Regional Carbon Emission Forecasting Model Considering Temporal Characteristics and Analysis of Peak Carbon Assessment in Typical Scenarios

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Abstract. Leading high-quality economic development with green development is an important development concept for Chinese-style modernization, and achieving the dual-carbon goals of carbon peaking and carbon neutrality is a key initiative to promote high-quality economic and social development. In order to explore the correlation between carbon emissions and population, economy and energy consumption, and to propose a reasonable carbon emissions prediction model, this paper proposes an evaluation index system integrating fossil energy consumption and new energy consumption by analyzing the sample data obtained from the research in a hierarchical, industry- and sector-specific manner. And then, we compare the reliability of the results obtained from the multiple linear regression prediction model based on the above index system and the Kaya carbon emissions prediction model, respectively. By comparing the reliability of the results obtained from the carbon emission multiple linear regression prediction model based on the above index system and the Kaya carbon emission prediction model, it is initially determined that the Kaya model will be used for regional carbon emission prediction. In order to optimize the sensitivity of the model to the temporal Characterization of the indicators, a carbon emission prediction model that incorporates the temporal characteristics of the data is set up. Lastly, the carbon emission is predicted according to the three typical scenarios analyzed according to the intensity of the macro-policy, and the year of carbon peak and the year of carbon peak are analyzed for the scenarios. Three typical scenarios are analyzed according to the intensity of macro policies, and carbon emissions are predicted under different scenarios, and the year in which each scenario reaches the carbon peak is analyzed, as well as the correlation with the implementation of related policies and energy use, with a view to providing support for the planning of the dual-carbon target value and the path of achieving it, as well as the formulation of related policies.

Keywords: Multiple Linear Regression; Kaya Model; Temporal Characterization; Typical Scenarios; Carbon Emission Prediction.

1. Introduction

The world's unprecedented changes are accelerating, and the environmental crisis and international games triggered by global climate change are intensifying, becoming a major problem on the world's round table. In the face of ecological and environmental challenges, mankind is a community of destiny that thrives and loses at the same time. Promoting high-quality economic and social development aims to realize economic growth while improving people's quality of life, protecting the environment and enhancing the capacity for sustainable development [1]. However, the traditional economic growth model is usually accompanied by high energy consumption and high emissions, which contradicts the requirements of carbon emission reduction [2]. On the one hand, economic growth is usually accompanied by an increase in energy consumption, which mainly relies on the combustion of fossil fuels, resulting in an increase in carbon emissions. On the other hand, reducing carbon emissions requires reducing the carbon intensity of energy consumption, i.e., using energy more efficiently and reducing dependence on fossil fuels in economic development [3].

Breaking the contradiction between development and emission reduction is a complex and long-term task, in order to explore the correlation between carbon emissions and population, economy, energy, and get the relevant prediction model to better achieve the dual-carbon goal, this paper adopts the regression analysis, correlation analysis and other methods to explore the links between economic growth and energy consumption and energy consumption and carbon emissions, using data statistical analysis methods and regression analysis, time series Using statistical data analysis methods and mathematical models such as regression analysis, time series analysis and forecast analysis, this paper analyzes, evaluates and forecasts the impact of key projects such as energy efficiency improvement, industrial (product) upgrading, energy decarbonization and electrification of energy consumption on carbon emissions, with a view to laying a foundation for policymakers and researchers, helping to formulate and implement emission reduction policies, promoting sustainable development, and providing scientific support for achieving the goal of carbon neutrality.

In recent years, the global research on carbon emission prediction has received increasing attention, and many domestic and foreign research institutes and scholars have actively carried out related work. ZHANG et al [4] studied the impact of demographic factors on carbon emissions based on China's national and regional levels, and at the national level, population aging and population quality contribute to the scale of China's carbon emissions, and at the regional level, the impact of population aging shows regional differences in terms of carbon emissions. carbon emissions show regional differences. WANG Jianxiong et al [5] studied the influencing factors of carbon emission scale in the Beijing-Tianjin-Hebei region, and empirically found that the regional structure effect, the output scale effect, and the energy intensity effect have a greater impact on the region. YANG Shengdong et al [6] analyzed and found that different nature of environmental regulation has different impacts on carbon emissions, voluntary environmental regulation and command environmental regulation will reduce carbon emissions, while economic environmental regulation will have a positive impact on carbon emissions. Hou Bo et al [7] examined the influencing factors of carbon emissions in Shanghai, and the results showed that the degree of industrial agglomeration and the area of green space in the city have a significant impact on carbon emissions, and the spatial and temporal heterogeneity is obvious. He Qing et al [8] analyzed the impact of agricultural industry agglomeration on agricultural carbon emissions in China and found that the relationship between the two presents an "inverted U" type characteristic. HUANG et al [9] studied the impact of energy patents on China's carbon emissions, although empirical evidence shows that the impact is not significant but found that energy patents of enterprises and scientific research institutes can effectively inhibit carbon emissions. emissions.

