Optimization Analysis of Energy Structure in Jinhua City, Zhejiang Province Based on Carbon Peak Constraints

Jiansheng Hou[1], Honghui Huang[1], Lina Zhang[2], Yingcong Wang [1*]

[1]State Grid Jinhua Power Supply Company, Jinhua Zhejiang 321000, China
[2]Jinhua Electric Power Design Institute Co. LTD, Jinhua Zhejiang 321000, China

Abstract. As China's economic development has entered a new normal, it is in China’s self-interest to achieve carbon peaking before 2030. and the decomposition and analysis of the influencing factors of carbon emissions are not only conducive to predicting the peaking time of carbon emissions, but also crucial to develop differentiated emission reduction policies in Jinhua. This paper firstly decomposes and analyzes the influencing factors of carbon emissions in Jinhua based on LMDI decomposition technology and hidden Markov chain, and then the dynamic relationship among the influencing factors of carbon emissions in Jinhua is explored by the panel vector autoregressive model. In addition, this paper also uses STIRPAT model to forecast and analyze the peaking time of carbon emissions in Jinhua and puts forward targeted suggestions.

1. Introduction

Currently, countries around the world are facing severe environmental challenges caused by global warming. The primary cause of this problem is the increasing emissions of greenhouse gases, especially carbon dioxide. Recognizing the urgency, countries worldwide have proactively adopted effective measures to slow down or prevent further temperature rise (Lin, 2019)[1]. As a populous country and a major energy consumer, China is the world’s largest emitter of carbon dioxide, imposing even greater challenges and responsibilities for emission reduction. In response to climate change, China has set the carbon reduction targets of “committing to peak carbon dioxide emissions before 2030 and achieve carbon neutrality before 2060”. The goals of “carbon peaking” and “carbon neutrality” (hereinafter “dual carbon” goals) have been included as key priorities in the “14th Five-Year Plan” of every province across the nation, accompanied by the development of respective carbon reduction policies (Ji et al., 2023)[2].

In recent years, an increasing number of scholars have conducted research on the implementation of the “dual carbon” goals. When analyzing the influencing factors, scholars mostly associate economic factors with these goals, particularly discussing the Environmental Kuznets Curve (EKC), which suggests an inverted U-shaped relationship between economic growth and environmental pollution (Yuan et al., 2014)[3]. Zhang and Wang (2022)[4], using panel data from Chinese provinces for the years 1997-2019, found that the regression results between China’s economic growth and carbon emissions consistently decrease and remain positive, indicating that China is still in the ascending phase of the EKC. Zhu et al. (2019)[5] explored the influencing factors of carbon emissions in China using data from 1978 to 2014 and found that population and energy consumption structure significantly affect carbon dioxide emissions. Additionally, many scholars have investigated the impact of carbon emissions from the perspectives of industrial structure, urbanization, and other factors (Xu et al., 2023[6]; Liu et al., 2023[7]; Wang et al., 2018[8]). Since the introduction of the “dual carbon” goals, many scholars have made predictions. Mujeeb Sana et al. （2023）[9]quantifies the impact of carbon emission projections and renewable energy based on deep learning.Li et al. (2023),[10] utilizing a GA-ELM model and panel data from 30 provinces (autonomous regions and municipalities) in China from 1997 to 2020, suggested that in a green development scenario, seven regions in China could achieve the carbon peaking before 2030. Wang et al. (2019)[11] argued that for mega-cities, peaking carbon dioxide emissions before 2030 is contingent on a rapid decline in energy intensity. Wang et al. (2022)[12], from an industry perspective, proposed that accelerating the development of clean and renewable energy is an inevitable choice for the power industry to achieve the carbon peaking before 2030.Rahmaditio M R et al.(2023)[13] projections of diesel, biodiesel and pure electric vehicle carbon emissions in Indonesia based on the transportation sector to compare their carbon reduction policies.

It is a well-established fact that energy consumption and production, as the primary sources of greenhouse gases, contribute to climate change and global warming issues(Aras Serkanet al.,2022)[14].Against the backdrop of rapid economic growth and a continuous increase in population, China’s demand for energy consumption has been growing day by day. As a result, carbon emissions

* Corresponding author: 2758368169@163.com

related to energy consumption have also been on the rise. In order to promote high-quality and sustainable development of the Chinese economy, it is necessary to adjust the energy mix, develop a low-carbon economy, and improve energy efficiency (Zhou et al., 2011)[15]. Improving the energy mix has become an important pathway to promote the development of a low-carbon economy. Fan et al. (2015)[16] pointed out that the main influencing factors of energy consumption structure include energy consumption constraints, carbon emission constraints, economic growth, population, and industrial structure. Specifically, when energy intensity and carbon intensity remain constant, constraints on energy consumption and GDP growth directly drive the optimization of the energy consumption structure, while constraints on carbon emissions and energy consumption overall have a restraining effect on the optimization of energy consumption structure. Tang et al. (2023) [17] argued that the optimization and transformation of the energy mix are a prerequisite and a key measure to achieve the goal of carbon neutrality.

