formulating and adjusting CO_2 reduction strategies [1]. Currently, numerous studies have been devoted to exploring the prediction methods of CO_2 emissions, among which statistical models, economic models, and machine learning methods are widely used. However, since CO_2 emissions are affected by a variety of economic, social, technological and policy factors [2-4]. There is a large uncertainty in the prediction work, and there is an urgent need to synthesize a variety of methods to improve the accuracy of prediction [5,6].

This study aims to construct a combined forecasting model that integrates Autoregressive integrated moving average (ARIMA) time series model and multiple regression model. The use of this model not only analyzes the statistical patterns of historical time series data, but also accurately captures the complex relationship between CO_2 emissions and other economic and technological variables [7,8]. The ultimate goal of the study is to provide decision support for regional CO_2 emission reduction [9-11]. Based on the accurate prediction of future CO_2 emission trends, this study further explores and proposes corresponding emission reduction strategies. In order to address regional CO_2 emission forecasting and the formulation of CO_2 reduction strategies, this paper first constructs a comprehensive indicator system for measuring the economy, population, energy consumption and CO_2 emissions in Jiangsu Province, China, and quantitatively analyzes its contribution to the impact of CO_2 emissions; then, an energy consumption forecasting model based on demographic and economic changes and a regional CO_2 emission prediction model; finally, based on the above prediction model, the indicator system was reconstructed under two set scenarios of unmanned interference and CO_2

peak state, the prediction relational equation was corrected by using BP neural network [12], and the state and growth rate of CO_2 emission were calculated. Policy recommendations for energy saving and emission reduction measures were proposed [13]. This study used a variety of data analysis and mathematical modeling methods to explore in depth the relationship between CO_2 emissions and multiple factors, providing strong support for the formulation of CO_2 emission reduction policies and sustainable development.

2. Current Situation Analysis

Since there are too many indicators describing the economy, population, and energy consumption, this paper extracts 15 indicators to quantitatively represent and analyze the above three categories, as shown in Table 1.

Table 1. Description of Economic, Demographic and Energy Consumption Indicators and Codes

Title 1	Title 2
A_1	CO_2 emission
A_2	Regional economy
A_3	Regional population
A_4	Regional energy consumption
A_5	Agroforestry Consumption GDP
A_6	Energy supply sector GDP
A_7	Industrial consumption sector GDP
A_8	Transportation consumption sector GDP
A_9	Consumption sector GDP
A_{10}	CO_2 emissions from agroforestry consumption
A_{11}	CO_2 emissions from the energy supply sector
A_{12}	CO_2 emissions from the industrial consumption sector
A_{13}	CO_2 emissions from the transportation consumption sector
A_{14}	CO_2 emissions from the building consumption sector
A_{15}	Consumer CO_2 emissions

Based on the means of statistical analysis, the data of the 15 indicators, as above, are plotted on a state chart of their changes over time, as shown in Figures 1-6:

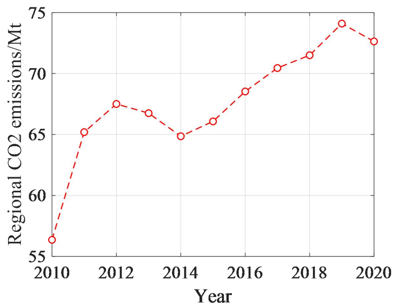

Figure 1. Map of Total Regional CO_2 Emissions

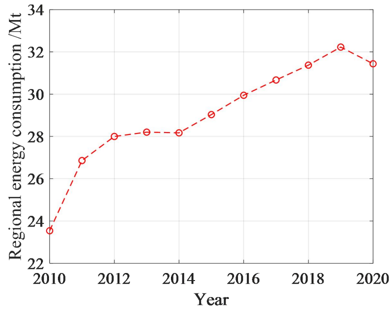

Figure 2. Map of Total Regional Energy Consumption

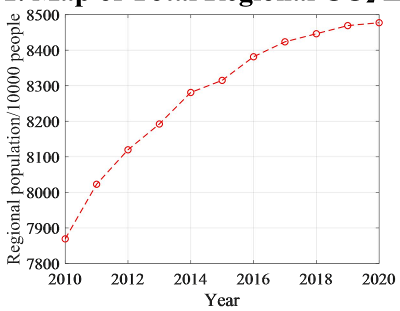

Figure 3. Map of Total Regional Population

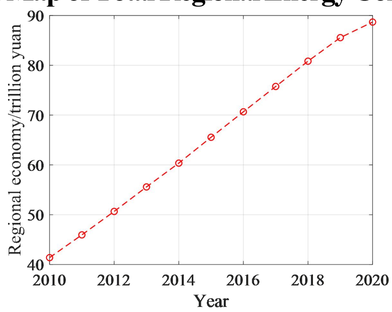

Figure 4. Regional Total Economic Map

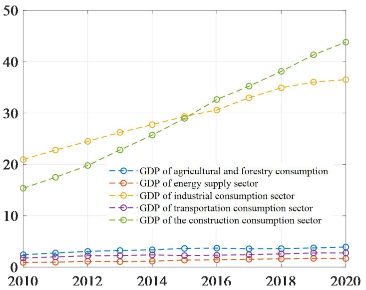

Figure 5. Regional GDP Maps by Sector

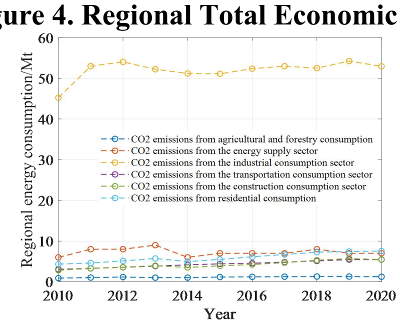

Figure 6. Map of Energy Consumption by Sector in the Region

According to the data in the Figures 1-6 above, the region's economic growth in the decade from 2010 to 2020 shows a linear growth trend with a certain coefficient, which is consistent with the country's strategic policies. Regional CO_2 emissions and energy consumption first experienced some growth during this period, but then the growth trend began to slow down. This change in trend is related to the CO_2 neutral policies developed by the country. At the same time, the region's population growth showed a gradual slowdown over the decade, and the reduced rate of population growth may be related to family planning policies as well as other factors. Overall, population migration and natural increase rates are declining. The data graph also shows that the industrial consumption sector consumes more energy and contributes relatively more to GDP. In addition, GDP consumption in the construction sector shows a clear linear growth trend over the decade [14].

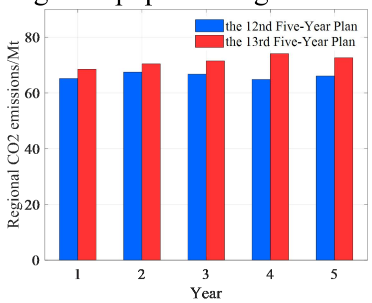

Figure 7. CO_2 Emissions Over Two Five-Year Periods

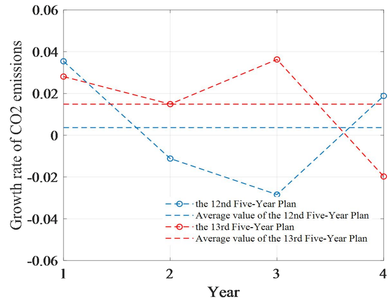

Figure 8. Growth Rate of CO_2 Emissions Over Two Five-Year Periods

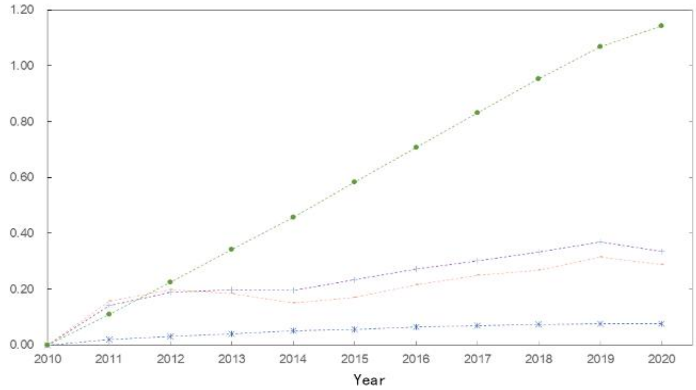

Figure 9. Year-on-Year Growth Chart

As shown in Figures 7-8, according to the results of data analysis, it can be observed that the total amount of CO_2 emissions basically remained stable during the 12th Five-Year Plan period, but during the 13th Five-Year Plan period, the total amount of CO_2 emissions clearly showed an upward trend.