The marginal contribution of this paper lies in the establishment of a personalized dual-carbon quantitative evaluation index system based on the measured data of a region, and then the construction of a dual-carbon universal comprehensive evaluation system and a universal carbon emission path prediction model. In order to improve the robustness of the model, the temporal characteristics of the data are integrated into the classical Kaya carbon emission prediction model, and a carbon emission prediction model that takes into account the temporal development characteristics of a single indicator and the interconnected characteristics of multiple indicators is established, and the above model is used to establish three typical regions for trial calculations, with a view to helping the formulation and implementation of emission reduction policies, promoting sustainable development, and providing scientific support for the realization of the goal of carbon neutrality.

2. Research design

2.1. Model assumptions

This paper puts forward the following hypotheses:

(1) In the short term, the energy structure will not change drastically and the proportion of consumption of each energy source will be relatively stable.

(2) Global climate change will not have a serious impact on regional economic development, energy consumption and carbon emissions.

(3) In terms of economic growth, GDP in 2035 will double compared to the base period (2020); and in 2060 it will quadruple compared to the base period.

(4) For carbon consumption, the carbon consumption of ecological carbon sinks in 2060 is 10% of the carbon emissions in the base period, and the carbon consumption of engineering carbon sinks or carbon trading in 2060 is 10% of the carbon emissions in the base period.

(5) Continuing trend aspect, it is assumed that the historical trend will continue for some time in the future and will continue to develop in this direction in the future.

(6) Correlation, which assumes that there is a linear or non-linear correlation between carbon emissions and population, GDP, and energy consumption, and that this relationship can be analyzed from historical data.

2.2. Data presentation

The data used in this paper were collected from the accounting report of a municipal government in a region along the southeast coast of China, which has a flat topography, convenient water and land transportation, dense population, developed economy, rich scientific and educational resources, but relatively scarce energy and ecological carbon sink resources.

After searching relevant literature and public information, we obtained the population, gross domestic product (GDP) and the distribution of output value of the three industries and sectors, the total energy consumption and the distribution of energy consumption of the three industries and sectors, the total energy consumption and the distribution of fossil and non-fossil energy sources, the variety structure of the three industries and sectors of energy consumption, the total amount of carbon emissions and the distribution of the three industries and sectors, the total amount of carbon emissions and the distribution of the three industries and sectors, and the distribution of the three industries and sectors of carbon emissions, and the total amount of carbon emissions and the distribution of the three industries and sectors of carbon emissions. emissions of the three industries and sectors, the structure of energy varieties, and the carbon emission factors of various types of energy related to carbon emissions. The data obtained were subjected to preliminary processing, such as outliers and normalization, to lay the foundation for the following data analysis and model building. Among them, the carbon emissions from 2010 to 2020 are shown in Figure 1 below, showing a steady upward trend.

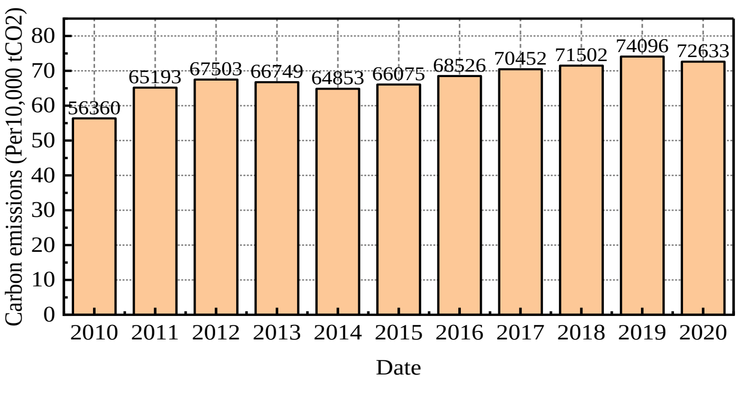

Figure.1. Summary of carbon emissions from 2010 to 2020

3. Modeling and problem-solving

In order to select evaluation indicators that can reflect the carbon emission status of the region, the study is based on three perspectives: economy, population and energy consumption. Based on the correlation analysis of the indicators, the economic aspect constructs indicators that can reflect the carbon emission status of different sectors (including the energy supply sector, the industrial consumption sector, the construction consumption sector, the transportation consumption sector, the living consumption of the residents, and the agriculture and forestry consumption sector), such as the total GDP of each sector. For population, select indicators related to the size of the population, such as the total population. For energy consumption, choose indicators that reflect energy consumption and are related to carbon emissions.