Answering the call of “dual carbon” goals, Zhejiang province has enacted policy documents on a regular basis such as the Regulation of Zhejiang province on Environment Protection, the "14th Five-Year Plan" for energy development in Zhejiang province, and the Zhejiang province 14th Five Year New Energy Storage Development Plan. These policies aim to align with the requirements of ecological civilization construction and the “dual carbon” goals, leveraging digital reforms to support and promote green and low-carbon transformation of the energy sector, ultimately aiming to become a nationally recognized province for clean energy demonstration. As the core city in central Zhejiang province, Jinhua recorded a regional gross domestic product (GDP) of 535.544 billion yuan in 2021, with industrial added value reaching 119.826 billion yuan. The energy consumption of large-scale industries in Jinhua amounted to 8.7478 million tons of standard coal, while the energy consumption of seven energy-intensive industries reached 4.7009 million tons of standard coal. As GDP has been increasing year by year, carbon emissions have also been rising. However, in order to achieve the goal of “enable carbon dioxide peaking before 2030”, active participation and coordinated cooperation from various departments in Jinhua are necessary.

Based on this, this paper takes Jinhua in Zhejiang province as an example to analyze its current carbon emissions, identify important factors influencing carbon emissions, sort out the dynamic relationships among these factors, and use scenario analysis to reasonably forecast the peaking time of carbon emissions. This research holds theoretical significance and provides valuable references for provinces and cities across the country in achieving their carbon peaking goals.

2. Decomposition of Carbon Emissions Influencing Factors

2.1 Calculation of Carbon Emissions

Considering the representativeness and generalizability, this paper adopts the methodology provided in the IPCC Guidelines for National Greenhouse Gas Inventories published by the Intergovernmental Panel on Climate Change (IPCC) in 2006 to calculate carbon dioxide emissions. The specific calculation equation is as follows:

$$\begin{aligned} CO_2 &= \sum\nolimits_i E_i * \delta_i \\ &= \sum\nolimits_i E_i * NCV_i * CEF_i * COF_i * \frac{44}{12} \end{aligned} \tag{1}$$

where CO_2 denotes carbon dioxide emissions, i represents the type of energy, E signifies energy consumption, NCV means the average lower heating value, which is the carbon content per unit of heat generated. CEF represents the carbon emission factor, indicating the carbon content level per unit of heat. COF denotes the carbon oxidation factor, indicating the carbon oxidation rate during energy combustion. 44/12 is the ratio of carbon dioxide to carbon molecular weight. δ signifies the carbon dioxide emission factor of energy. Table 1 shows the carbon dioxide emission factors for various types of energy.

Table 1 Carbon Emission Accounting Parameters of Various Energy Sources

Energy Type	Lower Heating Value (kJ/kg; kJ/m^3)	Carbon Content Per Unit of Calorific Value (kg/GJ)	Carbon Oxidation Ratio (%)	Carbon Emission Factor (kg/kg; kg/m^3)
Raw Coal	20908	26.37	94	1.90
Cleaned Coal	26344	27.40	94	2.49
Other Washed Coal	10454	27.40	94	0.99
Briquette	17761	33.60	90	1.97
Coke	28435	29.50	93	2.86
Coke Oven Gas	16726	12.10	98	0.73
Other Gases	15054	12.10	98	0.65
Crude Oil	41816	20.10	98	3.02
Gasoline	43070	18.90	98	2.93
Kerosene	43070	19.60	98	3.03
Diesel	42652	20.20	98	3.10
Fuel Oil	41816	21.10	98	3.17
Liquefied Petroleum Gas	50179	17.20	98	3.13
Refinery Dry Gas	45998	18.20	98	3.01
Natural Gas	38931	15.30	99	2.16

2.2 Decomposition of Carbon Emissions

Regarding the decomposition of carbon emissions, this study applies the Logarithmic Mean Divisia Index

(LMDI), which effectively addresses residual and zero-value issues and is more suitable for carbon dioxide emissions decomposition research (Meng et al., 2022)[18].

The Kaya identity expands on the IPAT model, and it holds significant importance in the field of carbon emissions influencing factors research (Hu et al., 2018)[19]. The calculation expression of the Kaya identity is as follows:

$$C = P * \left(\frac{C}{E}\right) * \left(\frac{E}{GDP}\right) * \left(\frac{GDP}{P}\right) \tag{2}$$

where C represents carbon emissions, P denotes population size (representing electricity demand scale), E signifies energy consumption, $\frac{C}{E}$ means carbon emissions per unit of energy consumption, $\frac{E}{GDP}$ indicates energy intensity per unit of GDP, $\frac{GDP}{P}$ represents per capita GDP.