Taking 2010 as the base year, the data from 2020 to 2011 were compared with the 2010 data. Data processing and plotting were performed to generate a year-on-year change Figure 9.

The following trends can be observed in the Figure 10: rapid GDP growth, slow popu-lation growth, increasing total CO_2 emissions, and consistent trends in energy consump-tion and CO_2 emissions.

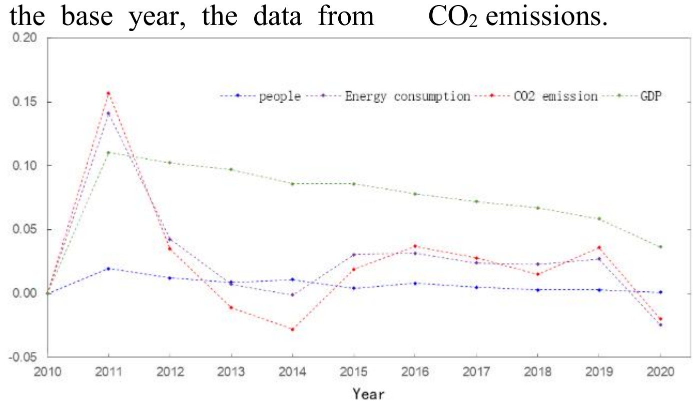

Figure 10. Comparative Growth Charts

The following conclusions can be drawn from the chain growth chart 10, which shows that the overall economy of the region has continued to grow, but at a slower rate year by year. At the same time, there is a close positive correlation between CO_2 emissions and energy consumption, which means that economic development is inevitably accom-panied by an increase in CO_2 emissions. However, with the advancement of science and technology and the implementation of CO_2 neutral policies, future economic development will be less and less dependent on CO_2 emissions and energy consumption.

In addition, after extracting and analyzing the correlation coefficients of the data for each year of the sample, a heat map of the correlation coefficients was drawn as shown in Figure 11.

On this basis, CO_2 emissions were selected as the target amount, and the correlation between the target amount and the weights was solved using the 14 indicators as weights, as shown in the Table 2 below.

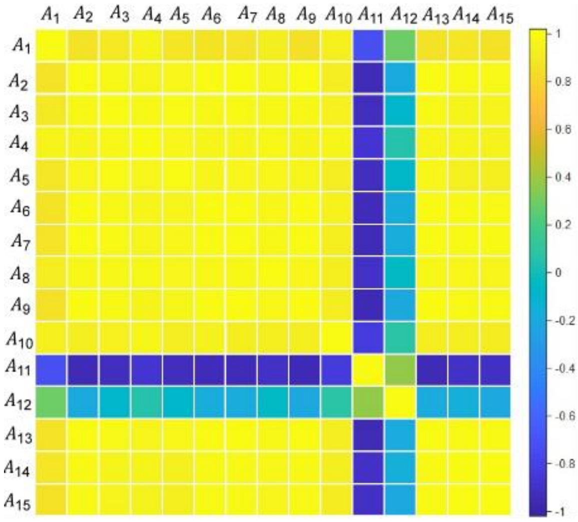

Figure 11. Heat Map of Correlation Coefficients of Indicators

Table 2. Relationship of indicators to regional CO_2 emissions.

	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}	A_{11}	A_{12}	A_{13}	A_{14}
Relatedness	0.71	0.84	0.95	0.81	0.77	0.80	0.87	0.61	0.80	0.88	0.95	0.79	0.76

From Table 2, it can be concluded that there is a high correlation between CO_2 emis-sions and the 14 indicators mentioned above. In order to determine the degree of influence of each indicator on CO_2 emissions in the region, a factor analysis was calculated for the above indicators. The top six indicators in terms of cumulative contribution and their contribution rates are listed below:

The cumulative contribution of these indicators reaches 0.98, indicating that their influence on CO_2 emissions is very significant. Therefore, in the subsequent analysis, it is possible to focus on these indicators in order to predict CO_2 emissions more accurately.