After comprehensive consideration and analysis, and taking into account the available data and relevant literature, a total of 19 secondary indicators, including total population, total GDP by sector, and energy consumption by sector, have been identified as primary indicators for the economy, population and energy consumption, as shown in Table 1, and the changes in these indicators can serve as the basis for the prediction of carbon emissions and help to assess the status of carbon emissions in the region.

3.1. Regional carbon emissions projection model

3.2.1 Multiple Linear Regression Model

The multiple linear regression was used to fit the regression parameters based on the 19 indicators proposed above, with the specific values shown in Table 1 below, to establish a linear regression model for predicting carbon emissions, expressed in the form of:

$$CO2 = a_1 A_1 + a_2 A_2 + ... + a_{18} A_{18} + + a_{19} A_{19} \tag{1}$$

CO_2 is the regional carbon emissions; a_i is the linear fitting coefficient of each secondary indicator; A_i is the specific value of each secondary indicator; And the order of i is consistent with the order in Table 1 below.

Table.1. System of Indicators

Serial No.	Level 1 indicators	Level 2 indicators	Fitting coefficient	Serial No.	Level 1 indicators	Level 2 indicators	Fitting coefficient
1	Population indicators	Total population (ten thousand persons)	7.903+	11	Economic indicators	GDP per Capita (billions of dollars/person)	0.000
2		Rate of Population Growth(%)	0.000	12		GDP-Agriculture and Forestry Consumption Sector (billions of dollars)	-0.205
3	Energy consumption indicators	Energy Consumption-Agriculture and Forestry Consumption Sector (ten thousand tce)	-49.007	13		GDP-Energy Supply Sector(billions of dollars)	12.299
4		Energy Consumption-Industrial Consumption Sector(ten thousand tce)	-5.922	14		GDP-Industrial Consumption Sector (billions of dollars)	-1.713
5		Energy Consumption-Transportation Consumption Sector (ten thousand tce)	0.000	15		GDP-Transportation Consumption Sector (billions of dollars)	6.048
6		Energy Consumption-Building Consumption Sector (ten thousand tce)	0.000	16		GDP-Construction Consumption Sector (billions of dollars)	0.835
7		Energy Consumption-Residential Consumption (ten thousand tce)	-12.266	17		GDP Growth Rate-Agriculture and Forestry Consumption Sector (%)	0.000
8		Variety Structure of Energy Consumption-Fossil Energy (ten thousand tce)	4.623	18		GDP Growth Rate-Industrial Consumption Sector (%)	0.000
9		Energy Consumption Variety Structure - New Energy (ten thousand tce)	8.005	19		GDP Growth Rate-Construction Consumption Sector (%)	0.000
10		Energy Consumption per Unit of GDP (ten thousand tce)	0.000				

Based on the results of the multiple linear regression (MLR) model above, it can be seen that the predicted value of carbon emissions can be obtained when the predicted values of the 19 indicators are known. Now the 19 indicators are predicted in turn, in the process of analyzing the previous data, it is found that, except for the total population, the remaining 18 indicators basically grow linearly with the year, so the linear fitting regression model is used for prediction, and the total population is predicted by the logistic regression model. By combining the results of the above prediction models, the expected carbon emissions for the 14th and 21st FYPs were calculated as shown in Table 2 below.