The Kaya identity simplifies the decomposition of carbon emissions into important indicators such as population, economy, and technology. By quantifying and simplifying these factors, it achieves a decomposition result without residuals and provides strong explanatory power for the influencing factors. As electricity scale also influences carbon emissions, the carbon emissions factor decomposition model constructed in this study based on the LMDI model is as follows:

$$C = \sum_i C_i = \sum_i \frac{C_i}{E_i} * \frac{E_i}{E} * \frac{E}{Y} * \frac{Y}{N} * N \tag{3}$$

where C signifies carbon emissions, C_i denotes carbon emissions for i energy, E indicates total energy consumption, E_i means energy consumption for i energy, Y represents regional GDP, N signifies the total population of the region. The five terms on the right side of the equation are: C_i/E_i denotes the carbon emissions per unit of a specific type of energy, i.e., the carbon emissions coefficient for i energy. E_i/E indicates the proportion of energy consumption for the i energy, representing the energy mix. E/Y means the energy consumption required per unit of output, i.e., energy intensity. Y/N indicates per capita GDP, representing the level of economic development. N represents the scale of electricity.

Furthermore, the total carbon emissions can be decomposed into carbon intensity effect (I), energy mix effect (S), energy intensity effect (E), economic development effect (G), and electricity scale effect (N), as follows:

$$\begin{aligned} C &= \sum_i C_i = \sum_i \frac{C_i}{E_i} * \frac{E_i}{E} * \frac{E}{Y} * \frac{Y}{N} * N \\ &= \sum_i I_i S_i EGN \end{aligned} \tag{4}$$

According to the equation, the change in carbon emissions from year to year can be represented as:

$$\begin{aligned} \Delta C &= C^{t+1} - C^t \\ &= \sum_i I_i^{t+1} S_i^{t+1} E^{t+1} G^{t+1} N^{t+1} - \sum_i I_i^t S_i^t E^t G^t N^t \\ &= \Delta C_I + \Delta C_S + \Delta C_E + \Delta C_G + \Delta C_N \end{aligned} \tag{5}$$

where ΔC_I represents the carbon intensity effect, ΔC_S signifies the energy mix effect, ΔC_E denotes the energy intensity effect, ΔC_G means the economic development effect, and ΔC_N indicates the electricity scale effect. If the value of a decomposition factor is greater than 0, it indicates that the factor positively affects carbon emissions, i.e., increasing carbon emissions. If it is less than 0, the factor negatively affects carbon emissions, i.e., reducing carbon emissions.

Using LMDI decomposition technique, the effect equation of each decomposition factor from year to year is as follows:

$$\Delta C_I = \sum_i^m L\left(C_i^{t+1}, C_i^t\right) \ln\left(\frac{I^{t+1}}{I^t}\right) \tag{6}$$

$$\Delta C_S = \sum_i^m L\left(C_i^{t+1}, C_i^t\right) \ln\left(\frac{S^{t+1}}{S^t}\right) \tag{7}$$

$$\Delta C_E = \sum_i^m L\left(C_i^{t+1}, C_i^t\right) \ln\left(\frac{E^{t+1}}{E^t}\right) \tag{8}$$

$$\Delta C_G = \sum_i^m L\left(C_i^{t+1}, C_i^t\right) \ln\left(\frac{G^{t+1}}{G^t}\right) \tag{9}$$

$$\Delta C_N = \sum_i^m L\left(C_i^{t+1}, C_i^t\right) \ln\left(\frac{N^{t+1}}{N^t}\right) \tag{10}$$

where $L\left(C_i^{t+1}, C_i^t\right) = \left(C_i^{t+1} - C_i^t\right) / \left(\ln C_i^{t+1} - \ln C_i^t\right)$

2.3 Dynamic Relationship of Influencing Factors of Carbon Emissions

The VAR model is a vector autoregressive model, which utilizes Ordinary Least Squares (OLS) estimation to obtain its parameters. Due to the consistency of the parameter estimation, it is challenging to interpret the economic significance of individual parameter estimates. To analyze the VAR model and understand the dynamic relationships among the four influencing factors of carbon emissions, this study conducts further research using impulse response functions and variance decomposition.

2.3.1 Impulse Response Functions

Impulse response functions illustrate the trajectory of variables after being subjected to shocks, displaying the dynamic relationships among variables in the VAR model with different degrees of variance adjustment. Impulse response functions provide conditional predictions. In this study, "exogenous shocks" are applied to the four variables: carbon emissions, economy, energy consumption, and electricity consumption. The values at different time points after the shocks are estimated, and the impulse response graphs are obtained based on the changes in the trajectories following the shocks.