Table 3. Contribution of Indicators to Regional CO_2 Emissions

	A_2	A_3	A_4	A_6	A_7	A_{13}
Contribution rate	70.14%	8%	13.05%	2%	3.1%	3.71%

Therefore, based on the contribution of each indicator, the six most important indi-cators were finally selected for subsequent CO_2 emission projections, which include: re-gional economic level, regional population size, total regional energy consumption, Gross Domestic Product (GDP) in the energy supply sector, GDP in the industrial consumption sector, and CO_2 emissions in the industrial consumption sector.As shown in Table 3. Based on the ranking of these key indicators, the implementation of CO_2-neutral policies can be targeted and adjusted in terms of imple-mentation modalities and areas of focus, such as reducing reliance on traditional base fuels, increasing the development of new and cleaner energy sources, and encouraging cleaner modes of transportation.

3. Prediction Model

3.1 Prediction Model

ARIMA is the dif-ferential integrated sliding average autoregressive model, the parametric form of which is generally written as ARIMA (p, d, q) [15]. The core idea of the method is as follows: for smooth and non-smooth time series, a large class of parametric models is usedARIMA(p, d, q) carry out modeling. The first step is to choose, for a given time series, the appro-priate p, d, q;The specific parameter values in the model are then estimated using spe-cific methods such as least squares estimation, great likelihood method; finally, the ap-propriateness of the fitted model is tested and the model is improved by going back to the first step if necessary [16,17].

Based on the above theory in order to build a forecasting model of energy con-sumption based on ARIMA time series of population and economic changes. First of all it is necessary to test the smoothness of the population forecast time series to get the fore-cast as shown in Figure 12.

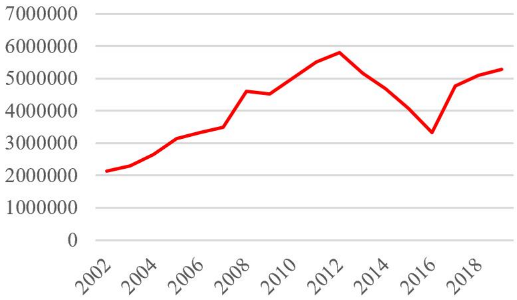

Figure 12. Population Projections of China, 2002-2019

Since the trend of the population projections in the graph is not characterized by a zero mean and the variance is constantly changing, it is tentatively concluded that the time series of the original population projections is not smooth. Calculate the predicted data for the p. We can determine that when the difference is divided into order 0, it is not significant on the level, indicating that the series is not smooth. When the difference is divided into 1st and 2nd order, it is significant on the level and the series is smooth. From the above analysis, we can see that the model is smooth after the difference of the first order, theThe parameters of the ARIMA model can be determined d is 1.

Finally, using the statistic VIF(Variance Inflation Factor)Detection of multicol-linearity was performed.

Table 4. VIF

	x_1	x_3	x_4	x_5	x_6
VIF	36.116	48.901	2.341	75.252	2.215

From Table 4, it can be seen that the multicollinearity is severe except for x_4 and x_6, and because x_5 has the largest VIF value, the variable x_5 is excluded, and after excluding the variable x_5, the regression model is built as follows:

$$y = -66433.819 + 9.726x_1 - 55.750x_4 + 14203.5x_6 \quad (1)$$

Finally the (0,1,0) test table for out ARIMA model is obtained as shown in Table 5.

Table 5. ARIMA Model Parameter List

	Notation	Value
	Df Residuals	16
sample size	*N*	18
Q statistic	Q_6	0.248(0.618)
	Q_{12}	2.765(0.838)
Information guidelines	*AIC*	502.634
	BIC	504.3
Goodness of fit	R_2	0.701

From the principle of AIC minimization the model parameters can be automatically determined as p =q = 0, d = 1.The Q statistic shows that the model does not satisfy the significance on Q_6, which indicates that the variables in the residuals of the model are independently and identically distributed at any point in time. And the coefficient of determination of the model is 0.701, which is at a high standard, indicating the applicability of the model.