Table.2. Carbon Emission Prediction Results from Multiple Linear Regression Model

Period		Carbon Emissions (ten thousand tce)	Period		Carbon Emissions (ten thousand tce)
The Fourteenth Five-Year Plan	2021	74188	The Twenty-first Five-Year Plan	2056	84870
	2022	75066		2057	91474
	2023	75929		2058	96079
	2024	76781		2059	96685
	2025	79624		2060	97291

3.2.2 Kaya Model

In order to further compare and verify the accuracy of the model, this paper establishes a carbon emission Kaya calculation model that can characterize the correlation between regional population and economic and energy consumption based on the correlation analysis of indicators and the recursive relationship of regional characteristics [10], and the basic calculation formula is:

$$CO_2 = P \times \frac{GDP}{P} \times \frac{E}{GDP} \times e \tag{2}$$

$\frac{GDP}{P}$ is Gross Domestic Product per capita(GDP); $\frac{E}{GDP}$ is energy consumption per unit of GDP; e is carbon dioxide emissions per unit of energy consumption, Specifically $e = \frac{CO_2}{E}$ can be expressed as a carbon emission factor for energy consumption.

As can be seen from the above equation, the results of the Kaya generalized model for calculating carbon emissions are not only related to the population, total regional gross domestic product GDP, and regional energy consumption *E*, but also closely linked to the arithmetic relationship between the indicators. The functional expression of the above model relationships allows the carbon emission values to be linked to the type of energy consumption and supply sector, energy consumption varieties, and energy utilization in the region. In order to obtain the predicted values of carbon emissions for the sample region, the population, *GDP* of each sector, energy consumption *E* and carbon emission factor *e* for each energy consumption variety in each sector were predicted separately. As the mean and variance of the respective variable data are close to a constant value, the original data series has a smooth change characteristics, so the ARIMA model was selected to predict the independent variables, and the predicted data to meet the parameter test were brought into the Kaya model to calculate the value of carbon emissions from each energy consumption output of multiple industries and sectors, and the sum was obtained to get the total carbon emissions prediction value. The final carbon emission forecasts calculated by Kaya model are shown in Table 3.

Table.3. Carbon Emission Projection Results from Kaya Model

Period		Carbon Emissions (ten thousand tce)	Period		Carbon Emissions (ten thousand tce)
The Fourteenth Five-Year Plan	2021	69656	The Twenty-first Five-Year Plan	2056	68832
	2022	71573		2057	67331
	2023	71941		2058	67276
	2024	72596		2059	66309
	2025	74096		2060	66391

3.2.3 Model Comparison and Evaluation

Through the above analysis, based on the regional characteristics, this paper establishes two carbon emission prediction models, the multiple linear regression model takes into account the correlation between the indicators and tries to build an indicator system that can cover the overall characteristics of the region, and the Kaya model takes into account the linkage between the indicators and mathematically establishes the linkage between the indicators of different categories of economy, population and energy consumption. The carbon emissions calculated by the two models are now compared, as shown in Figure 2. As can be seen from the figure, the carbon emissions predicted by the multiple linear regression model show a continuous upward trend, and the carbon emissions predicted by the Kaya model show an upward and then downward trend. Analyzing with the actual policy situation in the region, due to the influence of relevant technical, economic, policy and other factors, the carbon peak will occur between 2021 and 2060, and the carbon emissions will reach the peak state, and the Kaya model predicts that the results are consistent with this objective fact. And the multiple linear regression model, due to the excessive number of indicators to be predicted in the calculation process, is initially considered to have a large accumulation of errors, leading to bias in the prediction results. In conclusion, Kaya model is chosen as the final carbon emission prediction model.

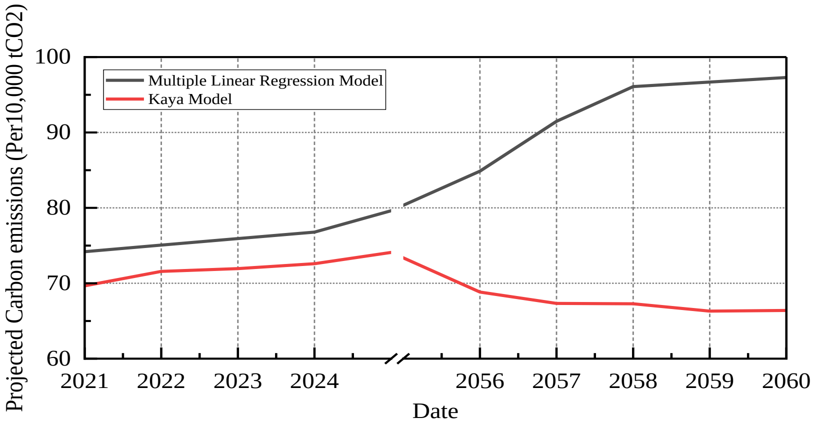

Figure.2. Comparison of data prediction results

3.2.4 Model Optimisation

In order to predict the ideal years for different scenarios to reach the carbon peak and carbon neutrality targets respectively, with a view to quantitatively evaluating the effects of energy saving and carbon reduction in different scenarios and providing management departments with implementation references for formulating macro-control policies. In this section, the quantitative evaluation is based on the selected Kaya carbon emission prediction model. In order to reduce the calculation error and highlight the time-series characteristics of each indicator as much as possible, the following formula is obtained by taking the partial derivative of time after taking the logarithm of the general formula:

$$\delta CO_2 = \delta P + \frac{\delta GDP}{\delta P} + \frac{\delta E}{\delta GDP} + \frac{\delta CO_2}{\delta E} \tag{3}$$

δCO_2 is the relative rate of change of regional $CO2$ emissions to the base year; δGDP is relative rate of change in regional GDP to a base year; δE is the relative rate of change in energy consumption E with respect to a base year.

In order to highlight the significant time-periodic characteristics of the indicators characterizing the region, the above equation was differentially transformed to obtain a functional model for calculating carbon emissions using the rate of change of the indicators for each parameter and the year as shown in the following equation:

$$CO_{2\_n} = \delta CO_2 \times CO_{2\_n-1} = (\delta P + \frac{\delta GDP}{\delta P} + \frac{\delta E}{\delta GDP} + \frac{\delta CO_2}{\delta E}) \times CO_{2\_n-1} \tag{4}$$

CO_{2_n-1} is the total regional $CO2$ emissions for the previous year.

Through the above steps, the Kaya model is improved to establish a carbon emission prediction model that takes into account the characteristics of time series, solves the problem of poor sensitivity of the Kaya model to the analysis of data with temporal characteristics, and fully takes into account the influence of the characteristics of the main indicators of the scenarios of the previous time step on the next time step, which is expected to realize the accurate prediction of the target time of regional carbon peaks.

3.2. Analysis of carbon emissions in different scenarios

3.3.1 Scenario setting

In order to fully characterize the region, the design considers three typical regional scenarios, which represent the natural scenario with no human intervention, the baseline scenario with on-time carbon peak and carbon neutrality, and the ambitious scenario with the first carbon peak and carbon neutrality and predicts carbon emissions under different scenarios to address the differences of the different scenarios. The specific settings are shown in Table 4 below.

Table.4. Scenario Categorization Setting

Scenario	Natural Scenario	Baseline Scenario	Ambitious Scenario
Characteristic	Natural scenario under the law of natural change, no relevant carbon and energy control policy constraints, carbon emission pathway based on the development of the region's own economic structure and industrial structure	Baseline scenario with some policy guidance, constrained by medium-intensity carbon and energy control policies, with carbon emission paths constrained by timelines	Ambitious scenarios guided by active policies, constrained by high-intensity carbon energy control policies, earlier achievement of carbon neutrality targets
Policies and Measures	No specific policies or measures	General policies and implementation intensity	Strong policy and implementation intensity
Potential impact	Late achievement of the "dual carbon" target and high carbon emissions	Decrease in carbon emissions compared to the natural scenario due to a reasonable timeframe for the region to reach the "double carbon" target under policy control;	A larger proportion of energy restructuring, a lower carbon emission factor per unit of energy consumption, more efficient technological innovations and the share of non-fossil energy, etc.

3.3.2 Scenario parameterization and model solution

(1) Indicators of improvement in the effectiveness of unit energy consumption and the proportion of non-fossil energy consumption

The variables that differ in different scenarios are the carbon reduction effect per unit of energy consumption and the proportion of non-fossil energy consumption in total energy consumption, which are affected by the policy implementation strength in different scenarios. The rate of change of energy consumption per unit of GDP ($\delta \frac{E}{GDP}$)is used as an indicator of the improvement of carbon reduction effect per unit of energy consumption in different scenarios, and the rate of change of CO2 emission per unit of energy consumption δe ($\delta e = \frac{\delta CO_2}{\delta E}$) is used as an indicator of the proportion of non-fossil energy consumption in different scenarios.