In the impulse response graphs, the plots in the same row depict the response trajectories of different variables to the same exogenous shock, while the plots in the same column compare the effects of different exogenous shocks on the same variable. The horizontal coordinates represent the unit time estimated by the VAR model (in this study, it is yearly), and the vertical coordinates represent the corresponding units of each variable. Figure 1 presents the impact results within 10 years after the shocks occur.

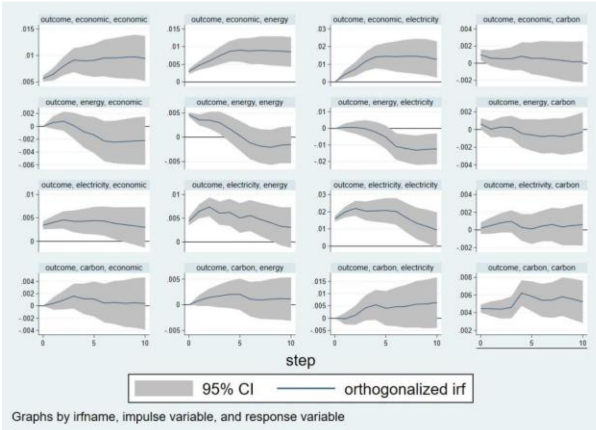

Figure 1. Dynamic response between carbon emissions and economy, energy consumption, and electricity consumption

After applying a one-standard-deviation shock to Jinhua's economy, the response trajectory of the VAR model is shown as the graph in the first row. The economy absorbs the shock entirely and shows an increase in the corresponding unit percentage, continuously affected throughout the 10-year observation period. Energy consumption responds to the shock by initially rising and then starting to decline after the fourth year. Electricity consumption exhibits a similar pattern to energy consumption, while the trajectory of carbon emissions shows a decrease followed by an increase and subsequent decrease. The second row represents the results of the shock on energy consumption. The economy, energy consumption, and electricity consumption all experience a slight decline in the first seven years, followed by a stable period, with a minor overall decrease in carbon emissions. The third row illustrates the results of the shock on electricity consumption. Both energy consumption and electricity consumption exhibit a significant initial increase followed by fluctuating declines, while the changes in the economy and carbon emissions remain relatively stable. The fourth row presents the results of the shock on carbon emissions. The impact of carbon emissions on the economy, energy consumption, and electricity consumption gradually rises, and this impact is not fully absorbed even after 10 years.

2.3.2 Variance Decomposition

Variance decomposition in the VAR model is used to analyze the contribution of structural shocks to the endogenous variables. It helps determine the importance of the relationships between variables. By conducting variance decomposition, information regarding the relative importance of each random disturbance in influencing the variables in the VAR model can be obtained. Orthogonal variance decomposition methods are well-suited for describing the degree of influence. Therefore, this study adopts orthogonal variance decomposition. According to the equation:

$$y_{it} = \sum_{j=1}^{k}\left(c_{ij}^{(0)}\varepsilon_{jt} + c_{ij}^{(1)}\varepsilon_{jt-1} + c_{ij}^{(2)}\varepsilon_{jt-2} + c_{ij}^{(3)}\varepsilon_{jt-3} + \cdots\right) \quad (11)$$
$$i = 1,2,\ldots,k, t = 1,2,\ldots,T$$

we can derive:

$$\operatorname{var}\left(y_{it}\right) = \sum_{j=1}^{k}\left\{\sum_{q=0}^{\infty} c_{ij}^{(q)^2}\sigma_{jj}\right\} \quad (12)$$
$$i = 1,2,\ldots,k; t = 1,2,\ldots,T$$

Defined as the contribution of the uncorrelated variables in k, the degree to which the measuring variance contributes to the shock is as follows:

$$RVC_{j-i(\infty)} = \frac{\sum_{q=0}^{\infty} c_{ij}^{(q)^2}\sigma_{jj}}{\operatorname{var}(y_{it})} = \frac{\sum_{q=0}^{\infty} c_{ij}^{(q)^2}\sigma_{jj}}{\sum_{j=1}^{k}\left\{\sum_{q=0}^{\infty} c_{ij}^{(q)^2}\sigma_{jj}\right\}} \quad (13)$$
$$i, j = 1,2,\ldots,k$$

This is known as the relative variance contribution (RVC), which shows the dynamic relationship between variables relative to the benchmark variance.

Generally, $c_{ij}^{(q)}$ of $s=\infty$ is used to analyze the result, and the corresponding shock effect can be obtained by analyzing the variance.