3.2 Regional CO2 Emission Prediction Model Based on Multiple Regression

Using the available data and supplementary data, after normalizing the base data, the following functional equation with regional economy, regional population, regional energy consumption as independent variables and regional CO_2 emission as dependent variable was obtained by inverse solving:

$$A_1 = 1.1325A_3 + 0.2852A_2 + 0.667\frac{A_4}{C_1} + 0.0042A_4C_2 \quad (2)$$

As shown in Figures 13-14, the predicted and actual values are plotted in comparison and the error is calculated between the real and predicted data according to the requested relational modeling.

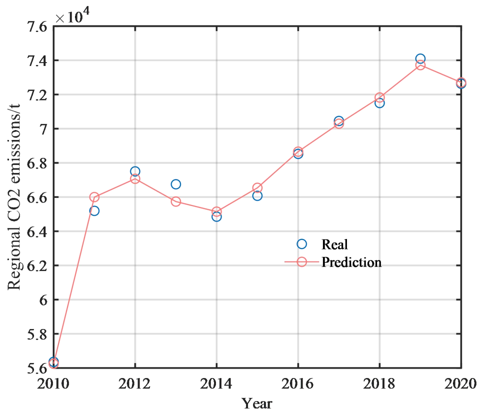

Figure 13. Comparison of Regional CO_2 Emission Projections

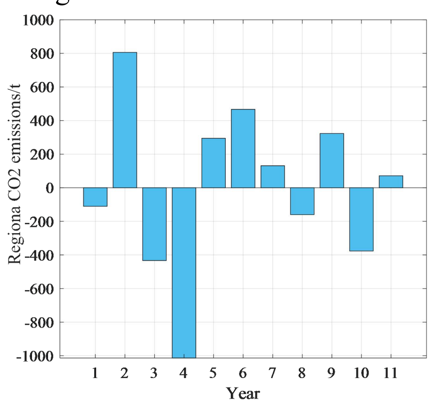

Figure. 14 Errors in Regional CO_2 Emission Projections

Based on the error profile in the above Figures 13-14 and the comparison graph between the true and predicted values, it is clear that the prediction model has a high degree of accuracy. By calculating the maximum error weight, the maximum error is only 1.4% of the total predicted value. This means that there is a very small difference between the predicted and actual values of the model. In the prediction of CO_2 emissions, we can be confident that our model can accurately predict the CO_2 emissions in the future years. In conclusion, through the preliminary theoretical analysis, feature selection and modeling work, an accurate and perfect prediction and assessment system has been successfully established.

4. Targets and Paths

In this paper, the relevant data used in the study of industrial CO_2 emissions are mainly from the website of the National Bureau of Statistics, limited to the availability of some data, so the EPS data platform is used as a supplement, individual data such as the amount of coal production in 2010, the absence of investment in the energy industry in 2018, the use of time-series analysis to deal with the energy supply and demand equilibrium of provincial and municipal industrial CO_2 emissions from 2000-2019. From 2000, the balance of energy supply and demand provinces and cities in industrial CO_2 emissions increased year by year, from 2011, with the "Twelfth Five-Year Plan", the balance of energy supply and demand provinces and cities in the rate of growth of CO_2 emissions continued to reduce the growth rate is slowly becoming smaller, to 2015 into a downward trend and then gradually flattened out, the industry began to reach a stable range, no significant changes in the trend.

4.1 Analysis of Factors Affecting CO_2 Dioxide Emissions

The factors affecting CO_2 emissions selected by this paper using the weighting variables of the neural network model are shown in Table 6 below.

Table 6. Factors of Control Variables

Variable	Classification	Name (Indicator)	Unit
Dependent		variable Industrial CO_2 emissions	million tons
Independent variable	Industrial development factors	Investment in the energy industry	billions
	Industrial structure factors	Energy production	million tons
		Energy consumption	million tons
	Industrial technology factors	Industrial end-use consumption	million tons
		Processing conversion inputs	million tons
		end consumption	million tons

4.2 CO_2 Dioxide Peak Prediction Results

In this paper, BP neural network is used for the construction of CO_2 peak prediction model.BP neural network model. The mean absolute percentage error (MAPE) is 0.03%, and the prediction model passes the validity test and meets the accuracy requirements. As seen in Table 7 below, the absolute value of the error between the predicted value and the original value of this model is below 0.20% except for the percentage error values of 2001, 2006, 2013, and 2018, which are above 0.25% and below 0.30%, and the absolute value of the remaining percentage error is below 0.20%, and the accuracy is able to meet the prediction requirements.