The Nature scenario considers peak *CO2* emissions in 2040 and neutralization in 2060, the Baseline scenario considers peak *CO2* emissions in 2030 and carbon neutrality in 2050, and the Ambition scenario considers more aggressive policy measures than the other two scenarios to peak *CO2* emissions in 2025 and achieve the *CO2* neutrality target in 2045. neutrality target by 2045. By setting different indicator coefficients to quantitatively represent the indicators of improvement in the effectiveness of unit energy consumption ($\delta \frac{E}{GDP}$)and the proportion of non-fossil energy consumption δe ($\delta e=\frac{\delta CO_2}{\delta E}$). Based on the sample data analysis and policy research, the $\frac{\delta E}{\delta GDP}$ and δe indicator data under the three scenarios are set as shown in Table 5.

Table.5. Indicator Setting Parameters

	Natural Scenario	Baseline Scenario	Ambitious Scenario
$\frac{\delta E}{\delta GDP}$	0.978	0.976	0.970
δe	0.975	0.970	0.965

(2) Population Growth Rate Indicators

Aiming at the characteristics of non-linear changes in population, the model is used for quantitative assessment and forecasting of population growth. After fitting residual analysis and comparative analysis of the goodness-of-fit values, the model parameters are determined to be $ARIMA(2,2,1)$, and the values are obtained by calculation. The projected total population and rate of change in population growth from 2021 to 2060 is shown in Figure 3 and Figure 4.

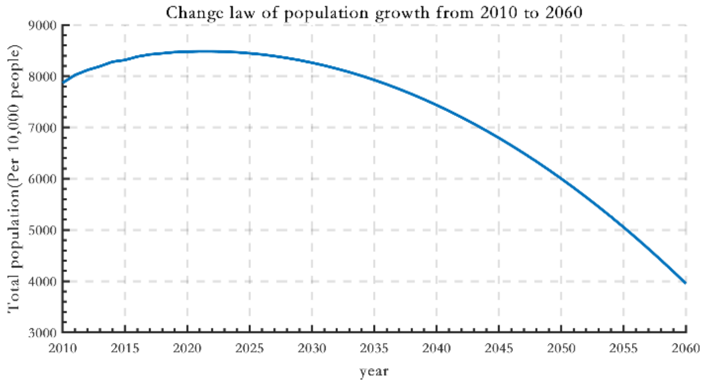

Figure.3. Projected total population, 2010-2060 (people of ten thousand)

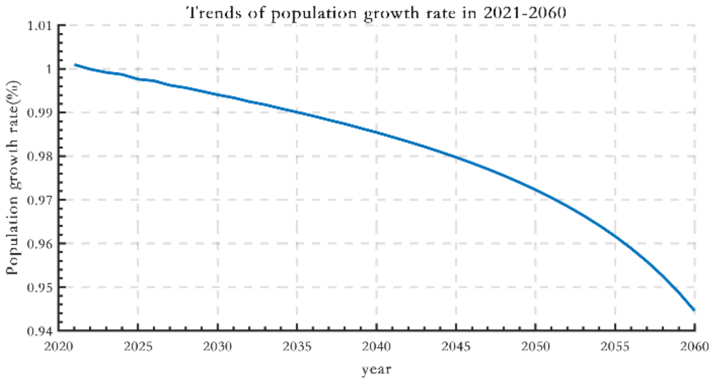

Figure.4. Rate of change in population growth, 2021-2060(%

(3) Indicators of gross regional product

Taking the regional GDP change data as a sample, the GDP in 2035 is doubled compared to the base period (2020), and quadrupled compared to the base period in 2060, and based on the above recursive relationship, the GDP prediction model for 2020-2060 is established. Set the GDP indicator reflecting the economic level of the population in the base period of 2020 as GDP_0, the GDP of the population economy in 2035 as GDP_1, and the GDP of the population economy indicator in 2060 as GDP_2, set the GDP indicator in the base period to satisfy $GDP_0=1$, and set up the following regression model of the regional GDP:

$$\begin{aligned} GDP_n &= \beta_0+\beta_1 X_1+\beta_2 X_1^2 \\ GDP_2 &= 2\times GDP_1 \\ GDP_3 &= 4\times GDP_1 \end{aligned} \tag{5}$$

$X_i, i = 1,2,3,.....,n$ indicates the year from 2020-2060. Solving yields the following functional equation with year X as the independent variable and regional GDP_n as the dependent variable:

$$GDP_n = 0.0003X^2\text{-}1.285X\text{+}1236.567 \tag{6}$$

The formula for obtaining the rate of change of GDP for the region is as follows:

$$\delta GDP = 0.0003 \times 2X\text{-}1.285X \tag{7}$$

(4) Calculation of carbon emissions under each scenario

Taking the regional total carbon emission data of 7.26×10^8 tons in the region in 2020 as the base year data, using the total carbon emission prediction model established in this paper, the projected values of carbon emissions from 2021 to 2060 under the three scenarios are calculated. Specific numerical calculation results are shown in Table 6, and the change trend is shown in Figure 5.