The forecast error variance for the early period of the $\mathrm{VAR}(p)$ model is:

$$C_0\varepsilon_t + C_1\varepsilon_{t-1} + C_2\varepsilon_{t-2} + \ldots + C_{s-1}\varepsilon_{t-s+1}, C_0 = I_0$$
$$RVC_{j\to i(s)} = \frac{\sum_{q=0}^{\infty} c_{ij}^{(q)^2}\sigma_{jj}}{\sum_{j=1}^{k}\left\{\sum_{q=0}^{\infty} c_{ij}^{(q)^2}\sigma_{jj}\right\}}, i, j = 1,2,\ldots,k \quad (14)$$

where $RVC_{j\to i(s)}$ satisfies:

(1) $0 \le RVC_{j\to i(s)} \le 1, i, j = 1,2,\ldots,k$

(2) $\sum_{j=1}^{k} RVC_{j\to i(s)} = 1, i, j = 1,2,\ldots,k$

By conducting variance decomposition on the economic factor in the carbon emissions influencing factors, it is found that the forecast variance of the economic factor is entirely derived from the economic factor itself (60.03%), while the remaining 25.62%, 11.23%, and 3.12% come from energy consumption, electricity consumption, and carbon emissions, respectively. This result indicates that the economy is mainly influenced by itself, while the roles of energy consumption, electricity consumption, and carbon emissions are relatively small. The variance decomposition results for energy consumption show that 79.45% of the variance comes from energy consumption itself, with 17.11% coming from the economy, 2.69% from electricity consumption, and 0.74% from carbon emissions. For electricity consumption, 7.15% of the variance is from itself, 60.34% is from energy consumption, 30.60% is from the economy, and 1.91% is from carbon emissions. The variance decomposition results for carbon emissions show that carbon emissions are primarily influenced by the economy (66.64%), followed by energy consumption (27.03%), electricity consumption (16.12%), and finally, by itself (1.03%).

3. Analysis of Jinhua "Carbon Peaking" Goal

3.1 Prediction Method of Carbon Emissions

The STIRPAT model has been widely used in environmental impact assessment (Zhu et al., 2010)[20], and its equation is given as: $I = aPbAcTde$, where I represents the environmental pressure, a signifies the model coefficient, P denotes the electricity factor, A means the economic factor, T represents the technological factor, and e signifies the error term. The STIRPAT model is an expandable stochastic assessment model that extends the factors included in the traditional STIRPAT model to evaluate and analyze multiple factors influencing the environment. Taking the logarithm of the basic expression, we obtain the following equation:

$$\ln I = \ln a + b\ln P + c\ln A + d\ln T + \ln e \quad (15)$$

Combining the results obtained from the LMDI decomposition technique and existing research, this study adds the energy mix factor and industrial structure factor to the existing electricity scale, economic factor, and technological factor. It should be noted that energy intensity reflects the energy consumption per unit of output and can reflect the production efficiency and production technology. Therefore, this study uses energy intensity (EE) to measure the technological factor and uses the proportion of coal consumption in energy consumption (ES) and the proportion of value added by the secondary industry in regional gross domestic product (IS) to measure the energy mix and industrial structure, respectively. The expanded STIRPAT model is as follows:

$$\ln I = \ln a + b\ln N + c\ln G + d\ln EE + f\ln ESI + g\ln IS + \ln e \quad (16)$$

where a is the constant term, b, c, d, f, g are the coefficients of each index term, and e is the error term.

The estimation results of the expanded model using OLS show an adjusted R^2 of 0.98 and an F-value of 154.612. However, multiple independent variables have VIF values greater than 10, indicating that the multicollinearity test is not passed. To address the issue of multicollinearity, ridge regression estimation is employed, and the ridge trace plots for each variable under different parameter values K are obtained, as shown in Figure 2.

According to the results displayed in the ridge trace plots, when the standardized regression coefficients of all explanatory variables approach a stable state, the value of K is 0.01. Therefore, taking K=0.01, a second ridge regression is conducted, resulting in an adjusted R^2 of 0.98, significant F-test and T-test results for all variables, and obtaining the model regression equation:

$$\ln I = -26.386 + 4.016\ln N + 0.559\ln G + 0.392\ln EE + 0.311\ln ES + 2.166\ln IS$$

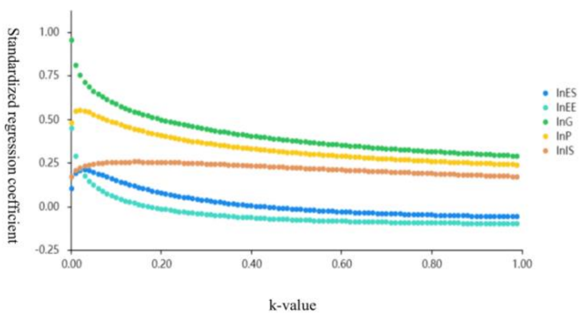

Figure 2. Ridge trace plot

3.2 Scenario Analysis

Based on the development trends and changes in different influencing factors in Jinhua in recent years, three forecasting scenarios, namely the baseline, low-carbon, and high-speed scenarios are determined. For each scenario, the boundary settings for the variables related to population factors, economic factors, and technological factors influencing carbon emissions are defined to forecast the development trend of carbon emissions in Jinhua and predict the peaking time of carbon emissions and the time to achieve carbon neutrality.