Table 7. Comparing BP Network Model Forecast Data with Original Values, 2000-2019

Year	Original value (tons)	Forecast value (tons)	Percentage error
2000	45319.28826	45308.46008	0.02%
2001	46489.89796	46363.67681	0.27%
2002	47903.12302	47896.14256	0.01%
2003	58877.14263	58780.54833	0.16%
2004	64296.69116	64394.29508	-0.15%
2005	74594.89988	74635.4745	-0.05%
2006	83409.16895	83188.63584	0.26%
2007	92572.68387	92549.88668	0.02%
2008	97236.28306	97158.70235	0.08%

2009	105348.5286	105462.9422	-0.11%
2010	115517.8177	115387.8544	0.11%
2011	131393.0185	131540.943	-0.11%
2012	136014.9625	135930.4152	0.06%
2013	138946.9024	138632.4038	0.23%
2014	141800.819	141534.009	0.19%
2015	138302.4883	138420.5629	-0.09%
2016	137838.0361	138021.6159	-0.13%
2017	141272.157	141162.24	0.08%
2018	142291.4447	142652.3915	-0.25%
2019	148229.3126	148212.2626	0.01%

The predicted data can be brought into the built BP neural network to derive China's industrial CO_2 emissions in the future 2020-2040, as shown in Figure 15.

In the next 20 years, industrial CO_2 dioxide emissions from 1.5 billion tons in 2020, declining year by year to reach a relative minimum value of 1.481 billion tons in 2023, and then gradually stabilized to reach the CO_2 dioxide emissions plateau, the ups and downs are regular, fluctuations are obvious, the rise and decline in the highest and lowest values within the.

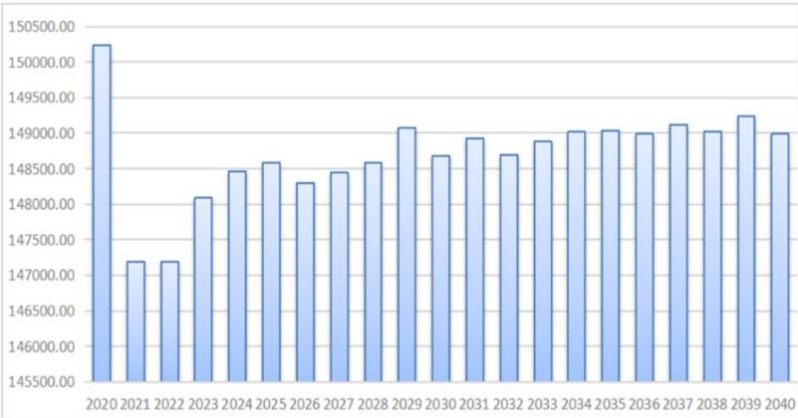

Figure 15. CO_2 Emissions by Year

As can be seen from Figure 15, under the condition that the control variables are uniformly reached, the peak of industrial CO_2 emissions in energy supply and demand balance provinces and cities will be reached in 2020, and then rise after the lowest value of CO_2 emissions in 2021, and then rise in the next four years to the standard level, there is a certain degree of fluctuation, and the latter 16 years as a whole to remain at a relatively stable level, and the trend of change is subsequently reduced and does not exceed the highest value reached in 2020. In 2020 there is a clear inflection point, so it is concluded that the balance of energy supply and demand in the provinces and cities of industrial CO_2 peaked in 2020.

Through the comparison of the results of the above analysis, according to the centralized weight of the variable indicators can be seen, as shown in Table 8 below, in which the total consumption of various types of energy and the proportion of terminal consumption is larger, so the industrial development and energy related to a larger degree, in the emission reduction strategy should also pay more attention to the above points.