Table.6. Projections of carbon emissions under different scenarios

Date	δP	$\frac{\delta GDP}{\delta P}$	Natural Scenario	Baseline Scenario	Ambition Scenario
2021	1.001	1.062	73553.6	73026.75	72203.71
2022	1.000	1.059	74275.69	73215.47	71574.42
2023	0.999	1.056	74813.98	73217.86	70770.05
2024	0.999	1.054	75182.04	73051.05	69813.02
2025	0.998	1.052	75392.67	72730.99	68723.77
2026	0.997	1.05	75457.91	72272.53	67520.9
2027	0.996	1.048	75389.14	71689.47	66221.32
2028	0.996	1.046	75197.04	70994.61	64840.35
2029	0.995	1.044	74891.69	70199.88	63391.91
2030	0.994	1.043	74482.56	69316.3	61888.55
2031	0.993	1.042	73978.54	68354.11	60341.64
2032	0.992	1.04	73388	67322.78	58761.38
2033	0.992	1.039	72718.81	66231.08	57156.98
2034	0.991	1.038	71978.32	65087.08	55536.66
2035	0.990	1.037	71173.44	63898.28	53907.8
2036	0.989	1.036	70310.66	62671.56	52276.97
2037	0.988	1.035	69396.04	61413.25	50650.01
2038	0.987	1.034	68435.26	60129.2	49032.08
2039	0.986	1.033	67433.62	58824.74	47427.74
2040	0.985	1.033	66396.08	57504.79	45840.99
2041	0.984	1.032	65327.26	56173.85	44275.31
2042	0.983	1.031	64231.49	54836	42733.72
2043	0.982	1.03	63112.78	53495	41218.82
2044	0.981	1.03	61974.88	52154.24	39732.83
2045	0.980	1.029	60821.25	50816.81	38277.61
2046	0.978	1.029	59655.15	49485.51	36854.7
2047	0.977	1.028	58479.55	48162.86	35465.38
2048	0.976	1.028	57297.24	46851.12	34110.64
2049	0.974	1.027	56110.78	45552.33	32791.25
2050	0.972	1.027	54922.54	44268.32	31507.79
2051	0.970	1.026	53734.7	43000.69	30260.61
2052	0.969	1.026	52549.29	41750.86	29049.94
2053	0.966	1.025	51368.14	40520.1	27875.83
2054	0.964	1.025	50192.95	39309.49	26738.21
2055	0.962	1.024	49025.26	38119.99	25636.88
2056	0.959	1.024	47866.49	36952.39	24571.54
2057	0.956	1.024	46717.93	35807.39	23541.82
2058	0.953	1.023	45580.74	34685.54	22547.24
2059	0.949	1.023	44455.97	33587.32	21587.26
2060	0.945	1.022	43344.57	32513.07	20661.31

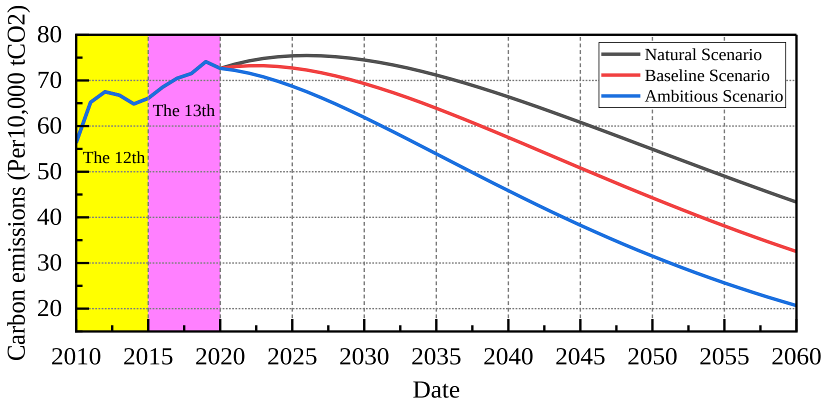

Figure.5. Carbon emission projections under different scenarios

From Figure 5, it can be seen that, in general, the sample data region selected in this paper reaches the peak of carbon emissions in each scenario around 2030, with the natural scenario realizing the policy target around 2027, the baseline scenario more optimistically projected to achieve the policy target around 2024, and the ambitious scenario expected to reach the peak of carbon emissions in the next year, and the carbon emission peak is gradually advanced due to the adoption of gradual and active policy control. The ambitious scenario expects carbon emissions to peak in the following year. The results show that there is a strong correlation between the intensity of policy implementation and the year in which regional carbon emissions peak, and that improving energy efficiency and enhancing the intensity of implementation of each policy under the specified timeline targets can help guide the realization of the dual-carbon goals in a timely manner.