3.2.1 Baseline Scenario

In the baseline scenario, the current development patterns of energy, electricity, economy and technology are maintained, and emission reduction policies are actively implemented to achieve economic development and increase household income as the main driving factors (Yin et al., 2021)[21]. The economic factor is set based on the established national economic development goals. The technological factor takes into account policy and planning targets related to energy mix and intensity, and appropriate trend changes are set.

Electricity factor: As electricity demand is closely related to social development, when the social development level and other relevant conditions are similar or fixed, electricity demand is proportional to the population size. In this study, the growth trend of electricity scale in Jinhua is deduced based on population. From 2003 to 2020, the average population growth rate in Jinhua was 1.02%. The population growth rates for different periods in the investigation period were as follows: 0.91% from 2005 to 2010, 0.79% from 2010 to 2015, and 1.68% from 2015 to 2020, showing a trend of initial decline followed by an increase. Considering the current situation of slow population growth in the social environment, the predicted range for the electricity demand growth rate will be between 0.1% and 0.9%, showing a slow declining and then rising trend.

Energy intensity: The total energy consumption in Jinhua increased by 48.5% from 2012 to 2020, with an average annual growth rate of 4.5%. During the “12th Five-Year Plan” and “13th Five-Year Plan” periods, the energy consumption intensity in the city decreased by 16.3% and 15.2%, respectively, exceeding the planned targets by 0.3 and 0.2 percentage points. From 2003 to 2020, the energy intensity in Jinhua showed a decreasing trend with an average annual growth rate of -4.66%. A lower energy consumption per unit of GDP is favorable for decoupling economic development from energy consumption. It is predicted that the energy intensity will gradually decrease by 0.01% each year.

Energy mix: By 2025, the target for clean energy consumption in Jinhua is striving to reach 23.1%, and coal consumption is controlled at around 26%. The share of coal consumption in energy consumption is expected to decrease from 31.9% in 2020 to 26%, while the share of clean energy will increase from 10.8% to 23.1%. To achieve the goals of the “14th Five-Year Plan”, the proportion of coal energy consumption is assumed to increase at a rate of -0.08%. Considering China's dual carbon development goals, the proportion of coal in energy consumption may become negligible or zero after achieving carbon neutrality. Therefore, it is expected that the growth rate of coal energy consumption will decrease annually by 0.3% starting from 2035.

Industrial structure: From the perspective of industrial structure, Jinhua has transitioned from being dominated by the secondary industry to being dominated by the tertiary industry. In 2016, the ratio of the three major industries in Jinhua was 7.24: 49.59: 43.16, and by 2020, it changed to 6.22: 46.3: 47.47, indicating a balance between the secondary and tertiary industries. Therefore, the predicted growth rate of the proportion of the secondary industry from 2020 to 2025 is 1.6%. The proportion of value added by the secondary industry in Jinhua gradually increased from 2003 to 2012 but began to decline after 2014. Based on the data, the proportion of the secondary industry in Jinhua initially increased and then decreased. It is predicted that the proportion of the secondary industry in Jinhua will decrease from 50% to 33% from 2025 to 2060.

Per capita GDP: According to the target of "annual average growth of 5.4% in per capita GDP by 2025", it can be inferred that Jinhua's per capita GDP will reach 92,000 yuan per person in 2025. The annual growth rates for per capita GDP from 2021 to 2025 are set at 9%, 7%, 5%, and 4%. Based on the results of the decomposition model mentioned earlier, the level of economic development has a significant impact on carbon emissions in Jinhua. Implementing carbon emission reduction measures may affect the economic growth rate. However, Jinhua has a solid industrial foundation and an active private economy, indicating potential economic strength. Therefore, the parameter is set at 9%, and the growth rate of per capita GDP will decrease annually after 2035.

3.2.2 Low-carbon Scenario

In the low-carbon scenario, the growth rates of electricity scale, per capita GDP, energy intensity, industrial structure, and energy mix are increased by 0.01%, 0.05%, 0.06%, 0.1%, and 0.06%, respectively, compared to the baseline scenario. In the low-carbon scenario, it is predicted that the proportion of the secondary industry in Jinhua will be adjusted from 50% to 30% from 2025 to 2060.

3.2.3 High-speed Scenario

In the high-speed scenario, the growth rates of electricity scale, per capita GDP, energy intensity, and energy mix are increased by 0.01%, 0.05%, 0.06%, and 0.08%, respectively, compared to the low-carbon scenario. In the high-speed scenario, it is predicted that the proportion of the secondary industry in Jinhua will be adjusted from 50% to 26% from 2025 to 2060.