Table 8. Importance Weights for Each Factor

Variable indicators	Centering weights
Energy industry investment (billion yuan)	30095.01
Crude coal production (tons)	21277.36
Crude oil production (tons)	3178.32
Natural gas production (billion cubic meters)	18233.58
Coal consumption (tons)	24862.54
Crude oil consumption (tons)	10999.25
Natural gas consumption (billion cubic meters)	65568.41
Energy consumption (tons of standard coal)	52592.18
Amount of energy available for consumption in the region (tons)	33158.72
Input volume of coal processing and conversion (tons)	22119.31

Crude oil processing and conversion input volume (tons)	39991.08
Natural gas processing and conversion input volume (billion cubic meters)	1423.84
Coal industrial end-use consumption (tons)	19853.84
Crude oil industrial end-use consumption (million tons)	17947.02
Industrial end-use consumption of natural gas (billion cubic meters)	41257.99
Coal end-use consumption (million tons)	21038.86
Crude oil terminal consumption (tons)	23797.71
Natural gas terminal consumption (billion cubic meters)	35887.78

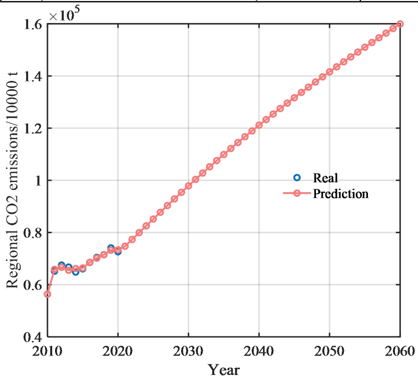

Figure 16. Unmanned Interference with CO_2 Emissions Projections

It can be seen from the Figures 18-19 that in the case of no human interference, the CO_2 emissions are in the growing, and therefore the derived bias coefficient is not zero and is at a certain value.

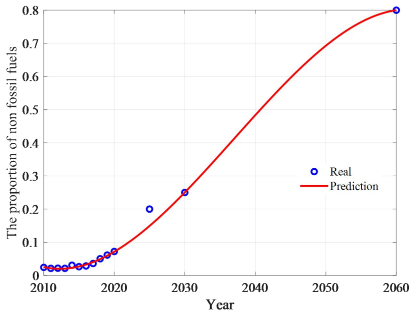

Figure 18. Projected Non-Fossil Energy Share Ratio

On this basis, we have plotted the data for CO_2 peaking and various scenarios based on the requested parametric data as in Figure 20:

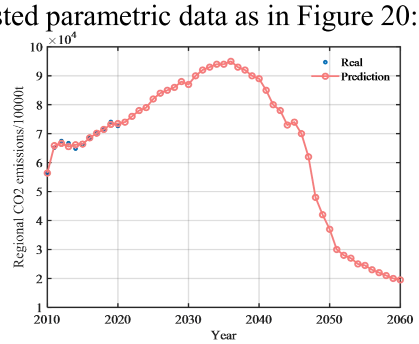

Figure 20. Projected CO_2 Emissions Under Multiple Scenarios such as Peak CO_2

The above Figure 20 shows that its CO_2 peak and CO_2 emissions under multiple scenarios are completely different from those under the state of no human interference, and under the policy guideline indicator, it is able to obtain that the CO_2 emissions will grow for a period of time, and then the data will show a decline, and then gradually converge to a certain range. And its bias diagram can also see its trend, found that the amount of data is also alternately changing, gradually declining, when its change is less than 0 or equal to 0, the solution to get the resultant amount. Its bias data plot is shown in Figure 21.