4. Conclusions

By analyzing the existing data in the region, this paper considers the establishment of an indicator system that can comprehensively reflect the status of the region's economy, population, energy consumption, and carbon emissions in various sectors. Based on this indicator, a carbon emission model is established, and by comparing the calculation results of the multiple linear regression model and the Kaya model, the Kaya model is selected as the prediction model, and the model is optimized according to the time characteristics of the data, and the carbon emission prediction model based on the Kaya model considering the characteristics of the time series is proposed, which takes into account the influence of the main characteristics of the indicators of the scenario of the previous time step on the next time step, and is expected to realize the accurate prediction of the target time of the regional carbon peak. The model takes into account the influence of the main indicator characteristics of the previous time-step scenario on the next time-step scenario and is expected to realize the accurate prediction of the regional carbon peak target time. Finally, different policy scenarios are set up, and the corresponding scenario calculation parameters are set according to the characteristics of different scenarios, and the projected values of carbon emissions from 2021 to 2060 and the year of reaching the policy target are obtained. The natural scenario achieves the policy target around 2027, the baseline scenario is more optimistic and is expected to achieve the policy target around 2024, and the ambitious scenario is expected to peak the carbon emissions in the next year. The ambitious scenario expects carbon emissions to peak in the following year, and the time to peak is gradually advanced due to the adoption of progressively more aggressive policy controls.

The personalized dual-carbon quantitative evaluation index system and the time-specific Kaya carbon emission prediction model constructed in this paper are intended to provide a solid foundation for policymakers and researchers to help formulate and implement emission reduction policies, promote sustainable development, and provide scientific support for achieving the goal of carbon neutrality.

References

[1] GUO Chaoxian, Carbon Neutrality in 2060 Leads to Fundamental Changes in China's Economic System[J]. Journal of Beijing Institute of Technology (Social Science Edition),2021,21(05):64-77.

[2] WEI Yanru. Investment Treaty Regulation of Fossil Fuels under the Carbon Neutral Goal[J]. Journal of Guangxi University (Philosophy and Social Science Edition), 2023, 45(03).

[3] WANG Lin. Global carbon emissions to hit another record high this year[N]. China Energy News, 2022-11-21(004).

[4] ZHANG C, TAN Z. The relationships between population factors and China's carbon emissions Does population aging matter[J]. Renewable & Sustainable Energy Reviews, 2016, 65: 1018-1025.

[5] WANG Jianxiong, LU Yanshu, LI Chenxi. Study on the Influencing Factors of Carbon Emission in Beijing-Tianjin-Hebei under LMDI Method and STIRPAT Model[J]. China Economic and Trade Review(C),2021(01):114-116.

[6] YANG Shengdong, YANG Xu, WU Xiangli, WU Yufei, ZHOU Jia. Impacts of environmental regulations on spatial and temporal differences in regional carbon emissions--an empirical analysis based on 32 prefecture-level cities in three northeastern provinces[J/OL]. Journal of Environmental Science,2020,1-10.

[7] HOU Bo,YUE Wenze,WANG Tengfei. Detection of spatial and temporal heterogeneity of carbon emissions in Chinese metropolitan areas and the factors affecting it--The case of Shanghai[J]. Economic Geography,2020,40(09):82-90.

[8] HE Qing, ZHANG Hu, ZHANG Junbiao. Nonlinear effects of agricultural industrial agglomeration on agricultural carbon emissions[J]. Statistics and Decision Making,2021(9):4.

[9] HUANG, J., LI, X., WANG, Y., et al. The effect of energy patents on China’s carbon emissions: Evidence from the STIRPAT model[J]. Technological Forecasting and Social Change,.2021,173.

[10] YANG P, LIANG X, Drohan P J. Using Kaya and LMDI models to analyze carbon emissions from the energy consumption in China[J]. Environmental Science and Pollution Research, 2020, 27: 26495-26501.