According to the growth rates set for different scenarios, the STIRPAT model is used to predict the carbon dioxide emissions in Jinhua from 2021 to 2060. The predicted results are shown in Figure 3.

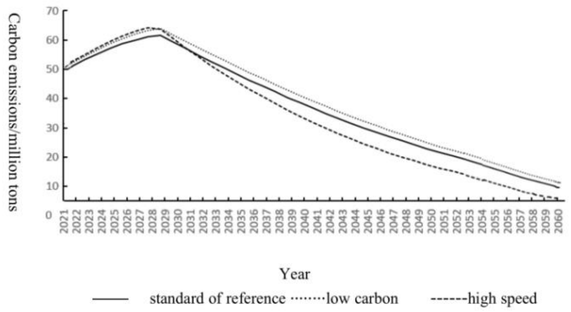

Figure 3. Carbon emissions trends under different scenarios in Jinhua

From Figure 3, it can be observed that the high-speed scenario reaches carbon peaking earliest. In the high-speed scenario, Jinhua's carbon emissions from energy consumption will reach their peak in 2027. In the low-carbon scenario, it is in 2028. And in the baseline scenario, it is in 2029. The carbon peaking values decrease in the order of scenarios, with the lowest peak value being 61.7 million tons.

In the post-industrial development stage, economic growth does not exacerbate the increase in carbon emissions, as seen in the downward part of the inverted U-shaped Environmental Kuznets Curve. Therefore, the high-speed scenario reaches the carbon emissions peak first. The low-speed development scenario represents a low-growth economy with high carbon emissions. Slow economic growth, lagging technological upgrades, low growth in electricity demand and energy consumption, and high energy intensity and imbalanced energy mix pose challenges to achieving low-carbon development (Li and Liu, 2022)[22]. Thus, Jinhua's carbon peaking is achieved latest in the low-speed development scenario. The baseline development scenario falls between the aforementioned scenarios. Therefore, the conclusion drawn is that the high-speed development scenario is the most favorable path for Jinhua to achieve carbon peaking. It enables high economic growth while promoting low-carbon economic development through technological progress, leading to a reduction in energy consumption and energy intensity. This path facilitates the achievement of carbon peaking and carbon neutrality goals.

4. Conclusions and Recommendations

Under the "dual carbon" goals, the optimization of the energy mix will present many opportunities for high-quality, low-carbon, and sustainable economic development. This study employs the LMDI decomposition technique and hidden Markov chain to analyze the factors influencing carbon emissions in Jinhua. Furthermore, the dynamic relationships between these factors are explored using a panel vector autoregression (VAR) model. Additionally, an improved STIRPAT model is used to predict the peaking time of carbon emissions in Jinhua, and the future trends of carbon emissions are forecasted based on three scenarios: baseline scenario, low-carbon scenario, and high-speed scenario. Based on the conclusions drawn from this study, the following policy recommendations are proposed:

Provide more guidance on the policy options. As carbon emissions have negative externalities which cannot be solved by market mechanisms alone, proactive government intervention is necessary to establish corresponding emission reduction policies, such as implementing a carbon tax market, which can encourage enterprises to reduce emissions by influencing the costs. Due to the technological constraints, renewable energy has relatively higher overall costs compared to coal. In this regard, the government in Jinhua can incentivize the use of clean electricity through policies such as policy incentives, carbon taxes, pollutants emissions trading and subsidies.

(2) Phase down coal consumption. Due to resource endowment and energy prices, coal remains the largest source of power generation in Jinhua. But the coal-based energy mix has caused environmental pollution. For a smooth-running economy, a drastic reduction in coal consumption is not feasible in the short term. However, considering the severe pollution caused by coal, Jinhua should strive for moderate development of the coal industry. The government should establish a reasonable coal development scale, accelerate the optimization and integration of the coal industry, and promote industrial upgrading while ensuring orderly supply. In addition, on the end-use side, efforts can be made to cut direct coal consumption and increase the proportion of clean energy sources in the energy system.

(3) Adopt multiple measures to achieve carbon neutrality. The key to achieving carbon neutrality lies in the clean transformation of the energy sector, which is reflected in the clean transformation of the energy mix. Given the coal-dependent energy system in China, a clean energy mix requires a long-term commitment to dual control on energy, market-oriented carbon emissions and the development of carbon capture and storage technologies. This entails a combination of administrative, market-based, and technological approaches.