Based on the model predecessor, the completion indicator is reconstructed and the CO2 emission projections for an unoccupied state are calculated as in Figures 16-17:

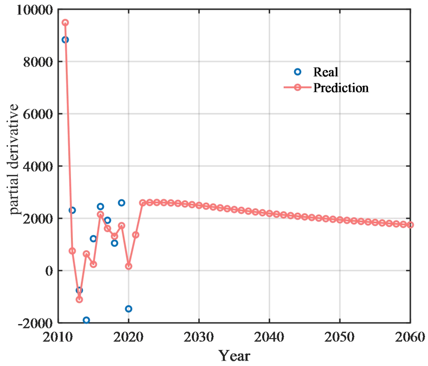

Figure 17. Unmanned Interference Biases CO_2 Emissions

And for the CO_2 peaking state and the overall influence factor conditions, the first iteration to predict the future energy utilization rate and non-fossil energy share ratio data is shown as in Figures 18-19:

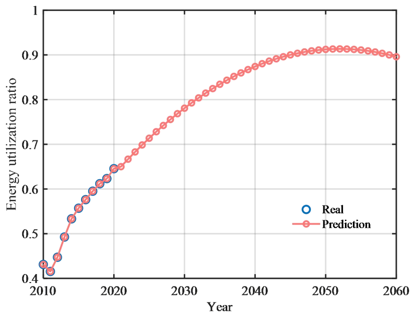

Figure 19. Energy Utilization Projections

4.3 CO_2 Reduction Policies Based on Forecast Results

Based on the above analysis, some measures and approaches are proposed as follows:

Promote the green transformation of industries in the region. Promote energy saving and emission reduction in the industrial structure. Promote technological innovation to improve energy utilization efficiency and reduce CO_2 emissions. Implement economies of scale to reduce CO_2 emissions through large-scale projects.

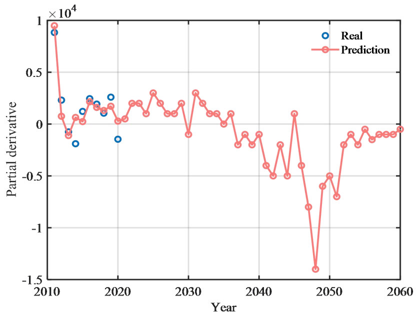

Figure 21. CO_2 Emissions Bias Maps for Multiple Scenarios such as Peak CO_2

For a region, there is a need to realize synergistic development of energy between regions, as well as to promote synergistic development between industries. In this process, it may face a number of constraints and barriers, ranging from hard constraints in terms of technology and finance, such as the investment problem of cross-regional energy infrastructure and inter-regional transfers, to soft constraints from systems, policies and mechanisms [18]. Therefore, we need to find innovative ways to solve these problems, including institutional and policy innovations, in order to promote the development of clean energy technologies as the most competitive source of electricity. In the future energy layout, institutions and mechanisms that limit the diffusion and utilization of technologies need to be reformed to ensure that these technologies can be fully utilized [19-23].

5. Conclusion

In this paper, a comprehensive analytical model of several indicators, such as economy, population, energy consumption, etc., was established by ARIMA time series and multiple regression model respectively to assess the current status of CO_2 emissions. And the parameters of the above models are corrected by BP neural network model. Finally, a regional CO_2 emission prediction model that can be analyzed scientifically and quantitatively was obtained. And the model a region to predict the future CO_2 emissions. Based on the results, a set of energy-saving and emission reduction strategy program was developed. The results of the study show that the prediction model can quantify the impacts of different impression factors on CO_2 emissions, so as to formulate scientific policies and strategies to achieve the goals of CO_2 peaking and CO_2 neutrality, and at the same time, ensure the sustainable development of the economy and society. Although the model shows good applicability in the current study, there are still limitations in the breadth of data and generalization of the model, which need to be further expanded and more types of impact factors should be considered. In the future, the research can be expanded in the following directions: first, actively explore and incorporate new prediction models and techniques to continuously optimize the model structure and improve its applicability and prediction accuracy in different regions and conditions; second, expand the research on relevant influencing factors, such as socio-economic, policy regulation and other multi-dimensional indicators, to form a more comprehensive analysis of the CO_2 emission impact mechanism; finally, propose more detailed and practical recommendations for specific regions and industries; and finally, propose a more detailed and practical approach for specific regions and industries to improve the CO_2 emission impact mechanism. Finally, we will propose more detailed and practical emission reduction measures for specific regions and industries, and evaluate their emission reduction effects and economic impacts, so as to provide stronger guidance and decision-making support for regional CO_2 emission reduction practices. Through these measures, we aim to promote the development of regional CO_2 emission prediction and management research to a deeper and wider level, and contribute wisdom and strength to the global response to climate change.

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