References

1. Lin,Y.F.(2019)China needs to deal with environment and climate change issues with a developmental perspective: the perspective of new structural economics[J]. Environmental Economics Research,4(04):1-7.
2. Ji,X.Q. ,Liu, H.M,Zhang,Y.S. (2023)Evolution of spatial correlation network structure and driving factors of carbon emissions from interprovincial land use in China[J]. Economic Geography,43(02):190-200.
3. Yuan,J.H,Xu,Y,Hu,Z,Zhao,C.H.,Xiong,M.P.,Guo,J.S.(2014)Peak energy consumption and CO 2 emissions in China[J]. Energy Policy,68.
4. Zhang,X., Wang, J.Y.(2022) Nonlinear Impact Analysis of China's Economic Growth on Carbon Emissions: An Empirical Study Based on PSTR [J]. Research on Technology Economy and Management,(11):27-32.https://fanyi.baidu.com/translate?query=&keyfrom=baidu&smartresult=dict&lang=auto2zh - ##
5. Zhu,B.Z.,Ye,S.X.,Wang,P.,He,K.J.,Zhang,T.,Xie,R., Wei,Y.M. (2019)Exploring the drivers of energy consumption-related CO2 emissions in China: a multiscale analysis[J]. Energy Efficiency,12(4).
6. Xu,J.W.(2023)Does population mobility suppress urban carbon emissions? --A Quasi-Natural Experiment Based on the Reform of Dualistic Household Registration System[J]. Journal of Hubei University (Philosophy and Social Science Edition),50(02):148-158.
7. Liu, X.Y.,Bao,J.H.,Sun,W.N.(2023) Carbon Emission Trading, Industrial Transformation and Upgrading and High Quality Economic Growth[J]. Technical Economics and Management Research,(01):116-122.
8. Wang,X,Tian,G,Yang,D,et al.(2018) Responses of PM2.5 pollution to urbanization in China[J]. Energy Policy,123:602-610.
9. Mujeeb Sana,Javaid Nadeem.(2023)Deep learning based carbon emissions forecasting and renewable energy's impact quantification[J]. IET Renewable Power Generation.17:873-884.
10. Li,J.C.,Lu,S.Q., Guo,Z.Q.(2023)A study of inter-provincial carbon emission forecasting and peaking scenario simulation in China[J]. Technical Economics and Management Research,(03):21-25.
11. Wang,Y., Xu, Z.Y., Zhang, Y.X. (2019)Influencing factors and combined scenario projections of carbon emissions peaking in Chinese megacities - a study based on the threshold-STIRPAT model[J]. Journal of Environmental Science,39(12):4284-4292.
12. Wang, L.J., Zhang, J., Wang, X.S., Chen, X.J., Song,X.H., Zhou,L.G. ,Yan, G. (2022)A study on the peak CO2 emission pathway in China's power sector[J]. Environmental Science Research,35(02):329-338.
13. Rahmaditio M R;Gardian P I.(2023)Projection of Carbon Emissions from the Diesel, Biodiesel, and Battery Electric Vehicle in Indonesia: A Policy Scenario Analysis for Decarbonization of Transportation Sector[J].IOP Conference Series: Earth and Environmental Science. 1199.
14. Aras Serkan,Hanifi Van M.(2022)An interpretable forecasting framework for energy consumption and CO2 emissions[J]. Applied Energy.328.
15. Zhou,Z.Y., Duan,J.N., Xiang,C.S.(2011)Gray correlation analysis of China's energy structure based on the perspective of low carbon economy[J]. Ecological Economy,03:55-58.

16. Fan,D.C., Wang,S.H., Zhang,W.(2015) Analysis of influencing factors of primary energy consumption structure under low carbon economy target[J]. Resource Science,04:696-703.
17. Tang,Y.N.,Yan,R.X., Zhou,Y.L. (2023)Structural Characterization and Optimization Path of Energy Policy under Carbon Neutral Vision[J]. Journal of Tsinghua University (Natural Science Edition),63(01):1-14.
18. Wang,M.,Zhu,C.Z.,Cheng,Y.,Du,W.B.,Dong,S.(2022) The influencing factors of carbon emissions in the railway transportation industry based on extended LMDI decomposition method: evidence from the BRIC countries.[J]. Environmental science and pollution research international,30(6).
19. Hu, Z.,He,J.J.,Wang,Y. (2018)Analysis of the factors of household carbon emissions in Japan based on the IPAT-LMDI extended model and implications[J]. Resource Science,40(09):1831-1842.
20. Zhu, Q., Peng,X.Z.,Lu,Z.M., Yu, J.(2010) Analysis model and empirical analysis of the impact of population and consumption on carbon emissions [J]. China Population, Resources and Environment,20 (02): 98-102.
21. Yin,L.,Yang,Y.Y., Zhang,L.C.(2021)Prediction and Analysis of Peak Carbon Emissions from Chinese Residents' Consumption [J]. Xinjiang Social Sciences, No.233 (04): 42-50+168.
22. Li,J.J., Liu,X. (2022)Impact factors of carbon emissions in Ningxia and prediction of carbon peak [J]. Journal of South Central University for Nationalities (Humanities and Social Sciences Edition), 42 (07): 116-124+185-186.